EXAMINING THE SPATIAL INFLUENCES OF NATURAL CAPITAL IN THE AUSTRALIAN AGRICULTURAL LANDSCAPE

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List of Abbreviations

^0C	Celsius
%	Percentage
ABARES	Australian Bureau of Agricultural and Resources Economics and Science
ABS	Australian Bureau of Statistics
ACO	Australian Certified Organic
ACOCL	Australian Certified Organic Corporation Limited
ACT	Australian Capital Territory
AET	Actual Evapotranspiration
AIC	Akaike Information Criteria
ALA	Atlas of Living Australia
AML	Adelaide and Mount Lofty ranges
ASGS	Australian Statistical Geography Standard
ATO	Australian Taxation Statistics
AUD$	Australian Dollar
AWAP	Australian Water Availability project
AW	Alinytjara Wilurara
BDRI	Bio-Dynamic Research Institute
BIC	Bayesian Information Criteria
BoM	Bureau of Meteorology
BSR	Bird Species Richness
CA	Conventional Agriculture
cm	Centimetre
CPI	Consumer price index
CSIRO	Commonwealth Scientific and Industrial Research Organisation
DAWE	Department of Agriculture, Water and the Environment
DEW	Department for Environment and Water

DISER	Department of Industry, Energy and Resources
DPTI	Department of Planning, Transportation , and Infrastructure
ECQ	Electoral Commission of Queensland
ECSA	Electoral Commission of South Australia
EP	Eyre Peninsula
EPA	Environment Protection Authority
ESRI	Environmental Systems Research Institute
FAO	Food and Agriculture Organization
FiBL	Research Institute of Agriculture
GA	Geoscience Australia
GHG	Greenhouse Gas
GIS	Geographic Information System
GNS	General Nesting Model
GPP	Gross Primary productivity
ha	Hectare
IFOAM	International Federation of Organic Agriculture Movement
IPBES	Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services
IPCC	Intergovernmental Panel on Climate Change
KI	Kangaroo Island
km	Kilometre
km^2	Square kilometre
m	Metre
mm	Millimetre
NASAA	National Association for Sustainable Australia
NCO	National Association for Sustainable Australia Certified Organic
NDVI	Normalised Difference Vegetation Index
NPP	Net Primary Productivity
NRM	Natural Resource Management

NSW	New South Wales
NSWEC	New South Wales Electoral Commission
NT	Northern Territory
NTEC	Northern Territory Electoral Commission
NY	Northern and Yorke
OA	Organic Agriculture
OFC	Organic Food Chain
OLS	Ordinary Least Square
OVG	Office of the Valuer-General
PET	Potential Evapotranspiration
PSR	Plant Species Richness
QLD	Queensland
R & D	Research and Development
RA	Remoteness Area
SA	South Australia
SA2	Statistical Area Level 2
SAAL	South Australian Arid Land
SAC	Spatial Autoregressive Combined
SAMDB	South Australian Murray Darling Basin
SAR	Spatial Autoregressive Model
SDEM	Spatial Durbin Error Model
SDM	Spatial Durbin Model
SE	South East
SEIFA	Socio-Economic Index for Areas
SEM	Spatial Error Model
SLX	Spatial Lag of X
SP	Sales Price
SXC	Southern Cross Certified Australia

TAS	Tasmania
TEC	Tasmanian Electoral Commission
UCL	Urban Centre and Localities
US$	American dollar
USA	United States of America
USDA	United States Department of Agriculture
VEC	Victorian Electoral Commission
VIC	Victoria
VIF	Variance Inflation Factor
VP	Valuation Price
WA	Western Australia
WEF	World Economic Forum
WG	Wentworth Group
WWF	World Wide Fund for Nature

Glossary of Terms

Actual evapotranspiration	Indicates estimated total evapotranspiration (water removal) from soil, vegetation, and groundwater.
Adoption	A change in practice and technology used by economic agents or a community
Biodiversity	Includes diversity within and among plant and animal species and ecosystems
Broadacre crops	Indicates large scale agricultural production of grains, oilseeds and other crops. The term is mainly used in Australia.
Certified organic farming	A less intensive farming system that follows the rules set by certification bodies and operates without the application of synthetic fertilisers, pesticides, herbicides, and genetically modified varieties.
Conventional agriculture	Refers to the farming systems which utilises synthetic chemical fertilisers, pesticides, herbicides, and other continual inputs and characterised by capital intensiveness and large-scale mechanised operations
Diffusion	The process by which an innovation is communicated through certain channels, over time, among members of a social system
Drought	Acute shortage of water and soil moisture mainly resulting from rainfall deficiency over an extended period of time. From an environmental and social perspective drought can be defined as: meteorological (determined by extent and severity of rainfall deficiency and evapotranspiration), hydrological (depletion of groundwater level usually after many months of meteorological drought), agricultural (reduction of crops and pastures yield because of reduced soil water availability and low rainfall) and socio-economic (adverse effects of the earlier mentioned droughts on society)
Ecosystems	The living and non-living components of the earth that interact with each other and provides benefits for humanity.
Ecosystem services	The benefits obtain from the ecosystems which has direct and indirect impact on human well-being
Environmental heterogeneity	An umbrella concept to describe the gradients in land cover, climate, soil, topography, and vegetation.
Environmental steward	An individual or entity engaged in the sustainable use of natural and environmental resources and its functions.
Geocoding	The process of transforming a description of a location (e.g. pair of coordinates, an address or a name of place) to a location on the earth's surface

Hedonic pricing	Most commonly used revealed preference non-market valuation methods used for differentiated market goods and services
Millennium drought	The prolonged hydrological drought that affected majority of south-eastern Australia with varying degree spanning between 2001/02 to 2009/10.
Native Vegetation Management Act 1991	The act was designed to protect the native vegetation in Australia from further clearing by setting out procedure for vegetation clearance application and ensures the protection of areas with high conservations values.
Natural capital	Refers to the stock of assets (renewable and non-renewable natural resources, such as native flora, soil, air, water, and native fauna) that provide the flow of ecosystem goods and services and which have direct and indirect impacts on the global economy and human wellbeing
Potential evapotranspiration	The amount of evaporation that would occur if sufficient water source were available
Spatial data	
Spatial dependence	Observations at one location are influenced by observations in the neighbouring areas.
Spatial econometrics	A subfield of econometrics, accounts for the interaction effects among geographical units (e.g. locations, zip codes, counties, regions, states, countries) and the behaviour of economic agents.
Spatial heterogeneity	Results from location factor/spatial units (counties and states) and contextual variation over space.
Species richness	The number of different species within a sample, community, or area.
Unbundling	The legal separation of water use rights from land rights.
Valuation price	Property valuation is estimated by comparing individual property values with recently sold similar types of properties in the same area or comparable locations, with relevant adjustments made according to market fluctuations. This valuation is used for rating and tax assessment purposes in Australia.

Abstract

Overall, this thesis seeks to explore – using three case studies - the environmental and economic influences and outcomes of on-farm natural capital in the Australian agricultural landscape over space and time. In particular, it explored: 1) the spatial influences on the adoption of certified organic farming (which is used as a proxy indicator of natural capital conservation technologies) at a regional level in Australia using agricultural census data from 2010/11 and 2015/16; 2) the association between the presence of certified organic farming and regional biodiversity at the postcode level over sixteen years in South Australia; and 3) the association between farm land value and natural capital in the forms of native woody vegetation coverage and climate in South Australia over sixteen years.

The first case study focused on Australia as a whole and modelled farmers' adoption behaviour of certified organic farming (using it as a proxy for sustainable agriculture technologies to conserve on-farm natural capital such as soil, water, and biodiversity). Spatial diffusion of organic farming represents an interesting case study, given the large amount of skills and knowledge regarding management of natural resources that organic farmers need to apply/learn for their farms' viability. Although farmers' adoption and diffusion behaviour is well studied in the literature, modelling of the role of spatial spill-over effects on diffusion intensity, especially in regards to the adoption of organic farming, is not well known. This thesis uses national Australian agricultural census data from 2010/11 and 2015/16 and a SLX Tobit model (N=2,134) to model the influences on the intensity of the diffusion of organic farming (namely percentage of organic land holding) in regional areas, and found statistically significant local spatial spill-over effects from neighbouring regions' characteristics. In addition, a higher share of organic farmland in regions is associated with regional characteristics such as: larger irrigated farms; lower stocking rates; increased proportion of grazing and horticultural land; increased labour supply; increased green vegetation; rural areas with low human population density; and higher community income.

The second study explored the associations between farmers' land use behaviour (i.e. the extent of certified organic farming in a region) and regional biodiversity outcomes (vascular plant and bird species richness) at the postcode level. This study put together a new dataset on certified organic farming presence and locations in South Australia, using databases from organic certifiers. The spatial association between biodiversity indicators and organic farming was

analysed using a spatial Durbin error model, while controlling for the effects of landscape attributes, human population footprint, climate and productivity from 2001 to 2016 (N=5,456) in South Australia. The results found that increased organic farming presence in postcode areas had a statistically significant positive association with vascular plant species richness, but little to no statistically significant association was found for bird species richness. Environmental heterogeneity in terms of land cover diversity, elevation range, and plant productivity seems to be the other prime determinants of plant and bird species richness.

The third study focused on the association between native woody vegetation on agricultural properties and their economic values in South Australia, using both sales and valuation prices of agricultural properties from 1998 to 2013 (N=10,513). Findings from the spatio-temporal Durbin model revealed that the presence of native woody vegetation on agricultural properties significantly increased the per hectare market price (i.e. price sold in the market), but at a decreasing rate as the proportion of vegetation increased. The marginal return of vegetation was highest for small size properties and lowest for larger properties. In addition, the direct effects of increased annual rainfall, increased soil natural productivity, increased market accessibility, proximity to locational amenities, smaller size properties, availability of irrigation, and higher commodity price were also positively capitalised into sales prices. On the other hand, increased drought and high soil erodibility significantly reduced per hectare sales prices. Comparing valuation price models with sales price models, it was found that the valuation prices seem to undervalue the presence of native vegetation on agricultural properties and hence provide weaker evidence of the value of on-farm natural capital in the South Australian context.

Declaration

I certify that this work contains no material which has been accepted for the award of any other degree or diploma in my name in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text. In addition, I certify that no part of this work will, in the future, be used in a submission in my name for any other degree or diploma in any university or other tertiary institution without the prior approval of the University of Adelaide and where applicable, any partner institution responsible for the joint award of this degree.

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Chapter 1 Introduction

1.1 Natural capital around the world

The current growth path of rising living standards (economic growth) accompanied by the massive increase in consumption of material resources and energy over the past century has led to overexploitation of the world's stock of natural and environmental assets beyond their capacity to sustain themselves (Foley et al. 2011; Tilman et al. 2011; Tilman et al. 2001). A healthy environment is fundamental to sustaining the economy and the wellbeing of society. To create a sustainable future it is crucial to understand the effects of environmental degradation on economic activity and social welfare. The World Economic Forum's Global Risk Survey in 2018 nominated loss of biodiversity and associated collapse of the ecosystem, water and food crises, extreme weather events, failure of climate change adaptation and mitigation as the top four long-term global environmental risks facing the world (WEF 2018).

Natural and environmental assets (i.e. natural capital) are under increased pressure across the globe due to intensified agricultural production practices to meet the growing demand for food (Reganold and Wachter 2016). 'Natural capital' refers to the stock of assets (renewable and non-renewable natural resources, such as native flora, soil, air, water, and native fauna) that provide the flow of ecosystem goods and services and which have direct and indirect impacts on the global economy and human wellbeing (Costanza et al. 1997; Daily et al. 2009; Zhang et al. 2007). The degradation and depletion of natural capital negatively impacts the functioning of ecosystem services on which the productivity and profitability of agricultural sectors rely (FAO 2015). Ecosystem services are broadly classified into four categories: provisioning (food, fibre, bioenergy); supporting (pollination, biological control, carbon accumulation, biodiversity, soil formation); regulating (climate regulation, water regulation, water supply, erosion control, nutrient retention); and cultural (aesthetic, recreational, spiritual) (Bryan 2013; Ma and Swinton 2011; Sandhu et al. 2012).

1.1.1 Global situation

Although agricultural intensification through increased use of chemical fertilisers, insecticides, pesticides, and herbicides has been successful in increasing yield across the world, it is argued that it has come at a cost. One such cost is a loss of biodiversity – 1.5 billion hectares of world's natural ecosystems had been converted for agricultural activities by 2014 (IPBES 2018); on average 68% species (birds, mammals, amphibians, and fish) population size declined between

1970 and 2016 globally (WWF 2020), which is projected to reach 38-46% by 2050 (IPBES 2018); 8.9% reduction of overall species richness as reported in a recent global meta-analysis based on 115 studies and 449 cases covering a variety of agricultural activities (Beckmann et al. 2019); 12.9% reduction of forest cover between 1990 and 2015 in the Southeast Asia (IPBES 2018).

Li et al. (2020) found a decline of bird biodiversity (3-4%) in the USA between 2008 and 2014 due to use of neonicotinoid insecticides in agriculture. Another study by Hallmann et al. (2014) in the Netherlands also found annual reduction of bird population by 3.5% associated with the concentration of neonicotinoid insecticides in the surface water of more than 20 nanograms per litre. Varah et al. (2020) estimated that resistance of weeds to herbicides in England led to a reduction in potential gross margins (7-37% per hectare) and significant wheat yield loss (5% of estimated average potential yield per hectare). Land degradation caused annual global emissions of carbon dioxide of up to 4.4 billion tonnes between 2000 and 2009 (IPBES 2018). In addition, the volatility of climatic conditions and more frequent extreme weather events, like flood and drought, aggravate the situation (IPCC 2019).

1.1.2 Australian situation

Agriculture is a dominant form of land use in Australia, occupying 51% of terrestrial land area during 2016/17 (ABS 2016f) and has critical impact and dependence on the stock of natural capital in the form of ecosystem services (Sandhu et al. 2012; Zhang et al. 2007). For example, in 2015/16, 59% of total water in Australia was used for agricultural activities (Jackson et al. 2020). Agriculture contributed 2.2% to the gross domestic product, 11% of all goods and services exports and was employed 2.6% of the total labour force in 2018/19 (Jackson et al. 2020), but, at the same time was a major contributor (13.5%) to nation's net greenhouse gas (GHG) emissions (DISER 2020).

Australia - the driest inhabited continent faces varying climatic condition and ecosystems (Daghagh Yazd et al. 2020; Hughes et al. 2019; Wheeler et al. 2020). Changing climatic condition - average temperature warmed by 1.44 ± 0.24^{o}C since 1910; altered winter rainfall pattern; more frequent and intense drought (reported in Figure A.1-Figure A.4 in appendix A) poses serious threat to Australian agriculture (BoM and CSIRO 2020) and have varying degree of socio-economic, agricultural, hydrological and environmental impacts depending on the duration and spatial extent of the event on Australian farmers (Daghagh Yazd et al. 2020; Fennell et al. 2016). The maximum temperature anomalies increased in size and frequency.

Although there is great volatility, the absolute volume of rainfall does not seem to have declined over the past 100 years (CSIRO 2012).

Agricultural development since the European settlement in 1788 in Australia has generated significant economic and social benefits, but these benefits have sometimes come at a high cost. Costs include the depletion of the stock of natural capital and associated ecosystem services such as soil compaction and erosion, salinity, loss of biodiversity through overgrazing and land clearing, greenhouse gas emissions, and water pollution (De Valck and Rolfe 2019; Pittock et al. 2012; Smith and Sullivan 2014; Wheeler 2011). Since European colonisation over 40% of forest and woodland have been cleared (Bradshaw 2019; Evans 2016; Reside et al. 2017) and Australia is one of the hotspots of deforestation – 30% of native bird species lost 30% of their potential natural habitat (Simmonds et al. 2019). This two-way linkage (positive and negative effects) between natural capital and agriculture emphasise the important role that agricultural landholders land management decisions have on the sustainable use of natural and environmental resources embodied to agriculture (Bryan 2013; Rolfe et al. 2017; Smith and Sullivan 2014).

The impact and dependence of primary industries, particularly agriculture, on natural and environmental capital (the core asset in a farm's balance sheets, as in any other business) is gaining increasing attention (Azad and Ancev 2020). As a result, initiatives are being undertaken for sustainable management of natural resources (Pittock et al. 2012; Rolfe and Harvey 2017; Rolfe et al. 2017; Wheeler and Marning 2019). To ensure sustainable management of natural resources, it is important to understand: their overall condition; how efficiently these resources are being used; and how anthropogenic land use is affecting these resources. It is important to know how the resources which underpin the sustainability of farm businesses are being valued by farmers, and whom are the primary de facto managers of a significant part of the world's portion of natural capital - such as water, biodiversity, and soil (Reganold and Wachter 2016; Smith and Sullivan 2014). The benefits of accounting for natural capital include:

- The ability to measure the performance (success and/or failure) of public investments (regions, local governments, states, territories, and national governments) in natural resource management;
- Increased efficiency of expenditure through effective targeting of investment;

- An increasingly informed community, leading to less conflict and enhanced community effort;
- A cost-effective pathway for industry, farmers, and other land managers, to demonstrate the sustainability of their business practices; and
- Providing the information that is needed for society to adapt as climate change imposes its footprint across the landscape (WG 2016).

In addition, the unaccounted environmental cost (in the form of GHG emissions, air and water pollution, loss of potential natural habitat) associated with agricultural activities widens the disparity between retail food prices and the true cost of food production, which frequently makes the output of conventionally[1] farmed (conventional agriculture) products cheaper than products which are produced more sustainably (FAO 2015; Wheeler 2011).

Numerous national and international organisations/groups in the private (e.g. National Capital Coalition), the public (e.g. Wealth Accounting and the Valuation of Ecosystem Services), and the financial (e.g. Natural Capital Declaration) sectors have been formed as one way to try to address and highlight the risks imposed by the degradation of natural capital. Such frameworks aim to put a monetary value on the stocks of natural capital to indicate the consequences of its degradation and better inform strategic decision-making (Ascui and Cojoianu 2019; Azad and Ancev 2020).

Farm management practices that aim to conserve natural capital at the farm-level, coupled with technological advancement, could open up opportunities for the long-term sustainability of agriculture (the front-line sector of climate change's impact) in the rapidly evolving, consumer driven, market in several ways. Firstly, for landholders, the productivity and profitability of agriculture depends on well-functioning natural capital such as soil, water, and vegetation (Wheeler and Marning 2019). Secondly, consumers are growing more concerned about the increasingly detrimental effects of intensified agricultural practices, leading to clearer recognition of (and the willingness to pay for) the adoption of various sustainable agricultural practices to achieve increased productivity in a sustainable manner (Läpple et al. 2017; Wheeler et al. 2019). Thirdly, in the agricultural land market, buyers and sellers of properties also take into account the value of properties' inherent natural capital stocks (Polyakov et al.

[1] Conventional agriculture refers to the farming systems which utilises synthetic chemical fertilisers, pesticides, herbicides, and other continual inputs and characterised by capital intensiveness and large-scale mechanised operations (Wheeler 2011).

2015; Samarasinghe and Greenhalgh 2013). Finally, for leading financial institutions, like the National Australia Bank and Rabobank, assessing the inclusion of on-farm natural capital stocks acts as buffer against credit risk in agricultural lending (Ascui and Cojoianu 2019; Azad and Ancev 2020).

The important role of alternative farm management practices that help to sustain the stock of natural capital is well recognised. Therefore, it is important to understand which factors influence the spatial adoption and diffusion process of alternative farm management practices. Also, its influence on the environmental and economic outcomes that underpins the profitability and productivity of agriculture in the long-run.

1.2 Organic agriculture and conservation of natural capital

Certified organic farming is a less intensive farming system that follows the rules set by certification bodies and operates without the application of synthetic fertilisers, pesticides, herbicides, and genetically modified varieties (Wheeler 2011). It follows the four key principles of the International Federation of Organic Agriculture Movements (IFOAM): *health* – sustain and enhance the health of soil, plants, animals, humans, and the planet as one and indivisible; *ecology* – base practices on living ecological systems and cycles, work with them, emulate them, and help sustain them; *fairness* - build on relationships that ensure fairness with regard to the common environment and life opportunities; and *care* – manage agricultural practices in a cautious and responsible manner to protect the health and wellbeing of current and future generations and the environment (IFOAM 2020).

Organic farming comprises various farming systems (for example biodynamics[2]). It is a composite of adoption decisions: farmers need to adopt a series of sustainable agricultural techniques, not just one farming technique (such as soil conservation, animal welfare and biodiversity measures). There is growing scientific evidence on the benefits of organic agriculture as a farming system in balancing overall (economic, environmental and social welfare) sustainability goals (Meemken and Qaim 2018; Reganold and Wachter 2016; Rigby and Cáceres 2001; Sandhu et al. 2008; Seufert and Ramankutty 2017; Wheeler and Crisp 2011).

[2] Biodynamics was the first movement of modern organic agriculture through which farmers and gardeners follow certain practices to produce sustainable products. Organic and biodynamic farming are similar because both are ecologically oriented and produce food and fibre without the use of chemical fertilisers and pesticides. A biodynamic farm has stricter rules than an organic farm, hence has its own certification, but it fits broadly into the overall certification/classification of organic farming (Reganold 1995).

However, there remains issues surrounding yield, increased costs and labour and the knowledge needed (Wheeler 2011). The following sections provide more discussion.

1.2.1 Economic and financial profitability and yield

A meta-analysis by Crowder and Reganold (2015) on the financial performance of organic agriculture at the global scale showed that, without price premiums, the financial performance of organic farming was significantly lower than that of conventional farming, with 7-8% and 23-27% lower benefit-cost ratios and net present values, respectively. However, in the presence of organic price premiums (even at the lowest level of 5-7%; the range varies between 29-32%) profitability increased significantly by 22-35% and the benefit-cost ratio increased by 20-24% over conventional farming. No significant difference was found in regard to total cost, but labour costs were significantly higher (7-13%) under organic management.

Previous economic studies show that organic farming generally has similar or higher returns than conventional farming because of price premiums, subsidies and overall lower input costs (despite often having higher labour costs). For example, organic sheep farming yielded higher net returns than conventional farming as a result of subsidies in Greece (Tzouramani et al. 2011); and price premiums for organic wine (Corsi and Strøm 2013), baby foods (Maguire et al. 2004) and organic lemon farming in Sicily (Sgroi et al. 2015) resulted in organic farming being economically and more financially sustainable. In the Netherlands, a comparative study conducted by Berentsen et al. (2012) found higher prices (but also higher production risks) associated with organic dairy farming. In contrast, Argilés and Brown (2010) found no significant difference in costs, yields and income of organic and conventional farmers. Australian studies found that organic farms have similar or higher financial returns than conventional farms because of the overall lower input costs and price premiums for their output (Wynen 1988, 2001).

In terms of yields, the consensus in the literature is that conventional farming performs much better overall than organic agriculture. Results of numerous field/farm level yield comparison studies show typically lower yields for organics; on average 8-25 % lower in organic farming compared to conventional practice (Badgley et al. 2007; de Ponti et al. 2012; Knapp and van der Heijden 2018; Lesur-Dumoulin et al. 2017; Lotter et al. 2003; Ponisio et al. 2015; Schrama et al. 2018; Seufert et al. 2012; Smith et al. 2019; Stanhill 1990). But it is clear that yield differences are industry specific. In the case of rice, corn, soybeans, and grass-clover, the yield difference is about 6-11%, and for wheat and fruits the differences was highest, at 27-28% (de

Ponti et al. 2012). Campiglia et al. (2015) assessed the influences of cropping systems (organic vs conventional), tillage management, and weather conditions on the yield and quality of durum wheat in Italy using long-term field experimental data from 2005 to 2011. Their results revealed that wheat yield was on average 15% (range 5-32% over time) lower under organic management. The presence of weeds and lower availability of nitrogen appeared to be the contributing factors to the low yield.

Wheeler and Crisp (2011) provide a comprehensive view of organic and conventional viticulture in South Australia in terms of yield, grape quality, prices, costs, workers' benefits, biodiversity and soil carbon content. There was an overall 10% per hectare yield and cost penalty for the organic blocks but no yield differences in similar varieties of grapes and there was, overall, higher-grade quality (and hence prices received) for organic red grape varieties. Some evidence was found to support the existence of higher levels of soil arthropods and mite populations in organic blocks than in conventionally managed ones but there were no statistically significant differences found in soil levels of organic carbon in both farming systems. In addition, incorporation of crop diversification techniques—crop rotation and multi-cropping—in organic farming systems reduces the yield gap by 8 and 9%, respectively (Ponisio et al. 2015).

Another consideration is that in drought conditions, organic farm yields are shown to be higher than in conventional agriculture (up to 70-90%) as found in a review by (Gomiero et al. 2011). Also Patil et al. (2014) assessed the sustainability of conventional and organic farming in India and their analysis revealed that in dry areas organic farming was more profitable and sustainable. According to Lotter et al. (2003), higher yields from organic farms in drought may result from the greater soil's water-holding capacity of organic farms because they have higher levels of organic matter in their soil.

1.2.2 Natural and environmental impact

Organic farming also has beneficial impacts on improving the structure and quality of soil. The higher availability of soil organic matter—7% higher than conventional farming (Tuomisto et al. 2012)—is due to higher soil moisture and organic manure (Bai et al. 2018; Blanco-Canqui et al. 2017; Cameron et al. 2000; Clark et al. 1998; Gattinger et al. 2012; Liebig and Doran 1999; Mäder et al. 2002; Reganold 1995; Reganold et al. 1987; Shepherd et al. 2002; Wander et al. 1994). This helps to increase the soil's water holding capacity, leading to increased yield after transition to organic practice (Martini et al. 2004). Legume based crop rotation and mechanical tillage lower the rate of soil erosion in organic farming systems (Reganold et al. 1987) and generate higher soil carbon sequestration (Mazzoncini et al. 2010). No significant difference was found between organic and conventional farms in terms of soil fertility, decomposition and arthropod abundance, but higher species richness and diversity of arthropods were found in organic farms compared to conventional farms in Kenya (Wanjiku Kamau et al. 2019). In addition, organic management enhances the biomass of the soil's microbial community through higher concentration of soil's organic carbon; 32 to 84 % higher levels of soil microbial activity (Lori et al. 2017; Martínez-García et al. 2018). The difference in soil microbial abundance and activity between organic and conventional farming systems also depends on land use, such as arable, horticulture and grassland; climatic zones and plant life cycle – annual or perennial (Lori et al. 2017).

Mondelaers et al. (2009) carried out a meta-analysis of the differences in the environmental effects of conventional and organic farming in terms of land use efficiency, soil organic matter, and nutrient leaching to water, GHG emissions and biodiversity. They concluded higher soil organic matter, positive contribution to agro-biodiversity and wildlife diversity is present in organic farming systems. But the effects of GHG emissions and nutrient leaching were not clear in their study. Another meta-analysis, performed by Tuomisto et al. (2012), systematically analysed the environmental impacts of conventional and organic farming in European countries. Their findings revealed that organic farming systems performed better in per unit of area rather than per unit of product and they had lower nutrient losses (nitrogen and phosphorous) per unit of area. A state-level longitudinal study in the USA over eleven years found that 1% increase in organic area significantly reduced GHG emissions by 0.049% while controlling for other confounding factors (Squalli and Adamkiewicz 2018). Moreover, there exist differences amongst organic industries in terms of energy use efficiency compared to conventional farming. Organic ruminant production system was more energy efficient, whereas organic poultry farming was less energy efficient and more renewable and human energy were utilised in organic farming compared to its conventional counterpart (Smith et al. 2015). In addition, the results from meta-analysis and long-term field trial also found lower emissions of nitrous oxide per unit of area, but higher emissions in terms of per unit of output for organic farming (Skinner et al. 2019; Skinner et al. 2014). In contrast, the results from the fixed-effect panel regression by McGee (2015) revealed that increases in organic area positively influenced GHG emissions in the USA rather than mitigating the effects of GHG emissions.

In Australia, Wood et al. (2006) provided an assessment of the environmental impact of organic agriculture compared to conventional farming at the farm level. They used a hybrid input-output life cycle analysis to capture both direct and indirect effects of water use, energy use, land utilisation, employment levels and emissions of greenhouse gases. Although they found direct higher energy use in organic farming, they concluded that it is necessary to account for the indirect impact of all the factors which makes the total environmental impact of conventional farming much higher especially for energy use and greenhouse gas emissions.

Wheeler et al. (2015) compared certified-organic and conventional irrigation water extraction in the Murray-Darling Basin, Australia. Although it was found that organic irrigation farms were less water-use efficient (i.e. water extraction divided by tonne of output), there was no significant difference in water extracted per irrigated hectare found overall. Indeed, when the results were broken down by industry sector, it was found that horticulture organic farms extracted less water on a per-hectare basis. Organic farms were also more water-use productive (i.e. water extraction divided by net farm income).

There is a general consensus that organic farming compared to conventional farming provides greater biodiversity benefits (Seufert and Ramankutty 2017; Winqvist et al. 2012), although the magnitude of the benefits vary depending on: a) *the spatial scale:* such as field, farm, and region (Schneider et al. 2014); b) *taxonomic groups*: benefits are most consistent for plants (Bengtsson et al. 2005; Tuck et al. 2014); and c) *landscape attributes*: simple (Batáry et al. 2011; Tscharntke et al. 2005) and complex (Goded et al. 2018; Hole et al. 2005). Results from meta-analyses and reviews showed on average 30% higher species richness and 50% more organism abundance in organic farming compared to conventional ones (Bengtsson et al. 2005; Tuck et al. 2014). Other meta-analyses and reviews by Rahmann (2011) and Stein-Bachinger et al. (2020) also supports the increased biodiversity benefits of organic farming.

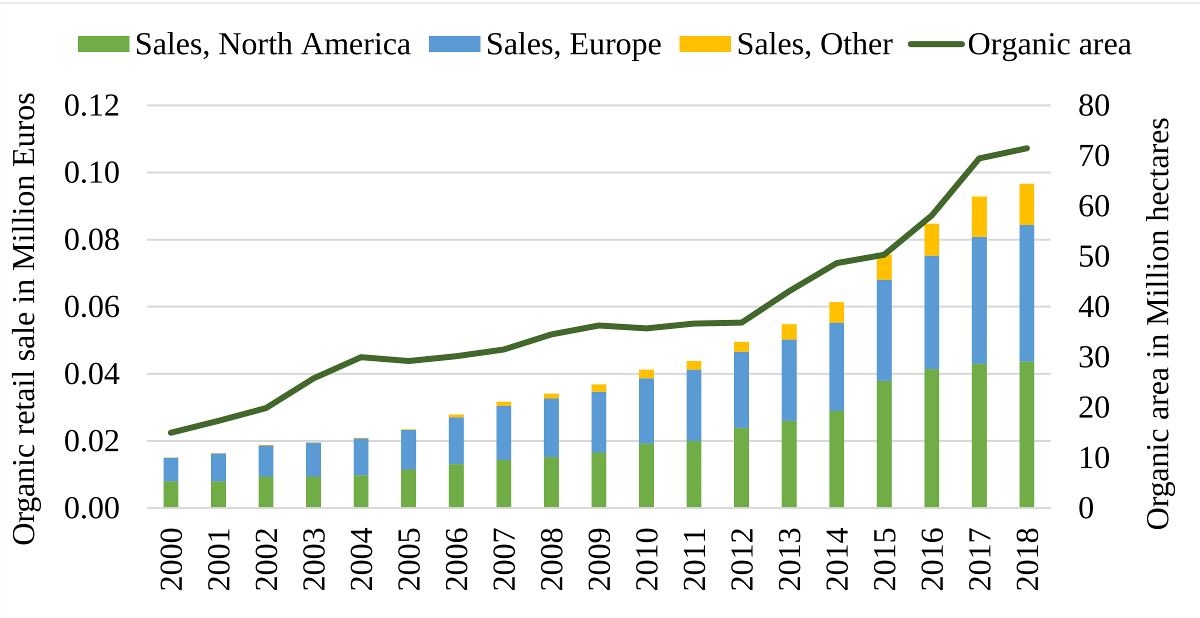
1.2.3 Food quality and safety

Increased concerns about the negative environmental effects of intensified agricultural practices, food quality and safety, well-being of farm workers and animal welfare have led to increased demand for organic produce (Läpple et al. 2017; O'Mahony and Lobo 2017; Reganold and Wachter 2016). But there exists considerable debate and contrasting findings from various studies (e.g. Bourn and Prescott 2002; Lairon 2010; Olson 2017) about nutritional differences, sensory quality and food safety between organic and non-organic foods. The results of a meta-analysis conducted by Barański et al. (2014) found that organic crops/crop based foods have on average higher concentration of antioxidants, lower concentrations of Cadmium, nitrates, and a lower rate of pesticide residues than their non-organic counterparts. The findings of Huber et al. (2011); Brandt et al. (2011) and Worthington (2001) also showed significant nutritional differences between organically and conventionally produced foods and its implications for human heath (Mie et al. 2017), such as higher concentrations of vitamin C, total omega-3 fatty acids, total antioxidants, and higher omega – 3 to 6 ratios in organic foods. But, on the other hand, systematic reviews by Dangour et al. (2009) and Smith-Spangler et al. (2012) found no strong evidence to support significant nutritional differences between organically and conventionally grown foods.

1.3 Adoption of certified organic farming around the world

Organic farming has developed from a fringe form of agriculture to a well-recognised form of sustainable agriculture around the world. Organic farming is now a worldwide phenomenon; practiced in 186 countries by 2.8 million producers and occupying 1.5% of total agricultural land (71.5 million hectares) globally in 2018 (Willer et al. 2020). Figure 1.1 shows the annual increasing trend in land area that is certified organically farmed throughout the world and retail sales by continent (North America, Europe, and others).

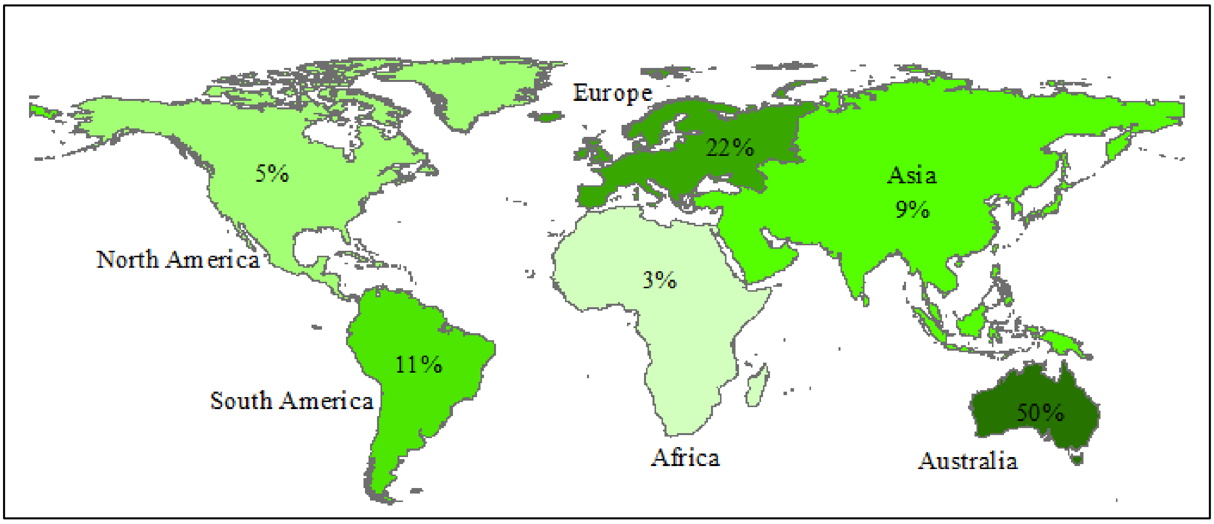
Figure 1.1 Annual global trends in hectares of organic land and retail sales of certified organic food



Own figure (data source: FiBL (2020))

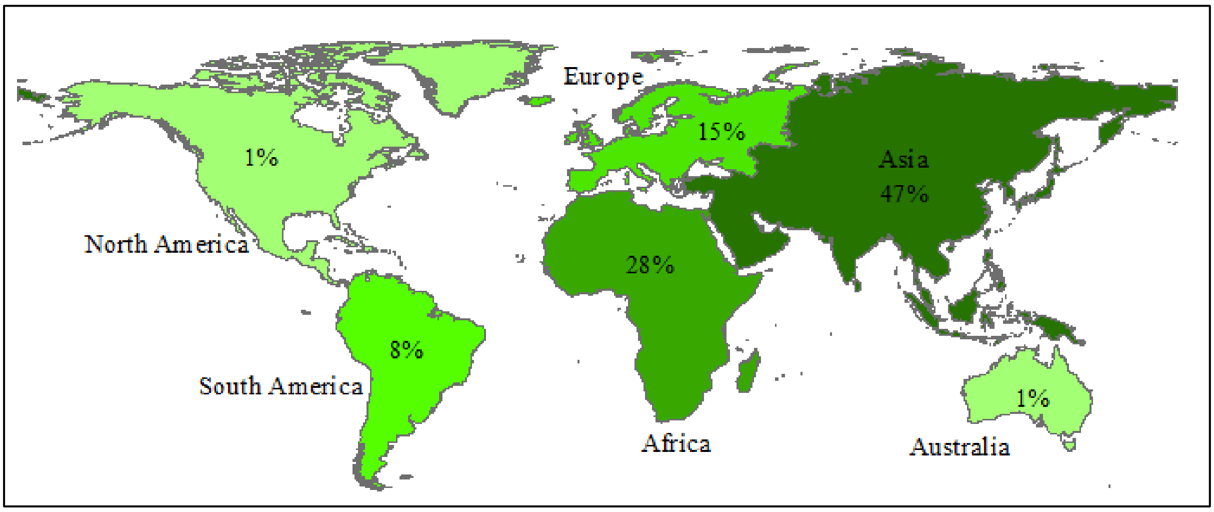
Figure 1.2 represents the continent wide, spatial distribution of the share of certified organic farming in 2018. In terms of organic farmland (including in-conversion land) Australia/Oceania leads the world with 50% of organic land world-wide, followed by Europe (22%), South America (11%), Asia (9%), North America (5%), and Africa (3%). But, in terms of the share of organic farms (producers), Asia has the highest share (47%), followed by Africa (28%), Europe (15%), South America (8%), and North America and Australia both with 1%, respectively (illustrated in Figure 1.3). Compared to the other continents there is a sharp contrast in the share of organic area and farms for the continent of Australia/Oceania where large amount of organic land is managed by very few producers – 35.7 million hectares owned by 1,828 producers in 2018 (Williams et al. 2019) . The majority of Australia's organic land approximately 97% is under large-scale pastoral operations especially for cattle and sheep production in the outback (Willer et al. 2020; Williams et al. 2019). Without the rangeland's contribution the share of Australia's organic land falls sharply. Growth of organic land by continent, countries that has more than 10% organic land, countries with largest organic market and highest per capita consumption were presented in Figure 1.4-Figure 1.7, respectively.

Figure 1.2 Share of organic farming area by continent in 2018



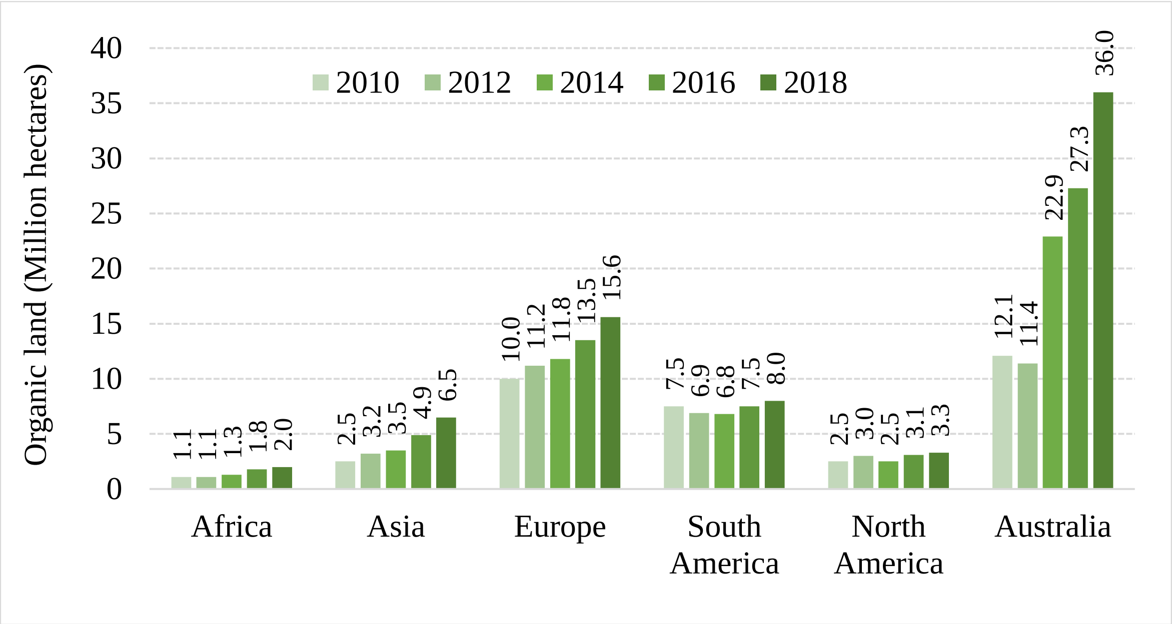
Own map (data sources: base map (ESRI 2010); share of organic area (Willer et al. 2020))

Figure 1.3 Share of organic farms (producer) by continent in 2018



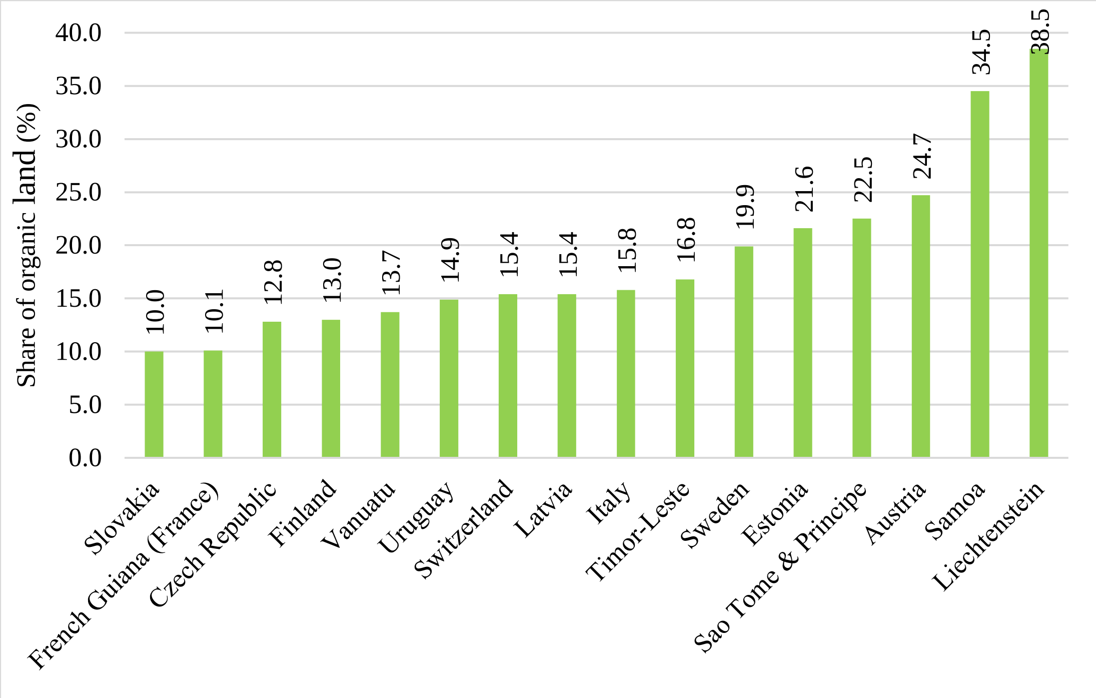
Own map (data sources: base map (ESRI 2010); share of organic farms (Willer et al. 2020))

Figure 1.4 Continent-wide growth of organic land, 2010-2018



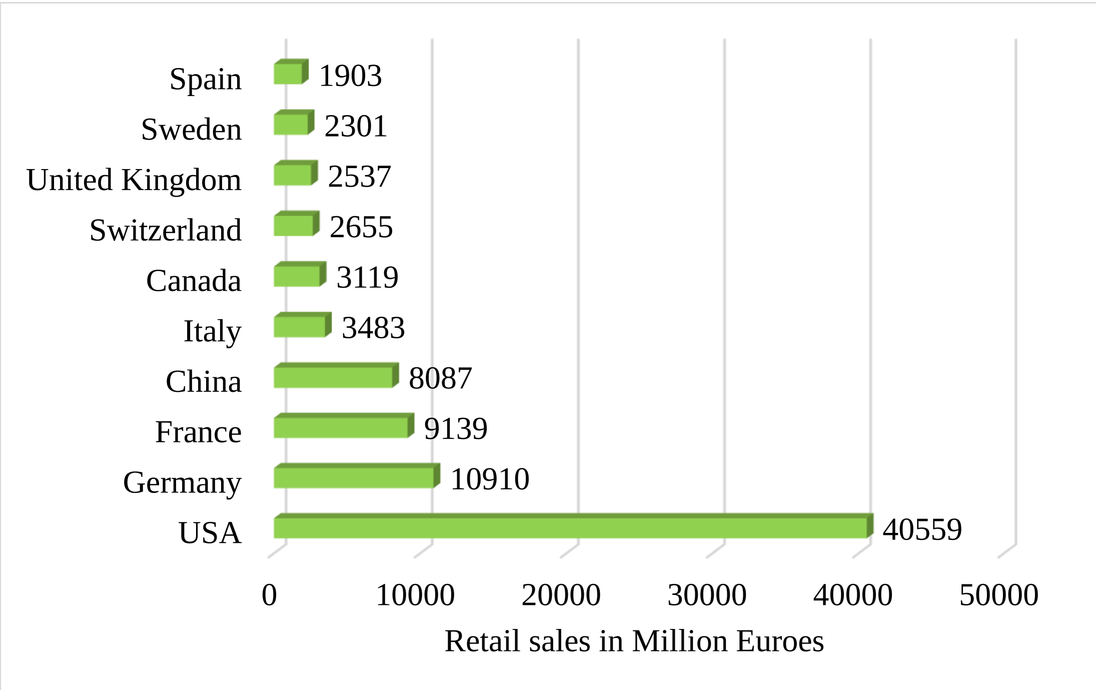
Own figure (data source: Willer et al. (2020))

Figure 1.5 Countries with highest share (minimum 10%) of organic land in total agricultural land, 2018



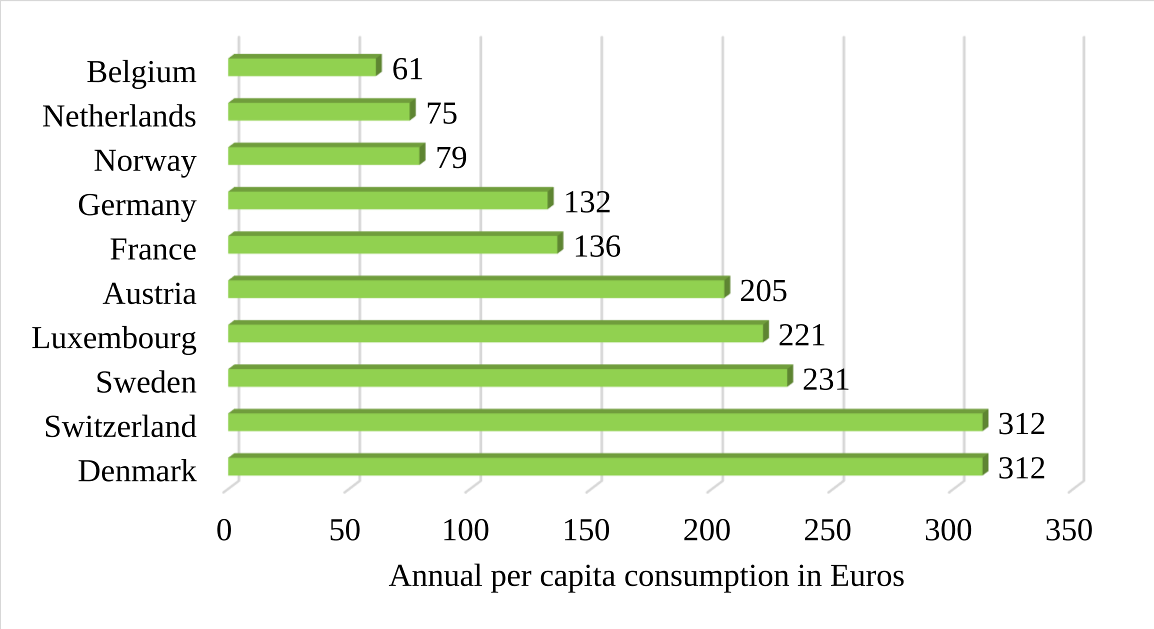
Own figure (data source: Willer et al. (2020))

Figure 1.6 Top ten countries with the largest market for organic food, 2018



Own figure (data source: Willer et al. (2020))

Figure 1.7 Countries with the highest annual per capita consumption of organic food, 2018

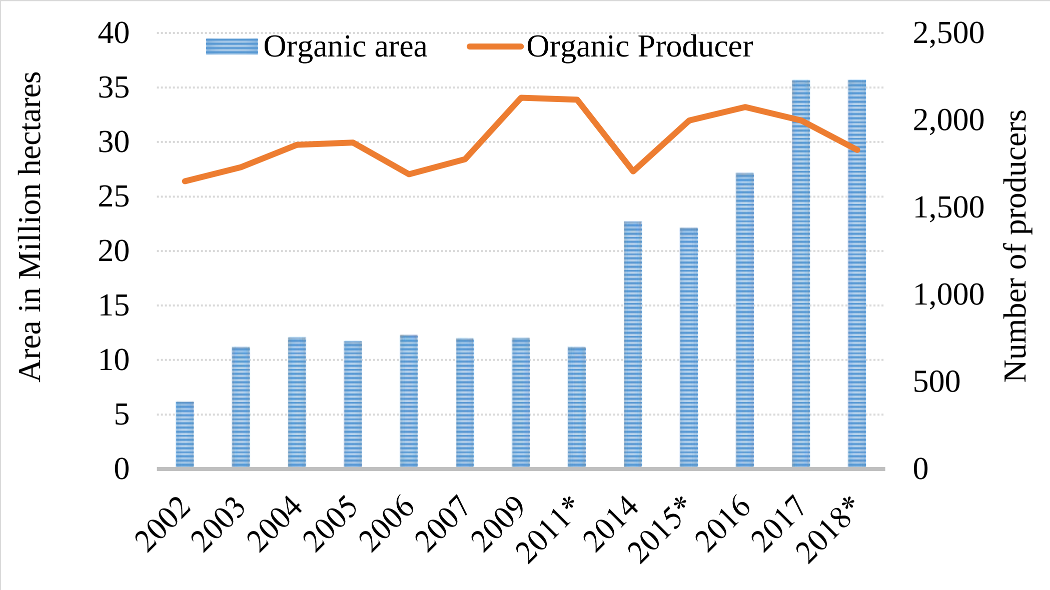


Own figure (data source: Willer et al. (2020)

1.4 Present status of certified organic agriculture in Australia

Organic agriculture is mainly driven by strong market demand and farmer choices in Australia; it does not have economic incentives, such as conversion subsidies, from the government, unlike many European countries (Paull 2019; Wheeler 2011). Although substantial growth has occurred in the organic industry in the last 20 years, the growth is much slower compared to Europe (Daugbjerg and Halpin 2010). In 1982 there were less than 500 organic farmers (estimated number) in Australia (Conacher and Conacher 1983), which increased to 1,828 organic producers in 2018 (Williams et al. 2019). Figure 1.8 shows the diffusion or organic farming in terms of organic area and number of producers. Australia is a special case in organic farming as half of the world's certified organic land (35.7 million hectares) is in Australia and this accounted for 9.6% of the world’s total agricultural land in 2018 (Paull 2019; Williams et al. 2019). However, much of this organic land is pastoral operations in the rangelands (Wheeler 2011); without the rangelands’ contribution, the share of Australia’s organic land falls sharply. Figure 1.9 - Figure 1.12 illustrates the comparative view of agricultural land use for various purposes (in terms percentage share in total area of agricultural holding) under organic and conventional farming in 2015/16.

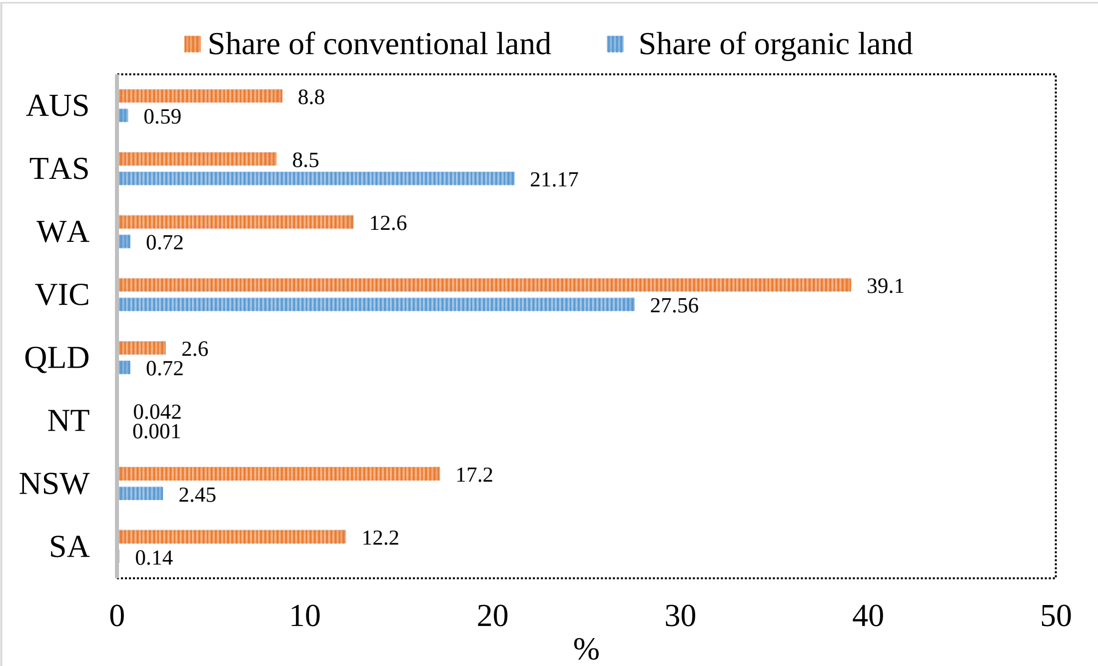
Figure 1.8 Diffusion of organic agriculture (total organic land and number of producers) in Australia from 2002 to 2018



Own figure (data source: (Williams et al. 2019))

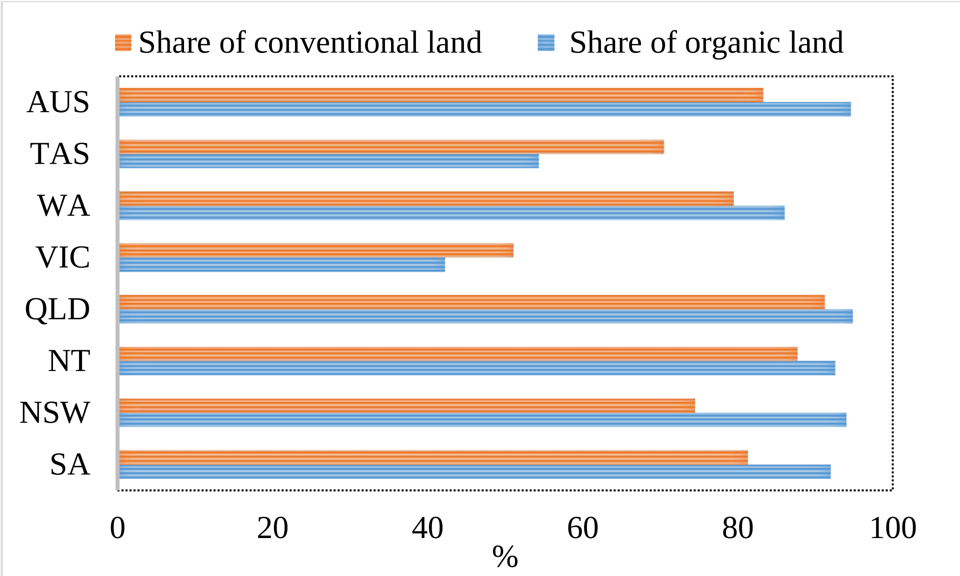
Note: Yearly values with asterisks may represent underestimates of organic area and producers.

Figure 1.9 Share of organic and conventional agricultural land used for cropping in total organic and conventional area of holding in Australia by state and territory, 2015/16



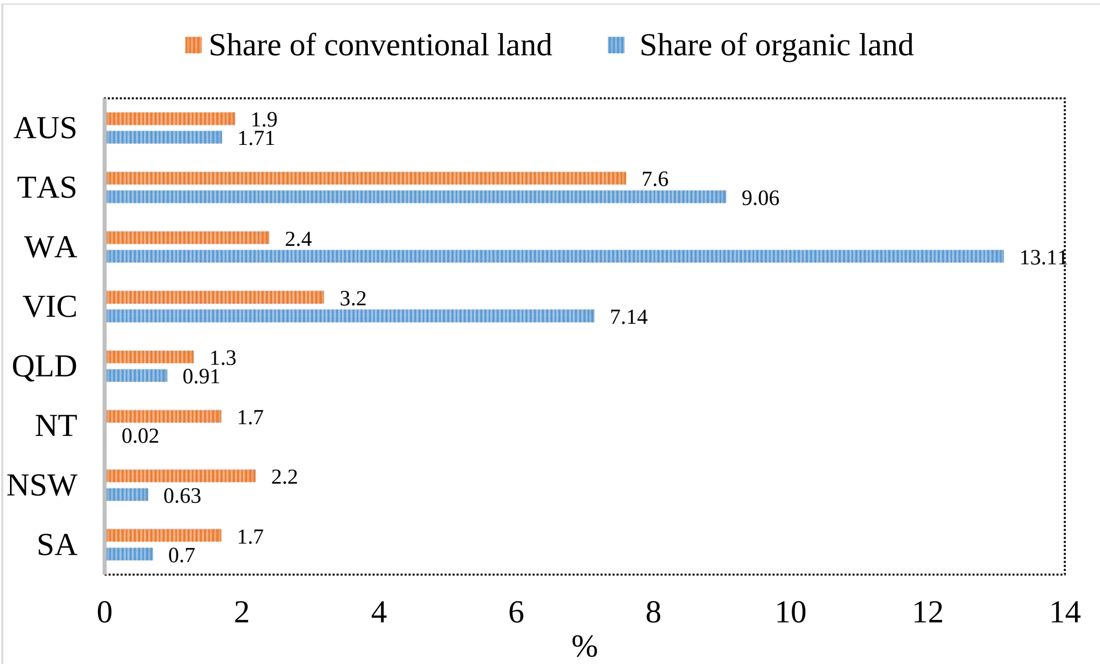
Own figure (data sources: customised data request from ABS)

Figure 1.10 Share of organic and conventional agricultural land used for grazing in total organic and conventional area of holding in Australia by state and territory, 2015/16



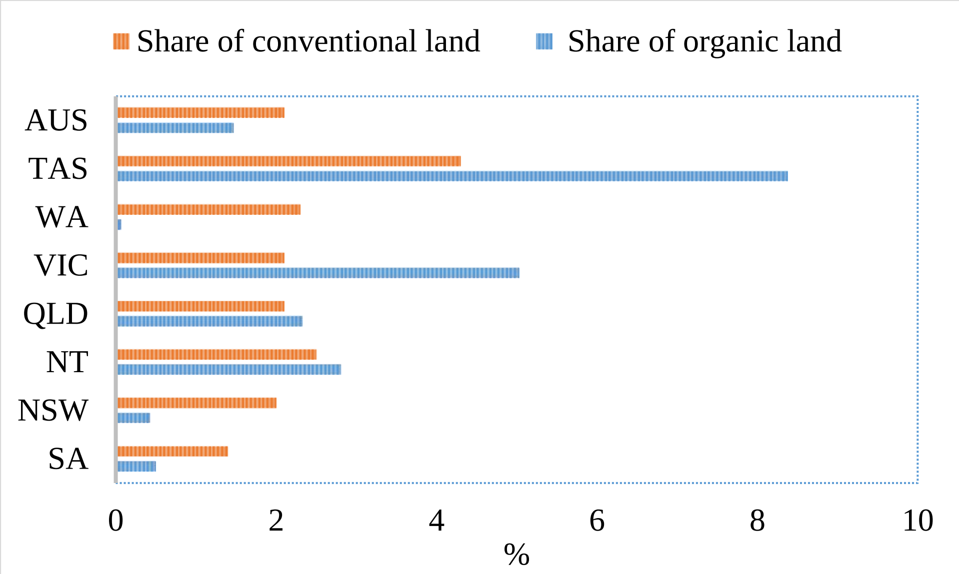
Own figure (data sources: customised data request from ABS)

Figure 1.11 Share of organic and conventional agricultural land set aside for conservation/protection purposes in total organic and conventional area of holding in Australia by state and territory, 2015/16



Own figure (data sources: customised data request from ABS)

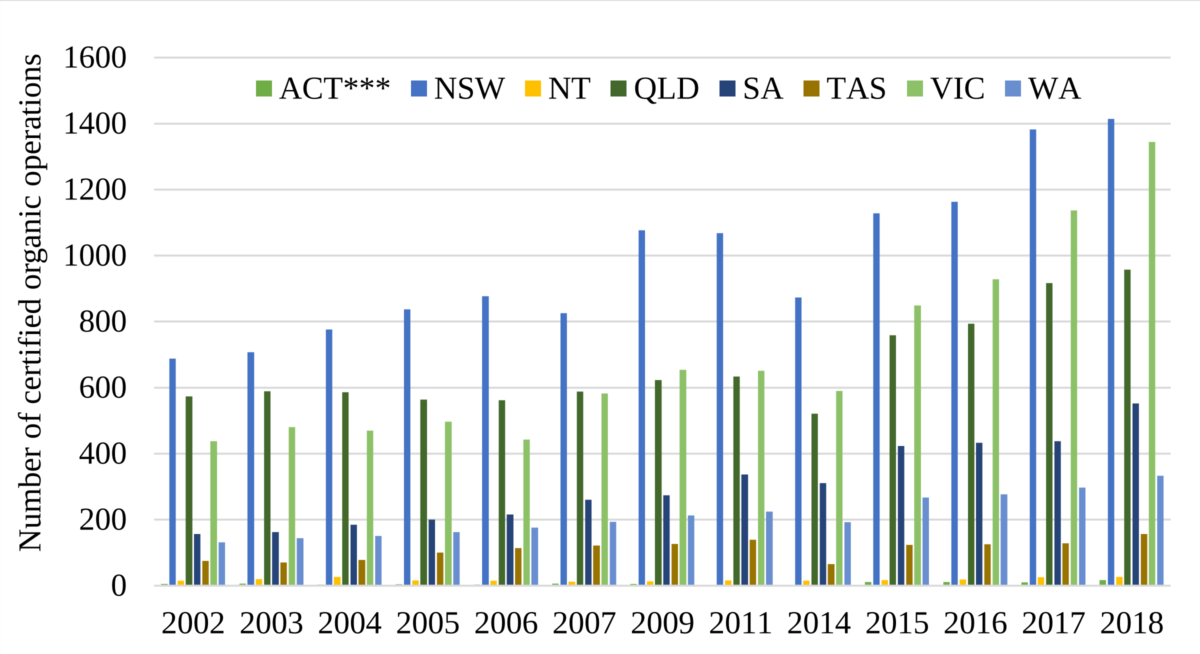
Figure 1.12 Share of organic and conventional agricultural land used for non-agricultural purposes in total organic and conventional area of holding in Australia by state and territory, 2015/16



Own figure (data sources: customised data request from ABS)

The certified organic industry (producers, processors, wholesalers, retailers, and handlers) is unevenly distributed across different states and territories in Australia (depicted in Figure 1.13). Each state and territory have its own organic niche. New South Wales (NSW) leads the organic industry in terms of number of operators, in 2018 it had 29% of total organic operations and the highest number of organic producers; Victoria (VIC) is known for its organic dairy industry and accounted for 28% of certified operations. Queensland (QLD) has its niche in organic beef and the livestock fodder industry and holds 20% of certified operations. The highest number of certified wine-makers is located in South Australia (SA) and the state accounts for 11% of certified operations; organic producers in the Northern Territory (NT) have the largest agricultural enterprises by area (on average 270,000 ha per producer); Tasmania (TAS) has the most intense organic industry — on average 90 ha of organic land is managed per producer, with a total of 70 producers in 2018; the NT, TAS, together with Western Australia (WA) and the Australian Capital Territory (ACT), account for 12% of the certified organic operations in Australia.

Figure 1.13 Organic operations* in Australia by state and territory, 2002-2010**



Own figure (data source: Williams et al. (2019))

Notes: *Organic operations includes producer, processors (marketer, wholesalers), handlers and others

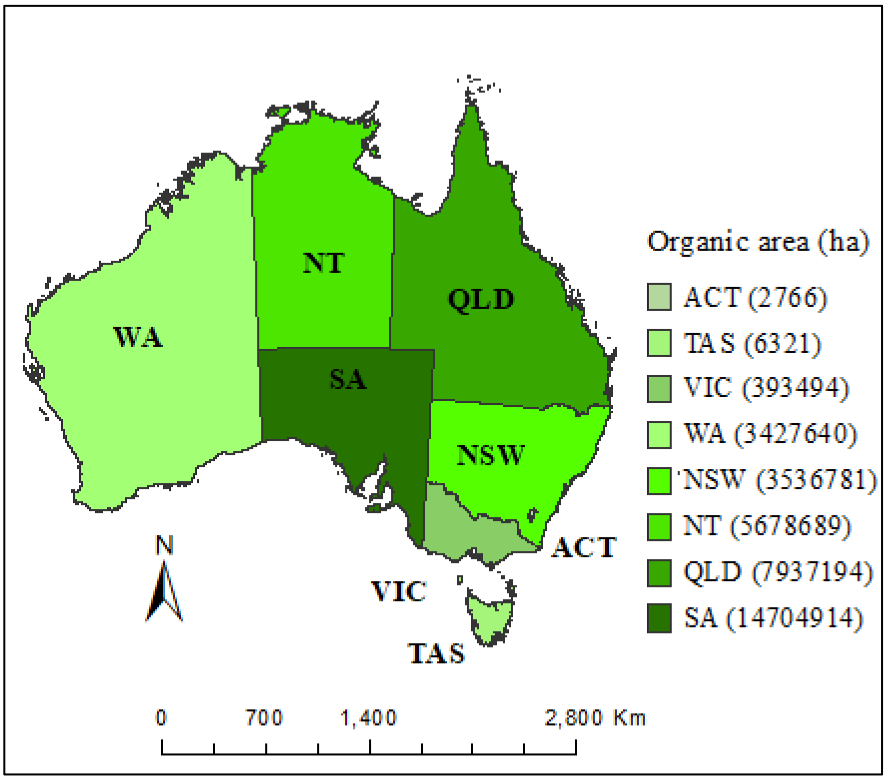
**Data from 2008, 2010, 2012, and 2013 was not available

***Values for certified operations in 2011 and 2014 for ACT was included in NSW

States and territories are shown as: ACT = Australian Capital Territory; NSW – New South Wales; NT – Northern Territory; QLD = Queensland; SA – South Australia; TAS – Tasmania; VIC – Victoria; WA – Western Australia

Total organic farm-land (in-conversion and certified land) in 2018 is depicted in Figure 1.14. In terms of the total value of organic production in 2018, the highest dollar value came from fruits, vegetables and nuts (43%), followed by meat (30%) (Lawson et al. 2018; Williams et al. 2019). Figure 1.15 shows the contribution of different organic industries as a proportion of total export tonnage in 2018.

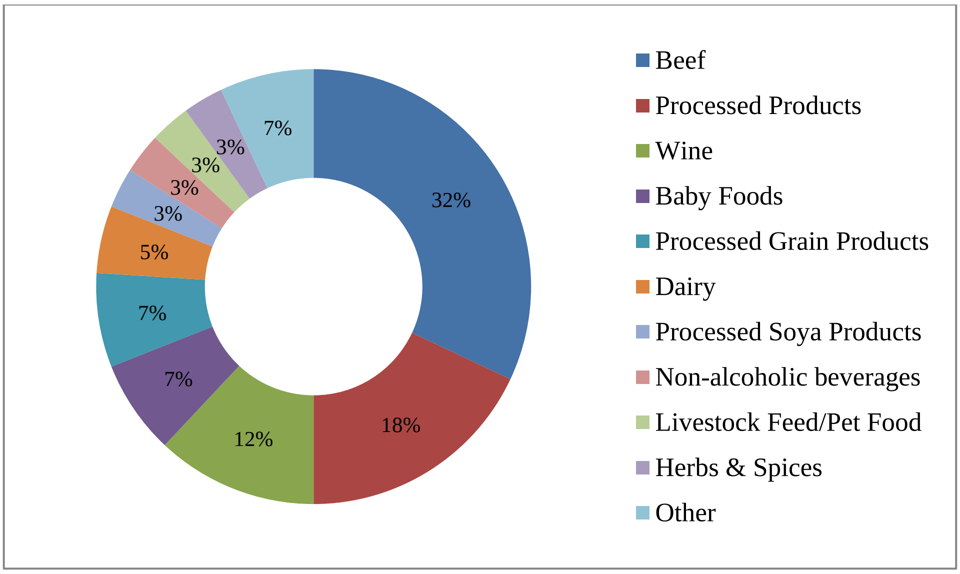
Figure 1.14 Certified organic farmland in Australia by states and territory, 2018



Own map (data sources: state borders (ABS 2016m); organic area (Williams et al. 2019)

<u>Notes:</u> States and territories are shown as: ACT = Australian Capital Territory; NSW – New South Wales; NT – Northern Territory; QLD = Queensland; SA – South Australia; TAS – Tasmania; VIC – Victoria; WA – Western Australia

Figure 1.15 Australia's organic export as a proportion of total organic export tonnage by industries, 2018



Own figure (data source: (Williams et al. 2019)

There are currently six active organic certifying organizations accredited by the Department of Agriculture, Water, and the Environment (DAWE 2020). These certifiers are: Bio-Dynamic Research Institute (BDRI); ACO Certification Limited (ACOCL), formerly known as Australian Certified Organic; NASAA (National Association for Sustainable Agriculture Australia) Certified Organic (NCO); AUS-QUAL; Organic Food Chain (OFC), and Southern Cross Certified Australia (SXC). They all certify in compliance with the minimum requirements of the national standards (National Standards for Organic and Bio-Dynamic Production) in addition to their own certification standards. The national standards came into force in 1992 and were last updated in 2016. Products that are produced in Australia and labelled as organic and exported from Australia must be certified by the one of the six certifiers in accordance with the law.

The organic certification process for producers takes an average of three years, depending on the condition of the farm at the time of audit and soil testing and other outcomes (ACO 2020b). Figure 1.16 depicts the three-year organic certification process for producers certified by ACOCL. The certification process is divided into three stages: firstly the farmer decides on the certifier organization. They need to apply and sign a statutory declaration to commit to follow its requirements and standards. Following the application process, an inspector will audit the farm and do the required tests, such soil tests. In the first year of certification, which is the pre-certification stage, farmers cannot market their products as organic. After that, in the in-conversion stage, products can be marketed with an “in conversion to organic” label. After fulfilling all the requirements and standards for 3 years the final status—organic certification—is achieved and products can be marketed with the “certified organic” label (ACO 2020b; SXC 2020).

Figure 1.16 Certified organic conversion process for producers

Source: (ACO 2020b)

The certification cost varies depending on the certifiers. According to the latest services and fees document (2020) of ACOCL, during the initial certification stage, farmers (for example domestic organic producers) incur costs in the form of application costs (AUD $520), regional audit fees (ranging between AUD $733 and $1,182, depending on the region), and soil or other tests if required. In addition to the initial costs, farmers incur costs in the form of annual audit fees, an annual industry development levy, which varies between AUD $484 and AUD $4,840 for gross annual sales of more than AUD $50,000, plus other ongoing costs (ACO 2020a).

The issue of adoption of organic farming over time in Australia raises questions regarding what has influenced its adoption over time. In addition, this thesis is also interested in understanding the impact on a broad range of land management decisions, especially the spatial spill-over of adoption.

1.5 Contribution of spatial analysis in agricultural land management decisions

1.5.1 Spatial econometrics

The importance of space and location has long been recognised in agricultural land use decision-making, starting with the pioneering work of Johann Heinrich von Thünen. His location theory, "the isolated state", used agricultural land market (land rent) to explain the important role of location, transportation costs to markets, yields, and perishability of agricultural commodities in agricultural land use decision-making and it explained that primary production units are not randomly distributed in space (Von Thünen et al. 1966). The intensity of agricultural production decreased with increased distance from consumers (i.e. the market) (Nelson 2002). Another prominent work that examined the importance of space was Tobler's first law of geography, which states *"everything is related to everything else, but near things are more related than distant things."* (Tobler 1970, p. 236)

Although various scholars have addressed the importance of spatial dependence, they did not explicitly measure the spatial interaction effects to address various research questions (Bockstael 1996; Ord 1975). This may be due to the limited availability of spatial data and spatial methods. The growing availability of so-called "big data", spatial panel datasets, and the advancement of econometric methods has created a wider scope to explore the impact of spatially heterogeneous natural and environmental resources (for example rainfall, temperature, land use, land cover, soil attributes, topography), market accessibility, and spatial interdependence, on agricultural land use decisions and their environmental implications (Villano et al. 2016).

Spatial econometrics, a subfield of econometrics, accounts for the interaction effects among geographical units (e.g. locations, zip codes, counties, regions, states, countries) and the behaviour of economic agents (Elhorst 2014). Spatial econometric methods have been widely used in various research fields, such as regional science, and agricultural and environmental economics, since they were introduced in the seminal works of Anselin (1988).

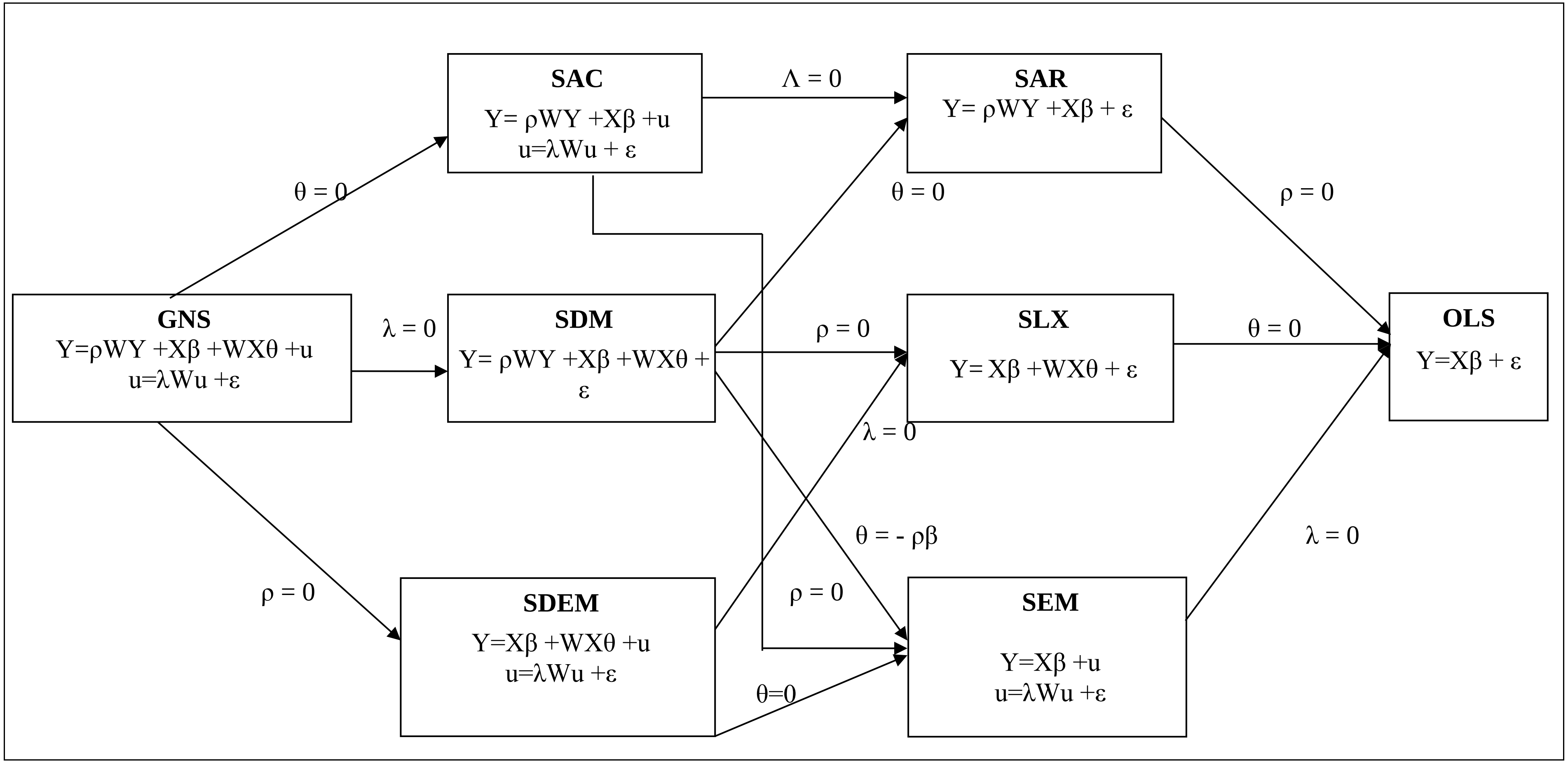
Ignoring the spatial dependence[3] and heterogeneity[4] that exists in spatially structured datasets, and the corresponding application of Ordinary Least Square (OLS) models to such data, may lead to inefficient and biased estimates of the parameters and cause inflation of Type I errors

[3] Spatial dependence means observations at one location are influenced by observations in the neighbouring areas (Elhorst 2010; LeSage and Pace 2009)
[4] Spatial heterogeneity results from location factor/spatial units (counties and states) and contextual variation over space (Anselin 1988)

(Case 1992; Legendre 1993; LeSage and Pace 2009). Spatially dependent datasets violate the basic assumption of OLS regression models that observations are independent of each other. Therefore, application of spatial econometric techniques is necessary to model such spatial data. Spatial dependence may arise because of endogenous interaction effects (an outcome variable at one location depends on the outcome variable located at another location); exogenous interaction effects (an outcome variable is not only a function of explanatory variables at one location, but is also influenced by explanatory variables at neighbouring location); and correlated effects, which stem from the spatially auto-correlated omitted variables (Elhorst 2010; Manski 1993).

In the early phases of the development of spatial econometrics (i.e. up to around the year 2007); the spatial autoregressive model (SAR), spatial error model (SEM), spatial autoregressive combined (SAC) model were widely applied to address many research questions. The SAR model is an extension of the classical linear regression model, namely by incorporating a spatial lag of the dependent variable (endogenous interaction) as an additional independent variable. The SEM augments the linear regression model by specifying a spatially auto correlated error term that captures the interaction in spatially correlated residuals, which may arise due to the spatial correlation of omitted variable(s), and /or data measurement error. The SAC model incorporates both the spatial lag of the dependent variable and spatially auto correlated error term. The spatial Durbin model (SDM) combines the endogenous (spatial lag of the dependent variable) and the exogenous (spatial lags of explanatory variables) interaction effects. The spatial lag of the explanatory variable (SLX) model extends the standard OLS models by incorporating the spatial lags of the explanatory variables in the model. The spatial Durbin error model (SDEM) augments the SLX model by incorporating a spatially auto-correlated error term. Finally, the general nesting model (GNS), also termed the Manski model, incorporates all three interaction effects (Elhorst 2010; Halleck Vega and Elhorst 2015; LeSage and Pace 2009). Figure 1.17 shows the relationships among the above-mentioned spatial models.

Figure 1.17 Overview of the spatial econometric models



Sources: adapted from Elhorst (2010); Halleck Vega and Elhorst (2015)

Notes: Here, Y is the dependent variable, X is a vector of explanatory variables; β is a vector of estimated parameters and ε is the classical error term; assumed to be independently and identically distributed; W is the *n* by *n* spatial weight matrix, which indicates the structure of spatial interdependence among the *n* observations; θ is the parameter of the exogenous interaction effect to be estimated; WX represents the indirect effects of spatially lagged exogenous variables; ρ is the scaler parameter, which indicates the strength of spatial lag dependence; Wy indicates endogenous interaction effects; and λ is the scaler parameter of spatial auto-correlated error.

1.5.2 Drivers of agricultural technology adoption and diffusion

Adoption of new technology plays a crucial role in agricultural productivity growth and a vast literature exists on agricultural technology adoption and diffusion (e.g. Feder and Umali 1993; Griliches 1957; Karakaya et al. 2014; Knowler and Bradshaw 2007; Pannell et al. 2006; Rogers 1962; Ruttan 1996; Ryan and Gross 1943; Zilberman et al. 2012). Adoption is defined as a change in practice and technology used by economic agents or a community (Feder et al. 1985; Zilberman et al. 2012); whereas diffusion (the aggregate adoption) is the process by which an innovation is communicated through certain channels, over time, among members of a social system (Feder et al. 1985; Rogers 2003). In their seminal work, rural sociologists Ryan and Gross (1943) studied the diffusion of hybrid corn, and revealed that salesmen were the most important source of information to farmers in acquiring knowledge about a new technology – while attitudes of neighbouring farmers were the most influential factor in the decision to adopt hybrid corn. According to the diffusion of innovation theory (Rogers 1962, 2003), social networks influence the spread of new ideas and practices; and people obtain information from their surroundings, especially from those who have adopted the same innovation.

Generally speaking, the cumulative adoption process follows an S-shaped pattern (Rogers 1962, 2003; Ryan and Gross 1943; Sunding and Zilberman 2001). During initial phases, the rate of adoption is slow; given few farmers possess knowledge about the new technology. As time passes, more information becomes available within the farmer's social network due to increased adoption, which lowers the associated risk and opportunity cost of learning about the new technology. Hence the rate of adoption increases gradually until reaching the threshold level, and finally the level of adoption tails off (Ryan and Gross 1943). The adopters were categorised as innovators, early adopters, early majority, late majority, and laggards on the basis of the dynamic adoption process (Rogers 2003).

In the field of economics, Griliches (1957) first introduced economic variables for explaining the diffusion of a new technology (hybrid corn) over time. Differences in the rate of adoption depended on the level of profitability. The speed of adoption was faster if the new technology was more profitable. Previous adoption literature demonstrates that economic factors influence the adoption of innovation – particularly if they are easy to implement and achieve the perceived benefits (Feder et al. 1985; Feder and Umali 1993; Pannell et al. 2006; Zilberman et al. 2012). Alternatively, sociological factors are important when the adoption of innovation requires new skills, which is especially the case for sustainable or natural resource management agricultural innovations (Niedermayr et al. 2016; Wheeler and Marning 2019; Wheeler et al. 2017).

Empirical works have identified several factors that may drive or hinder the adoption and diffusion of agricultural technologies. These factors include (among others): farm characteristics such as farm size, farm type, debt level, and distance to market (Foster and Rosenzweig 2010; Haensch et al. 2019; Staal et al. 2002); farmer characteristics such as age, education, gender, farming experience, profit orientation, perception and attitudes towards innovations and environment, and access to credit (De Souza Filho et al. 1999; Knowler and Bradshaw 2007; Lee 2005; Pannell et al. 2006); the heterogeneous environment in which farmers operate in terms of soil quality (Haensch et al. 2019; Saltiel et al. 1994), topography (Genius et al. 2014; Sampson and Perry 2018), climate (Assunção et al. 2019; Genius et al. 2014; Sampson and Perry 2018); socio-economic factors (Haensch et al. 2019); and finally risk or uncertainty involved with the innovation (Baerenklau 2005; Feder 1980; Marra et al. 2003).

Together with these factors, social interaction, farmer social network size, extension services, and other formal or informal sources of information, all play a significant role in the adoption and diffusion of agricultural technologies (Bandiera and Rasul 2006; Maertens and Barrett 2013; Wheeler et al. 2017; Wossen et al. 2013). Information transmission through extension services and learning from neighbours complement each other in the adoption and diffusion of irrigation technology (Genius et al. 2014). Furthermore, Krishnan and Patnam (2014) found that, initially, both learning from peers and extension agents induced the adoption and diffusion of improved seed and fertilisers in Ethiopia – but later on the effects of extension services were almost irrelevant for the diffusion process. Conley and Udry (2010) also revealed that farmers adjusted the level of input, following peers in their social network who were successful in the adoption of pineapple in Ghana. In the diffusion of high-yielding variety rice and wheat in India, Munshi (2004) discovered that social learning was weak within heterogeneous regions – wheat growers benefited from social learning, whereas rice growers mostly focused on 'learning by doing', due to the lack of social learning in the heterogeneous rice growing regions of India. Furthermore, studies have analysed the effects of social learning in terms of spatial proximity among adopters and have applied spatial econometric models. These effects are also referred to as neighbourhood effects, peer effects or spatial dependence by various authors within the adoption literature (Sampson and Perry 2018; Skevas et al. 2018; Stoker et al. 2019). Finally, literature findings also revealed that farmer adoption decisions were significantly shaped by those of their neighbours, with this influence decreasing as distance to neighbouring farm increased (Holloway et al. 2002; Skevas et al. 2018; Ward and Pede 2015).

1.5.3 Adoption and diffusion of organic agriculture – spatial impacts

In applied economic research, farmers' interaction effects are frequently mentioned as an important determinant of technology adoption but the study of neighbourhood effects on adoption decisions has been limited so far (Haensch et al. 2019). Hagerstrand (1968) first quantitatively analysed the spatial diffusion of innovation using the nearest neighbour ratio and suggested that farmers mostly collect information from informal sources, such as personal communication with neighbours. He called this the "neighbourhood effect". Case (1992) studied the neighbourhood effects on farmers' adoption behaviours in Indonesia and found anecdotal evidence of spatial dependence. Holloway et al. (2002) used a Bayesian spatial probit model to study spatial dependence in Bangladeshi farmers' adoption decisions about high yielding rice varieties. More recently, a growing numbers of studies have examined spatial dependence in technology adoption (Lewis et al. 2011; Nyblom et al. 2003; Parker and Munroe 2007; Schmidtner et al. 2012; Wollni and Andersson 2014) and land use and water decisions (Haensch et al. 2019; Skevas et al. 2018). Increasing numbers of studies have examined spatial patterns of organic agricultural adoption, with most of these in the USA and Europe, based on data from different spatial scales; for example: field level data (Parker and Munroe 2007); farm level data (Lapple and Kelley 2015; Lewis et al. 2011); and county level data (Marasteanu and Jaenicke 2015; Schmidtner et al. 2012). These were collected from survey and secondary sources of information.

Findings from previous studies suggest that there exists spatial heterogeneity and dependence in the distribution of organic farms (Allaire et al. 2015; Schmidtner et al. 2012). Spatial clustering of organic agriculture is associated with agglomeration effects (also called neighbourhood effects and spatial dependence) which may result from knowledge spill-over from nearby organic farmers, which reduces the cost of learning about new technology (Schmidtner at el. 2012; Lewis et al. 2011). Kuo and Peters (2017) also found the presence of spatially dependent organic agricultural clusters in the USA. High organic clusters differ from low clusters in terms of ecological, employment and socioeconomic characteristics.

Taus et al. (2012) examined the spatial distribution of organic farms in the USA using USDA agricultural census data. The authors found that the share of existing organic farms, the existence of full-time operators, and average farm size significantly influence farmers' decisions to convert to organic farming. On the other hand, Delbridge and Connolly (2017) found both positive and negative neighbourhood effects on farmers' organic adoption patterns in the USA. They suggest that the existence of nearby organic growers, or processors of the same type of farming, reduce the probability of conversion for conventional farmers due to increased competition in the local food market.

Parker and Munroe (2007) also investigated the spatial patterns of organic farms in California, using farm level data. In contrast to other studies, they identified edge effect externality as a reason for spatial patterns. Edge effect externalities are negative effects that arise from nearby conventional farms, which increase the cost of production for neighbouring organic farms. Furthermore, other research by Lewis et al. (2011) examined spill-overs associated with organic dairy farming adoption in the USA, using a 10-year panel dataset. They found spatial clustering at the local level and suggested that local biophysical conditions, location of the dairy farms and knowledge about organic farming may cause this clustering. Their results also affirm that the presence of neighbouring organic dairy farms significantly affects conversion decisions by lowering the fixed costs of learning.

Nyblom et al. (2003) studied the diffusion of innovation of organic agriculture using both cross-sectional and time-series data in Finland. The authors developed two hypotheses about the spatial diffusion process. Firstly, if diffusion of organic agriculture is a function of diffusion among neighbours (either socially or spatially), then there is chance of finding pairs of adopters; and, secondly, if it is a function of independent economic activity (such as incentives), adopters will be randomly distributed. They found pairs of adopters of organic farming, confirming the existence of neighbourhood effects.

Availability of information in farmers' neighbourhoods, membership of a farmer's group, social acceptance of organic farming and the existence of organic farmers nearby, were the major drivers of farm level adoption of organic farming in Honduras (Wollni and Andersson 2014). Bjørkhaug and Blekesaune (2013) also found neighbourhood effects, increased population, and access to consumers and farm processing of organic products influenced the diffusion process in Norway. In addition, Allaire et al. (2015) analysed spatial diffusion of organic agriculture in France from a territorial viewpoint. The authors argued that clustering is not just the result of spatial externality, but that territorial contexts, such as political, economic, and agro-ecological factors, also influenced the diffusion process.

A study conducted by Gabriel et al. (2009) showed that organic farms were spatially aggregated at regional and neighbourhood scales in England. These spatial concentrations were the result of neighbourhood effects. The authors suggested that organic farming was more likely to occur in less-favoured agricultural areas. However, they did not consider the influences of economic and sociological variables in conversion decisions. Ilbery and Maye (2011) examined the clustering and spatial distribution of organic farms in England. They found concentration of organic farms at a regional level but little evidence of spatial clustering, or neighbourhood effects, at the local level.

1.6 The gaps in the organic and natural capital spatial literature

A better understanding of the spatial spill-over effects on the diffusion of certified organic farming is crucial for first understanding, and second, promoting the wider adoption of sustainable farm management practices. Given the extent of organic farming land in Australia, there is much scope to explore in detail the regional spatial distribution pattern of organic farming in this country as a proxy for other sustainable agricultural practices. In addition, it is obvious that previous literature in this space is limited to the USA and European countries. The geographic patterns of the distribution of organic farms in Australia are unknown because, to date, detailed data on the Australian situation have not been readily available. Also, there is limited research that considers the influence of regional spatial spill-over effects (and explicitly differentiates the true nature of the spill-over process) on the diffusion of organic farming in Australia.

However, in spite of the potential benefits of organic farming for greater sustainability, existing studies are limited to field/farm levels and small geographical settings (e.g. Wheeler and Crisp 2011); only a few focussed on regional levels (e.g. Schneider et al. 2014; Winqvist et al. 2011). Further, most of the studies are limited by using single years (but there are a few exceptions) to capture the benefits. This does not show changes due to the presence of organic farming in a given area over time. The spatio-temporal association of the presence of organic farming on various biodiversity indicators (vascular plant and bird species richness), while controlling for biomass productivity, energy-water dynamics (e.g. rainfall, temperature, and evapotranspiration), habitat heterogeneity, and agricultural land use in a multifunctional agricultural landscape, remains unexplored. This study will therefore provide detailed insights into how the diffusion of organic farming over time is potentially associated with environmental sustainability (potential regional benefits/costs) and how farmers' natural resource management behaviour may be influenced.

In addition, there is scant literature that estimate how the presence of on-farm natural capital, in particular native woody vegetation, is valued by private agricultural landholders. Most existing studies estimating the impact of environmental amenity on agricultural property prices at the farm-level often involves smaller geographic areas, shorter time-periods, aggregated data at a regional/county level, or a specific type of land use. This often ignores the differential impacts of different agricultural industries (broadacre crops, grazing, and horticulture) and farm sizes (small, medium, and large) (there are some exceptions). The present study will add to existing literature by estimating the property value of native vegetation as a natural capital stock, using both market value (sale price) and valuation price across various farm sizes and agricultural industry types (cropping, grazing and horticulture) using a spatio-temporal Durbin model for South Australian agricultural properties over a sixteen (16) year timeframe.

1.7 Objectives and research questions

The core aim of this thesis is to understand the spatial influences of natural capital in Australian agricultural landscapes by addressing three objectives. The objectives and associated research questions are:

a) To explore the spatial influences on the diffusion of certified organic farming (which is used as a proxy indicator of natural capital conservation technologies) at a regional level in Australia.
   i. Is there any spatial spill-over (global or local) in the regional diffusion of organic farming?
   ii. What are the spatial influences of farm structural, natural and environmental, and socio-economic attributes and urbanisation on the spatial diffusion?

b) To estimate the spatial association between the presence of certified organic farming and vascular plant and bird species richness (indicators of landscape level biodiversity) in South Australia over time.
   iii. Is there any spatial dependence in the distribution of plant and bird species richness?
   iv. Is the presence of organic farming at landscape level associated with increased biodiversity?

v. How are landscape attributes (such as native habitat diversity, anthropogenic land use), climate and urbanisation associated with the species richness pattern?

c) To examine the association between native woody vegetation coverage and climate (which are used as proxies of various forms of natural capital) and South Australian farm land values:

vi. Does the per unit value of agricultural properties (sale and valuation price) depend on neighbouring property prices?

vii. Does the presence of a natural capital stock of native woody vegetation on agricultural properties become capitalised into property value? If yes, is there any difference in the sales and valuation price in capturing the price premium?

viii. What are the influences of other forms of natural capital (such as climate, water availability, and soil), drought, and socio-economic conditions on property value?

Sustainable farm management practices, such as organic agriculture, may reduce the negative impact of agricultural intensification on natural capital. For effective policy implementation the first objective is focussed on understating which factors are associated with the adoption and diffusion of certified organic farming (which is used as a proxy for farm management practice promoting natural capital conservation). The second objective helps to understand in detail the spatial associations between adoption of sustainable farm management practices (organic farming) and the effects of agricultural intensification on natural capital (e.g. namely bird and plant biodiversity). Finally, the third objective sheds light on how various natural capitals that are not directly valued, can be valued indirectly through related land market by estimating the value of native woody vegetation (and other capital such as climate) using agricultural property valuation and transaction prices.

1.8 Research design and methodology

To achieve the research objectives, spatial econometric models were applied to analyse various Australian panel datasets. These were collated, prepared, and combined using multiple sources at varied spatial levels (regional, landscape, and local - agricultural lots) and temporal scales. Chapter 2 focused on a broad spatial scale – regional level (defined the spatial boundaries of Australian Statistical Geography Standard[5]'s (ASGS) Statistical Area Level 2 (SA2). The

[5] ASGS provides framework of statistical areas that are comparable and spatially integrated and used by the Australian Bureau of Statistics (ABS) and other organisations to produce various statistics. ASGS is divided into two parts: ABS structures and Non-ABS structures. The ABS structures (such as SA2) remains stable over 5 years

spatial scale was narrowed down to a smaller scale depending on the data availability at landscape scale – defined by the spatial boundaries of postcode areas in Chapter 3, and a finer spatial scale – lot size of agricultural properties was used in Chapter 4. In Chapter 2, the collected spatial data were combined with agricultural census data (2010/11 and 2015/16) across all Australia to demonstrate the regional percentages of organic farming's land area and business numbers. In Chapter 3, a unique spatio-temporal organic certification dataset for South Australia that contained locations, certification dates, products produced, etc. for a period of sixteen years (2001-2016) was prepared through personalised access to databases of the major organic certifiers. This was combined with data on vascular plant and bird species richness, and other natural and environmental features of the agricultural landscape (by postcode area). In the last analytical chapter, an agricultural land parcel cadastre map, agricultural property valuation and transaction data, and different forms of natural capital assets, such as native woody vegetation, climate, and soil attributes were combined together for South Australia from 1998 to 2013. All the spatial variables' preparation, geocoding of organic farm business addresses (Chapter 4), and spatial exploratory analysis (cluster and outlier analysis) were done using Geographic Information System (GIS) software "ArcGIS 10.5.1". For the spatial econometric modelling statistical software "StataMP 16" was utilised. Figure 1.18 illustrates the overall research design.

1.9 Thesis structure

This thesis consists of five chapters. Following this introductory chapter, three analytical Chapters (2, 3, and 4) address the research objectives, and Chapter 5 presents the summary findings of the thesis. There is some repetition in the introduction and the econometric model sections of the three analytical chapters due the format of the thesis.

Chapter 2 explored the spatial influences on the diffusion of certified organic farming (which is used as a proxy indicator of natural capital conservation technologies) at a regional level (SA2) in Australia using agricultural census data from 2010/11 and 2015/16.

Chapter 3 analysed the spatial associations between farmers' land use behaviours (i.e. the extent of certified organic farming in a region) and regional biodiversity outcomes (vascular plant and bird species richness) using a novel dataset at postcode level on certified organic

which allows comparison over long time period, whereas Non-ABS structures updated annually depending on any major changes in the areas. The statistical area components and their interrelations of the ASGS's ABS and Non-ABS structures are depicted in Figure A.14 and Figure A.15, respectively (ABS 2016d).

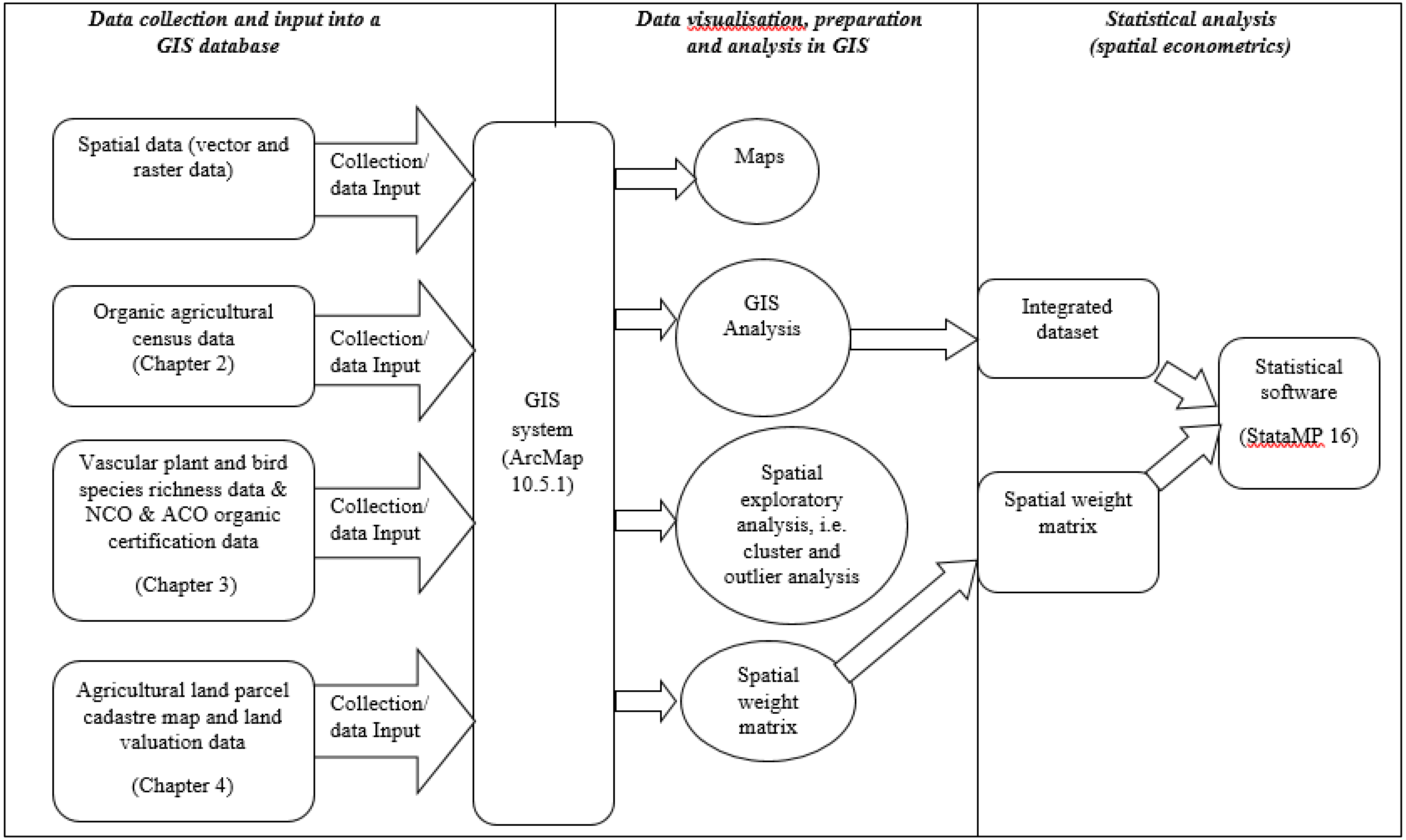
farming's presence and its location in South Australia from 2001 to 2016. This chapter narrowed down the spatial coverage in South Australia to a landscape scale (defined by the administrative boundaries of postcode areas) for which the organic certification data were available.

Chapter 4 explored the spatial correlation between native woody vegetation on agricultural properties and their economic values in South Australia, using both sales and valuation prices of agricultural properties from 1998 to 2013.

The last chapter summarises the research findings, provides policy implications, outlines the limitations of the study, and suggests future areas of research.

Appendices A to D provide the supplementary materials for the various chapters.

Figure 1.18 Research design



Source: Own figure

Chapter 2 Global vs local spatial spill-overs: what matters most for the diffusion of certified organic agriculture in Australia?

Abstract

Organic agriculture represents an interesting case study for investigating the impact of spatial networks on the diffusion of sustainable agricultural innovations. Although farmers' adoption and diffusion behaviour is well studied in the literature in general, dynamic modelling of the role of spatial spill-over effects on diffusion intensity is not well known. The aim of this study is to disentangle the role of spatial spill-overs and the impact of structural, environmental and socio-economic factors on the diffusion of certified organic agriculture in Australia, using national census data from 2010/11 and 2015/16. The results of the SLX tobit model shows significant spatial spill-over effects from neighbouring regions' characteristics, as well as the collective structural feature of a region (large farms with low stocking rates, higher share of irrigated business, grazing and horticultural land, increased labour supply), environmental factors (located in drought affected areas, increased vegetation, good quality soil and high altitude), and socio-economic characteristics (rural areas characterised by low human population density, higher community income and proximity to urban centres) significantly increase the intensity of the diffusion process.

Keywords: Organic agriculture; spatial diffusion; SLX tobit model; local spill-over effects; ecosystem services; Australia

Statement of Authorship

Title of Paper	Global vs local spatial spill-overs: what matters most for the diffusion of certified organic agriculture in Australia?
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Principal Author

Name of Principal Author (Candidate)	Maksuda Mannaf		
Contribution to the Paper	Conceptualisation and development of the study; undertook literature review; collected and prepared data for spatial econometric analysis and interpreted the results; wrote the manuscript.		
Overall percentage (%)	70%		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	1/12/2020

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Name of Co-Author	Sarah Ann Wheeler		
Contribution to the Paper	Supervised the conceptualisation and development of the study; provided organic (contacted the certifying organisations) and climate data; supervised and suggested econometric modelling; evaluated and edited manuscript.		
Signature		Date	3/12/20

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Contribution to the Paper	Supervised the conceptualisation and development of the study; provided climate data; supervised and suggested econometric modelling; evaluated and edited manuscript.		
Signature		Date	3/12/20

2.1 Introduction

Unlike the USA and European countries, where certified organic agriculture (OA) has been promoted through government support and market forces (Allaire et al. 2015; Lohr and Salomonsson 2000; Mosier and Thilmany 2016), the organic industry in Australia has been primarily driven by strong market signals (Wheeler 2011). There are both national demand – e.g. two out of three Australian households purchased organic products in 2016 and international demand drivers – e.g. certified exports grew by 17% between 2015 and 2016 (Lawson et al. 2018). In addition to concerns about the environmental effects of intensified agricultural practices, food safety, well-being of farm workers and animal welfare have led to increased demand for organic produce (Läpple et al. 2017; O'Mahony and Lobo 2017; Reganold and Wachter 2016). There is growing scientific evidence of the benefits of certified OA as a farming system that balances overall (economic, environmental and social welfare) sustainability goals (Meemken and Qaim 2018; Reganold and Wachter 2016; Rigby and Cáceres 2001; Sandhu et al. 2008; Seufert and Ramankutty 2017). Altogether, these factors contributed to the growing consumer demand as reflected in the growing global market share of sales of organic food and beverage of US$ 105.5 billion in 2019, more than a five-fold increase since 1990 (Willer et al. 2020). In any case, there exists considerable debate and contrasting findings from various studies about food quality and safety and their human health impact (Barański et al. 2017; Dangour et al. 2009; Smith-Spangler et al. 2012), and concerns over lower production yields (de Ponti et al. 2012; Ponisio et al. 2015; Schrama et al. 2018; Seufert et al. 2012).

Australia was ranked number one in the world in terms of certified organic farm land in 2018 (35.7 million hectares – 9.6% of its total agricultural land), whereas total organic agricultural land in the entire world was 71.5 million hectares (Willer et al. 2020). OA is not a typical innovation; it is often viewed as a new paradigm in agriculture (Padel 2001; Wheeler 2011). The diffusion of OA is different from other agricultural innovations because it requires different motives and changes in farmers' mindsets. Farmers need to learn a large number of skills and gain knowledge about natural resource management and the restructure and reorganisation of farming systems, which makes OA an interesting case study for analysing sustainable agricultural farming in general. In Australia, organic farmers have traditionally faced social exclusion from other farmers for their farming choices. Historically they have had low support (as well as discouragement) from government agencies, have had greater marketing and processing costs and have faced considerably high learning barriers in converting to organic farming (Paull 2019; Wheeler 2011; Wheeler 2008a). Especially in earlier years, farmers who chose to convert usually only had other organic farmers to learn from (which may cause clusters[6] of organic farms in some areas that are favourable for OA). Any learning gained from examining the diffusion of organic farming therefore may provide insights into farmer behaviour in regard to other sustainable agricultural innovations.

2.2 Spatial patterns of adoption and diffusion of organic agriculture: overview of literatures

The vast body of technology adoption literatures demonstrates the important role of formal and informal sources of information on adoption and diffusion of sustainable agricultural innovations: extension services; mass media; agricultural cooperatives, etc; social interaction in farmers' social networks (defined by spatial proximity or number of neighbours with whom they interact) in addition to farm, farmer, and environmental factors (Abdulai and Huffman 2005; Conley and Udry 2010; Foster and Rosenzweig 2010; Genius et al. 2006; Knowler and Bradshaw 2007; Krishnan and Patnam 2014; Pannell et al. 2006; Wossen et al. 2013). An overview of spatial and non-spatial factors influencing the adoption and diffusion of OA is presented in Table B.1 in the appendix B. The pioneering hybrid corn work of Ryan and Gross (1943) revealed that salesmen are the most important source of information for farmers in acquiring knowledge about a new technology but that the attitudes of neighbouring farmers' was the most influential factor in the hybrid corn adoption decision. Other seminal work (Rogers 2003) on the theory of innovation diffusion showed that social networks influence the spread of new ideas and practices and people obtain information from their surroundings, especially from those who have adopted the same innovation. In the field of economics, Griliches (1957) first introduced economic variables for explaining the diffusion of a new technology (hybrid corn) over time and found differences in the rate of adoption depended on the level of profitability. The speed of adoption was faster if the new technology was more profitable. In a broad sense, adoption decisions about "hard" technologies, such as adoption of new irrigation infrastructure (Wheeler et al. 2017), are mostly influenced by economic factors, especially if they are easy to implement and provide the perceived benefits. On the other hand, it seems that sociological factors may be more important for decisions on "soft" technologies where the adoption of innovation requires new skills and knowledge, which is

[6] Clusters refers to the geographic areas with positively correlated high attribute values (hot-spots), low attribute values (cold-spots) and negatively correlated attributes (outliers) (Marasteanu and Jaenicke 2016).

especially the case for alternative production systems or natural resource management agricultural innovations (Niedermayr et al. 2016; Wheeler and Marning 2019).

In applied economic research, Case (1992) was the first study to empirically model the social interaction effects in Indonesian farmers' adoption behaviours by defining farmers' social networks in terms of geographic proximity and found evidence that farmers are indeed influenced by their neighbours' adoption choices and failure to capture this spatial dependence results in significant bias in the parameter estimates. Manski (1993) identified three types of interaction effects to explain why observation at location *i* depends on observation at location *j* (spatial dependence). Firstly, the endogenous interaction effect, which in the context of this study, is likely to be present if OA adoption decisions in region *i* is impacted by the adoption level of region *j*, which is also termed global spatial spill-over because the impact passes through other neighbouring regions in a loop creating an endogenous feedback effect (e.g. from region *i* to region *j* to region *k* and *k* to *j*). Secondly, the exogenous interaction effect arises when adoption of OA in region *i* is influenced by the characteristics of neighbouring regions, also termed the local spatial spill-over. Finally, correlated effects stem from the spatially auto-correlated omitted variables that affect the adoption decision. The latter two effects do not have social multiplier effects. Most of the empirical studies implicitly assume global spill-over effects rather than local spill-over while studying the spatial dependence in adoption behaviour without explicitly distinguishing its true nature (Läpple et al. 2017).

There exists numerous literatures on farmers' adoption and diffusion behaviour of OA, but the number of studies that have explored the influence of spatial interdependence in OA adoption and diffusion are limited. The spatial dependence in the adoption and diffusion of agricultural innovations specially OA is explained by locational factors (e.g. soil, climate) and agglomeration economics, resulting from input sharing and knowledge spill-over from neighbours, which reduces uncertainty in learning about new technology and the overall transition costs (Lewis et al. 2011; Schmidtner et al. 2012; Wollni and Andersson 2014).

In addition, information availability in farmers social network (Läpple and Kelley 2014; Wollni and Andersson 2014); social acceptance (Delbridge and Connolly 2017; Marasteanu and Jaenicke 2016; Wollni and Andersson 2014); perceived positive externalities (Wollni and Andersson 2014); climatic and environmental factors (Gabriel et al. 2009; Schmidtner et al. 2012); market access (Marasteanu and Jaenicke 2015, 2016; Schmidtner et al. 2012), policy support (Schmidtner et al. 2012); socio-economic attributes (Allaire et al. 2015; Delbridge and

Connolly 2017; Marasteanu and Jaenicke 2015; Schmidtner et al. 2012); negative externalities – perceived productivity spill-over to neighbouring plots (Wollni and Andersson 2014) and negative spill-over effects of chemical fertilisers from neighbouring convention agricultural plots (Parker and Munroe 2007); and farm physical capital (Läpple and Kelley 2014) has been identified as significant determinants of the spatial adoption and diffusion OA.

The extent and intensity of spatial pattern of OA has been studied at varied spatial and temporal scales: farm/lot scale using survey data – extent of adoption (Boncinelli et al. 2017; Läpple and Kelley 2014; Parker and Munroe 2007; Wollni and Andersson 2014); intensity of adoption at municipality scale (Allaire et al. 2015; Bjørkhaug and Blekesaune 2013; Boncinelli et al. 2015; Schmidtner et al. 2015) and county level (Bredemeier et al. 2015; Delbridge and Connolly 2017; Marasteanu and Jaenicke 2015, 2016; Schmidtner et al. 2012). The influences of spatial interdependence is often explained by global spatial spill-over effects (i.e. how a unit of production's (farmer/region) adoption behaviour influenced by neighbours adoption choice) by controlling spatial lag dependence in the empirical modelling without explicitly exploring the local spatial spill-over effects (i.e. neighbouring farms/regional agricultural, environmental, socio-economic, etc. attributes which also has significant influence on adoption decisions). However, most of the spatial spill-overs are local in nature (LeSage 2014), with the exceptions of studies by Boncinelli et al. (2017) and Läpple and Kelley (2014) where both endogenous and exogenous interaction effects were controlled with the application of the spatial Durbin model (SDM) in analysing the extent of OA adoption.

In response to the recent criticisms of the SAR model, due to the problem of identifying causal relationships (Gibbons and Overman 2012; Pinkse and Slade 2010) and in growing recognition of the importance of local spatial spill-over effects (LeSage 2014), increased number of studies are exploring the true nature of spatial spill-overs in addressing various research questions. For example, Läpple et al. (2017) investigated the true nature of spatial spill-over effects on the adoption of sustainable milk recording technology among Irish dairy farmers by estimating comparing various forms of spatial models that accounted for the global and local effects. Their findings revealed that both global and local spatial spill-over effects significantly influenced the adoption decision, but the global spill-over effects were more pronounced. Intensity of regional spatial adoption of alternative crop (Styrian oil pumpkin) in Austria was analysed by Niedermayr et al. (2016) using a spatial lag of explanatory variables (SLX) tobit model which accounted for exogenous interactions effects and their findings suggested the influences of significant local spill-over effects on the intensity of adoption. The impact of spatial interdependence in farm exit decisions among Norwegian and French farmers was assessed by Storm et al. (2015) and Saint-Cyr et al. (2018), respectively, and their findings revealed statistically significant influences of neighbours' characteristics on farm exit decisions.

Despite Australia having a long history in OA, with the publication of the first organic journal in 1946 (Paull 2008), as well as the largest amount of certified organic farm-land in the world (Willer et al. 2020); to date there has been no study looking at the spatial diffusion process of organic adoption across the country. This is compared to the growing body of USA and European scientific literature (Bjørkhaug and Blekesaune 2013; Gabriel et al. 2009; Ilbery et al. 2016; Läpple and Kelley 2014; Marasteanu and Jaenicke 2015; Schmidtner et al. 2012; Wollni and Andersson 2014). To date the existing literature has been cross-sectional studies, with the exceptions of Allaire et al. (2015) which studied spatio-temporal diffusion of OA in France from 20017 to 2010 at municipality level by farming industries (crops, livestock, horticulture, viticulture, etc.) and Lewis et al. (2011) whom explored farm level spatial diffusion of organic dairy farms over 10 years in the south-western Wisconsin, USA.

In Australia the research has been even more limited. Australian organic agriculture research to date has focussed on impacts for individual farms and consumers' views (Conacher and Conacher 1998; Lockie and Halpin 2005; Wheeler et al. 2019; Wheeler et al. 2015; Wood et al. 2006). There has been little work on understanding farm adoption over time, or trying to understand any spatial spill-overs on the adoption of OA. Understanding farmers' adoption behaviours is crucial for formulation and implementation of well-defined policy. Accurate data about the size and growth of the organic industry at a finer spatial scale (farm level/aggregated data) are scarce in Australia due to the absence of regular systematic data collection (O'Mahony and Lobo 2017).

While there is growing recognition of local spatial spill-over effects in farmers decision making behaviour, no studies have explicitly explored the true nature of spatial spill-over effects (global vs. local) in the intensity of diffusion of OA. This research aims to fill this gap in the existing literature by understanding in greater detail the role of global and local spatial spill-over in the regional (SA2[7] level) diffusion process of certified organic farming in Australia, using the Australian Bureau of Statistics' (ABS) five yearly Censuses of Agricultural data from

[7] SA2 is the smallest geographical area in Australia's statistical geography standards (ASGS) for which ABS provides information related to certified organic agriculture. SA2s represents the administrative boundary within which a community interacts socially and economically. They vary in size and population (average population 10,000) and align with the state and national boundaries.

2010/11 and 2015/16. Questions related to OA were incorporated in the nationally representative survey of agricultural farms for the first time in 2010/11; this was later repeated in the latest 2015/16 census.

2.3 Methodology and econometric model

Depending on data availability, the adoption and diffusion of OA can be modelled in terms of 1) the extent of adoption - the presence/absence of OA at regional or farm level, using a binary choice model (Boncinelli et al. 2015; Wollni and Andersson 2014) and 2) the intensity of adoption - the proportion of a given area's agricultural land that is devoted to OA (Marasteanu and Jaenicke 2016; Schmidtner et al. 2012). In this study, intensity of OA diffusion aggregated at SA2 level is estimated using a censored tobit model[8] which is specified below as (Greene 2003):

$$y_i^* = X\beta + \varepsilon$$

where, y_i^* is the latent dependent variable; X is a vector of explanatory variables relating to a region's agricultural, natural and environmental and socio-economic factors; β is a vector of estimated response parameters and ε is the error term; assumed to be independently and identically distributed. The left and right censored (SA2s with 0 and 100% OA is treated as left and right censored observations) latent dependent variable y_i^* and the observed variable y_i, measured by the percentage of OA in an area's total agricultural holdings and the percentage of OA businesses in the total number of agricultural businesses, respectively, have a relationship defined as:

$$y_i = 0 \text{ if } y_i^* \leq 0,$$

$$y_i = y_i^* \text{ if } 0 < y_i^* < 100, \text{ and}$$

$$y_i = 100 \text{ if } y_i^* \geq 100.$$

Although most spatial spill-overs are local in nature (LeSage 2014), most of the studies explicitly assume that the nature of spatial spill-over is global. Hence, many apply a SAR model to capture the endogenous interaction effect (Elhorst 2010), without differentiating the true nature of spatial interaction. The application of SAR models has been criticised due to the problems of identifying causal relationships and the assumption of the constant ratio of spill-

[8] Due to large number of zeros in the dependent variables (nearly 70% of SA2s are without any certified organic agricultural activities) censored tobit regression model was used.

over effects and direct effects for all covariates (Gibbons and Overman 2012; Manski 1993). Gibbons and Overman (2012) proposed the spatial lag of explanatory variables (SLX) model to address these identification issues, which was also advocated by Halleck Vega and Elhorst (2015). Among the spatial models, SLX is said to be the most parsimonious one in capturing local spill-over effects and it makes it easy to interpret because the ratio of direct and indirect effects can vary for each covariates and can take different signs than the direct effect. In addition, LeSage (2014) suggests that if theoretical considerations suggest the causal relationship as a local spill-over, the spatial Durbin error model (SDEM) is the appropriate model to estimate (e.g. Storm et al. 2015) because it nests the SLX model when $\lambda = 0$ in equation (1) below and the spatial error model (SEM) when $\theta = 0$ in equation (1) below. If theoretical considerations suggest global spill-over (e.g. Lapple and Kelley 2015), the spatial Durbin model (SDM) is the appropriate model specification which also nests the spatial autoregressive (SAR) when $\theta = 0$ in equation (2) below. The SDEM, SDM, and SLX models are specified in equations (1), (2), and (3), respectively:

$$y = X\beta + WX\theta + u;\ u = \lambda Wu + \varepsilon \tag{1}$$

$$y = \rho Wy + X\beta + WX\theta + \varepsilon \tag{2}$$

$$y = X\beta + WX\theta + \varepsilon \tag{3}$$

Here, ρ is the scaler parameter, which indicates the strength of spatial lag dependence; Wy indicates endogenous interaction effects (global spill-over); W is the n by n spatial weight matrix (defined in the subsequent section), which indicates the structure of spatial interdependence among the n observations; θ is the parameter of the exogenous interaction effect to be estimated; WX represents the local spill-over effects of spatially lagged exogenous variables; λ is the scaler parameter of spatial auto-correlated error.

On the basis of previous literature, it is expected that both neighbouring regions' OA adoption choices and structural, environmental and socio-economic attributes have significant influences in OA's spatial diffusion. As prior knowledge about the spatial interaction is not available, four models - random effect panel non-spatial tobit, SDM tobit, SDEM tobit and SLX tobit models - were estimated to distinguish the true nature of spatial spill-over effects. All the models were estimated using the maximum likelihood technique.

To explore the structure of spatial interdependence in the observations a spatial weight matrix was specified. Specification of the weight matrix is often arbitrary because there are little or no theoretical guidelines to follow in spatial econometrics (Bell and Dalton 2007). In the field of environmental and resource economics, the most frequently used matrices are contiguity, inverse distance (with or without a cut-off distance beyond which spatial effect is assumed to be zero) and k-nearest neighbour (Elhorst 2014). Our dataset only contains SA2s with agricultural activities, hence creating some islands of SA2s without any neighbours. In these cases, a contiguity matrix will force some SA2s to be dropped from the sample. An inverse distance spatial weight matrix was specified with a cut-off[9] distance to ensure at least one neighbour for each observation in the sample. The inverse distance matrix was chosen over k-nearest neighbour as the former allows the strength of spatial influence to decrease as the distance increases, which is not possible for the nearest neighbour approach. The spatial matrix was specified as: $W = 1/d_{ij}$, where d_{ij} measures the Euclidian distance between the centroids of the SA2s *i* and *j*. Anselin (1988) and Elhorst (2001), suggested that a row normalised inverse distance spatial matrix may become asymmetric and cause the remote and central regions (in this case SA2) to have the same impact, hence the inverse distance spatial weight matrix W was normalised using the procedure described in Elhorst (2014). For example, suppose W_0 is the inverse distance matrix before normalization and D is the diagonal matrix consisting of the row sums of matrix W_0. The normalised inverse distance matrix is specified as: $W = D^{-1/2} W_0 D^{-1/2}$. Not all the explanatory variables were included in the specification of spatial models due to high collinearity with their spatial lags following Storm et al. (2015) and Niedermayr et al. (2016) – all of whom studied farmers' behaviour in regard to adoption of alternative farming system and farm exit by employing SLX and SDEM models, respectively. Correlation among explanatory variables were checked using correlation coefficient and variance inflation factor (VIF) and has commonly accepted level (correlation coefficient is <0.7 and mean VIF is <10) reported in Table B.4, Table B.5, and Table B.6, respectively to reduce the risk of multi-collinearity. Other independent variables for which data were collected, but not included in the final model due to high collinearity with other variables were: annual maximum temperature, net income /loss from agriculture, relative soil moisture, soil organic carbon, and remoteness index.

[9] The cut-off was 440km and 537km, respectively for 2010/11 and 2015/16. The number of SA2s with agricultural operations in both censuses were different, hence two different cut-off distances. The empirical model was also tested with another threshold distance at 335km and 273km, respectively for 2010/11 and 2015/16 as a sensitivity test. The key findings remained unchanged with the alternative matrix specification confirming the robustness of the model findings.

2.4 Data

2.4.1 Dependent variables

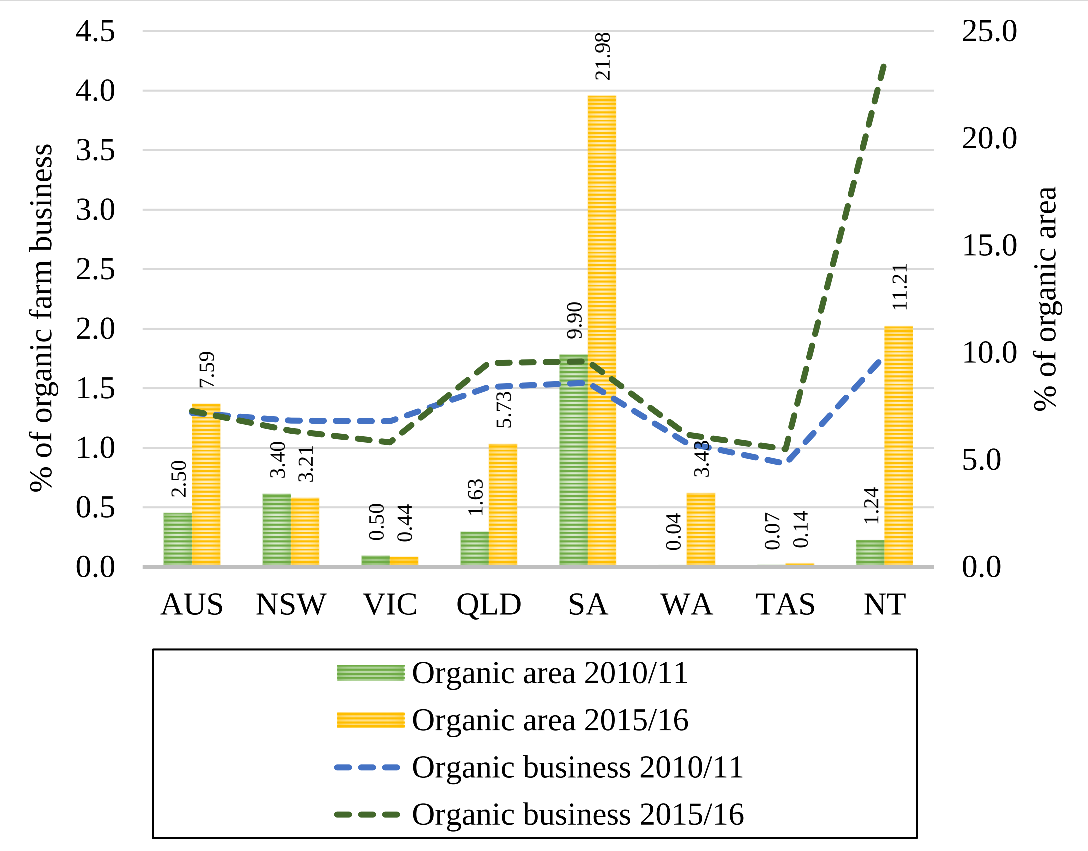
Data about OA operations (area and number of agricultural businesses) were sourced from the Australian Bureau of Statistics' (ABS) Census of Agriculture which is conducted every five years covering all agricultural businesses. Census questions related to OA operations (does the business hold current certified organic and bio-dynamic including in-conversion land or not) were asked for the first time in 2010/11[10] and were repeated in the 2015/16 census. In 2015/16, the ABS changed the scope of data collection by increasing the threshold of annual estimated value of agricultural operation from AUD$5,000 to AUD$40,000 or greater (ABS 2016i). There was an increase from 2.7% to 7.6% of land under certified organic management between 2010/11 to 2015/16, but the percentage of agricultural businesses that were holding partial or complete organic operations reduced to 1.3% in 2015/16 from 1.4% in 2010/11 (Wynen 2019), which may be partially due to changes in the scope of ABS data collection or consolidation of farms. The availability of data about potential organic adopters (size and number of all agricultural businesses) reported in the census creates scope to empirically model the intensity of OA diffusion. Two forms of dependent variables were calculated: the percentage of OA land in an area's total agricultural land holdings and the percentage of OA businesses of all agricultural businesses; to analyse the spatial diffusion of the intensity of OA in Australia at SA2 level. There were 1,201 and 1,080 SA2s with agricultural activities in 2010/11 and 2015/16, respectively.

Figure 2.1 and Figure 2.2 depicts the diffusion of OA (in terms of share of organic area in total area of agricultural holding and share of organic business in total agricultural business) at state and SA2 level respectively. As can be seen from Figure 2.2, there were 34 and 232 SA2s in 2010/11 and 2015/16, respectively with missing data about organic agriculture (area and number of business). The ABS does not report information regarding those SA2 where there were fewer than three farms in the 2015/16 census. Hence, censoring these SA2 at 0 (no organic farm) will be inaccurate. Hence, we assigned the same data from 2010/11 about the organic area and business numbers to the respective SA2s for which data were missing in 2015-16. Still, there were 72 SA2s with missing data which were not included in the final analysis. Additional sensitivity tests for checking the robustness of the empirical results were conducted by randomly generating average numbers of organic businesses at SA2 level for the missing

[10] Final data reported in both of the census (2010/11 and 2015/16) were based on the total population response rate of 88% and 85%, respectively for the financial year ended at 30 June for that respective year (ABS 2016i).

72 SA2s. The final unbalanced panel dataset contains total observations of 2,134[11] SA2s for the empirical analysis. An additional robustness check was also done using a balanced panel[12] dataset with 977 SA2s[13] from both censuses (total observations – 1,954) which shared the same geographic boundaries in both census periods.

Figure 2.1 Percentage share of organic area in total area of agricultural holding and percentage share of organic business in total number of agricultural business by state in Australia, 2010/11 and 2015/16



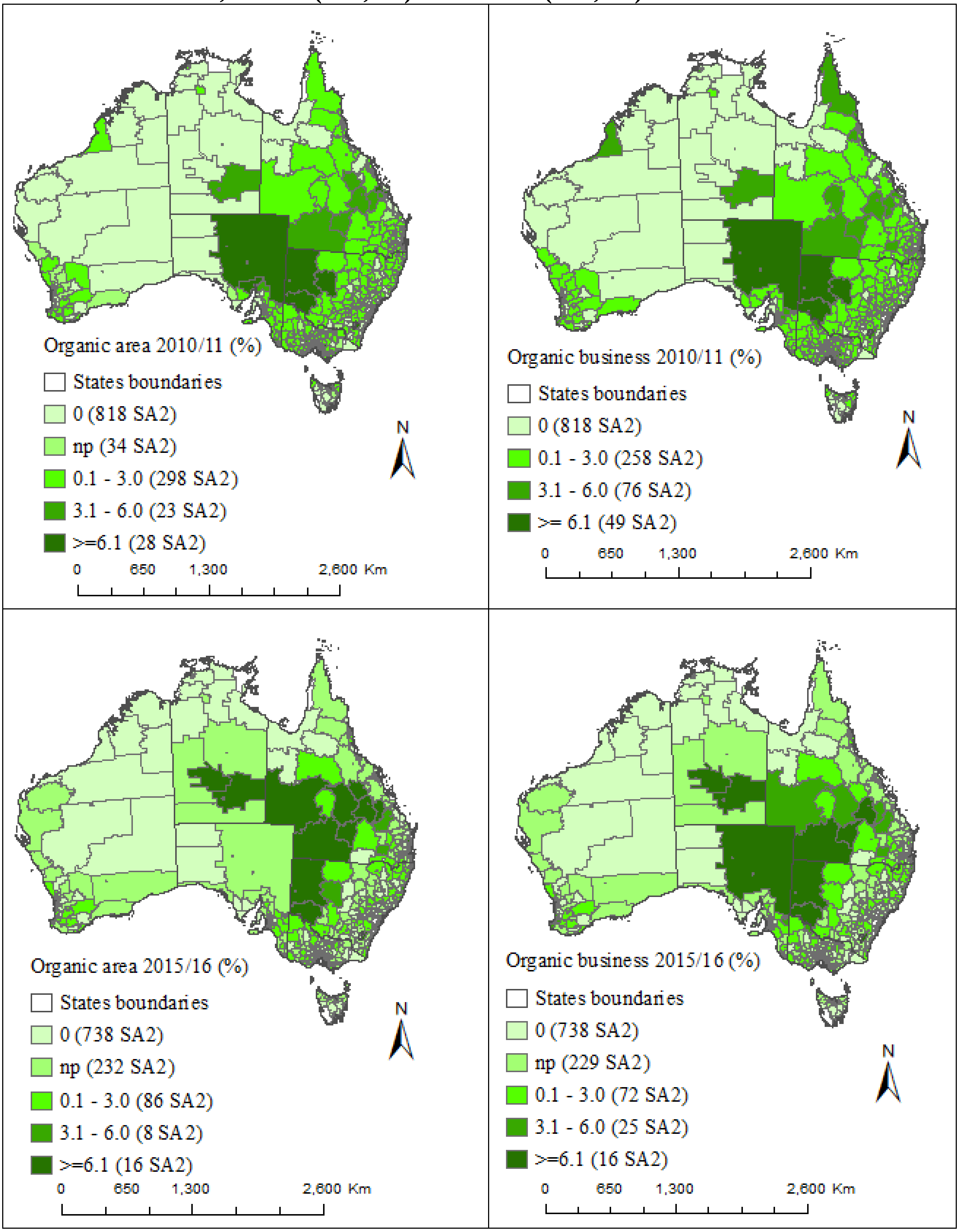
Own figure (Data sources: (ABS 2011b, 2016i))

[11] SA2s with missing data (total area of agricultural holding - 7, organic area and number - 72) were excluded. Due to the relative importance of territories with no organic activities (during the study period there was no organic farms in the Australian Capital Territory), 34 SA2s were also dropped, which results in 2,134 observations in total.

[12] To the best of the authors' knowledge the available estimation techniques for spatial panel tobit model are only applicable for balanced panel data.

[13] SA2s physical boundaries changed during these 5 years due to subdivision and merger of ASGS regions.

Figure 2.2 Spatial distribution of share of organic area and share of organic business at SA2 level in Australia, 2010/11 (N=1,201) and 2015/16 (N=1,080)



Own maps (data sources: share of organic area and farm (ABS 2011b, 2016i), base map (ABS 2011d))
<u>Notes</u>: np indicates data not available for publication by ABS. Figures in parenthesis indicates number of SA2s.

2.4.2 Independent variables

Based on findings from the literature (as reported in Table B.1 in the appendix B) and data availability, the following explanatory variables were collected and prepared at SA2 level for inclusion in the analysis.

2.4.2.1 Regional average farm structural characteristics

The five yearly Census of Agriculture and the Census of Population and Housing included variables indicating: the relative size of agricultural activities; the average size of agricultural land holdings; the percentage of irrigated agricultural businesses; livestock density (total number of cattle dairy and meat, sheep and lambs) per hectare of agricultural land and percentage of the labour force employed in agriculture. These were included in the empirical models. In addition, ABARES's "Catchment scale land use data" at a resolution of 50 metres was used to specify regional agricultural land use,[14] specialisation in terms of percentages of crop, grazing and horticultural land in the agricultural holding's total area. The proportion of land given to nature conservation and protection in the SA2's total area was also incorporated in the analysis. Figure B.1 in the appendix B depicts the catchment scale land use in Australia.

2.4.2.2 Climatic and environmental factors

Annual climate data included: total precipitation; potential evapotranspiration; and rainfall percentile grids at a resolution of approximately 5km were sourced from the Bureau of Meteorology (BoM) through a specialised data request and the CSIRO's Australian Water Availability Project (AWAP). The Aridity index - the ratio of total annual precipitation and potential evapotranspiration - was calculated to measure the level of dryness (a higher value was associated with increased wetness). Meteorological drought (severe drought) developed by the BoM was used in the study. Severe drought occurs when recorded rainfall sits within the lowest 5th percentile for the area over a period of three months or more. Annual rainfall 5th percentile grids and spatial boundaries of SA2 regions were overlayed to extract rainfall deficiency at the SA2 level, and a dummy variable "Drought" was created. A normalised difference vegetation index (NDVI), derived from satellite data which measures vegetation greenness, was also incorporated. The NDVI index value ranges between -1 to +1 and higher values are associated with higher density and greenness of plant canopy cover (BoM 2020e).

[14] Regional agricultural specialisation was calculated on the basis of Australian land use and management secondary hierarchy level classification (details provided in Table B.2 in the Appendix B)

To capture the difference in the natural productivity of the land two variables, soil texture index and pH level, were calculated. Soil pH ($cacl_2$) in the top-soil (0-5cm) was obtained from the CSIRO-developed “Soil Attribute Maps” at a resolution of approximately 90m. To capture the potential variability of soil and land attributes that affects the soil water holding and nutrient retention capacity an index of soil attributes was created using the average surface soil texture sourced from the CSIRO. Increased values of the index indicate higher clay content in the soil (1=sand; 2=sandy loam; 3=loam, 4=light clay/clay loam and 5=clay). Finally, a digital elevation model developed by Geoscience Australia, at a resolution of 25m, was used to derive the average elevation.

2.4.2.3 Regional socio-economic features

To control for organic commodity demand, three proxy variables included were: average net taxable income (calculated using Australian taxation office (ATO) taxation statistics at postcode level); annual average residential population and socio-economic index for areas (SEIFA) (sourced from Census of Population and Housing). The SEIFA index ranks areas on their relative socio-economic advantage and disadvantage (Haensch et al. 2019; Wheeler and Zuo 2017). This index is constructed using variables related to income, education, employment, occupation, housing and others. A high score for an area indicates relatively low levels of disadvantage and vice versa.

As an estimate of the potential local demand for OA, the percentage of first preference votes cast for the Green party, available from state Electoral Commissions, was used. State elections do not coincide with census years and they vary among states. Hence, state election results from the closest year before each census year were used for each state. The spatial boundaries of electoral divisions were spatially merged with the geocoded SA2 boundaries to calculate the share of the Green vote at SA2 level. Distance to major cities (ABS’s urban centres and localities with population 1,000 or greater) was included in the empirical model by calculating the Euclidean distance from the centroid of each of the SA2 to the urban centres and localities to account for the region’s relative access to markets.

All the variables from 2016 were converted to the SA2 boundaries of 2011 using ABS developed geographic correspondences to account for the mergers and subdivisions of SA2s between 2010/11 and 2015/16 (ABS 2016c). The variables were spatially and temporally matched. ArcGIS 10.5.1 software was utilised to extract the spatial regional variables for each year (ArcGIS tools are listed in Table B.3 in the appendix B) at SA2 level - the statistical geographic unit of analysis. State and year dummies were incorporated in the empirical models to control for spatially correlated omitted and unobserved variables which may affect the spatial interaction effects in the diffusion of OA. To minimise the risk of potential endogeneity, a one-year lag of most of the explanatory variables, depending on data availability, was used. Description of the variables with sources and descriptive statistics are provided in Table 2.1 and Table 2.2, respectively.

Table 2.1 Variables description and data sources

Variables	***Variables definition***	***Source***
Dependent variables		
Organic area (%)	Percentage share of certified organic area in a region's total agricultural holding	(ABS 2011b, 2016i)
Organic business (%)	Percentage share of certified organic farm businesses in a region's total number of agricultural businesses	
Independent variables: Average farm structural factors		
Farm size (ha)	Average size of agricultural holding in natural logarithm	(ABS 2011a, 2016a)
Livestock density (number/ha)	Livestock (total number of dairy and meat cattle, sheep and lamb) density per hectare of agricultural land	
Irrigated business (%)	Percentage share of irrigated businesses in a region's total agricultural businesses	(ABS 2011i, 2016p)
Agricultural labour (%)	Percentage share of labour force engaged in agriculture in a region's total labour force	
Crop (%)	Percentage share of cropland in a region's total agricultural land holding	(ABARES 2015, 2016c)
Grazing (%)	Percentage share of grazing land in a region's total agricultural land holding	
Horticulture (%)	Percentage share of horticultural land in a region's total agricultural land holding	
Climatic and environmental factors		
Aridity index	Ratio of annual rainfall and potential evapotranspiration (PET). The higher the index value the greater the wetness.	Rainfall: BoM - specialised request; PET (BoM 2020b)
Drought	Severe drought (when average rainfall lies below 5th percentile rainfall over an extended time period) dummy (1=drought;0=otherwise)	BoM -specialised
NDVI	Normalised difference vegetation index measures greenness of an area. Higher value of the index associated with increased green vegetation	(BoM 2020e)

Soil texture index	1=sand; 2=sandy loam; 3=loam, 4=light clay/clay loam and 5=clay	(CSIRO 2001)
Soil pH	Mean pH ($CaCl_2$) level in the top soil (0-5cm).	(Viscarra Rossel et al. 2014c)
Elevation (m)	Average elevation	(Geoscience Australia 2015)
Conservation land (%)	Percentage share of nature conservation and protection land in a region's total land area	(ABARES 2015, 2016c)
Locational factor		
Distance to cities (km)	Major cities are defined by the UCL's with population 1000 or more	(ABS 2011h, 2016o)
Socio-economic factors		
SEIFA index	SEIFA's index of relative advantages and dis-advantages ranks areas. The high value of the index for an area means that the area is relatively more advantageous compared to other areas.	(ABS 2012, 2016e)
Population	Residential population (numbers)	(ABS 2011e, 2016k)
Community income	Average net taxable income (nominal 1000 AUD$)	(ATO 2013, 2017)
Green vote	Percentage share of 1st preference votes[15] cast for Green party in total votes	Electoral boundaries (ABS 2011g, 2016n); State Electoral Commissions (EC) reports[16]
State dummies		
New South Wales (NSW)	NSW=1 if the SA2 areas falls within NSW's boundaries; 0=otherwise	(ABS 2011f, 2016m)
Northern Territory (NT)	NT=1 if the SA2 areas falls within NT's boundaries; 0=otherwise	
Queensland (QLD: base)	QLD=1 if the SA2 areas falls within QLD's boundaries; 0=otherwise	
South Australia (SA)	SA=1 if the SA2 areas falls within SA's boundaries; 0=otherwise	
Tasmania (TAS)	TAS=1 if the SA2 areas falls within TAS's boundaries; 0=otherwise	
Victoria (VIC)	VIC=1 if the SA2 areas falls within VIC's boundaries; 0=otherwise	
Western Australia (WA)	WA=1 if the SA2 areas falls within WA's boundaries; 0=otherwise	

[15] Elections results are only available at the electoral districts level. The electoral district boundaries were spatially joined with SA2 boundaries.

[16] (ECQ 2017; ECSA 2010, 2014; Green 2009, 2010, 2011a, 2011b, 2013; NSWEC 2011, 2015; NTEC 2016; TEC 2010, 2014; VEC 2014)

Table 2.2 Descriptive statistics of the variables included in the spatial tobit model, 2010/11-2015/16 (N=2,134)

Variables	*Mean*	*Standard Deviation*	*Minimum*	*Maximum*
Dependent variables				
Certified organic area (%)	0.83	5.63	0	100
Certified organic business (%)	1.21	5.52	0	100
Independent variables				
Farm size in natural logarithm (ha)	5.15	2.48	-3.00	13.73
Irrigated business (%)	40.72	35.16	0	100
Livestock density	0.83	1.03	0	10.49
Agricultural labour (%)	3.37	4.90	0	50
Crop (%)	13.49	23.20	0	100
Grazing (%)	62.02	35.29	0	100
Horticulture (%)	5.13	14.63	0	100
Aridity index	0.66	0.40	0.05	4.03
Drought	0.01	0.08	0	1
NDVI index	0.39	0.12	0.09	0.65
Soil texture index	2.72	1.02	1	5
Soil pH	5.44	0.90	2.32	8
Elevation (m)	171.83	194.03	0.75	1106.94
Conservation land (%)	19.17	20.42	0	100
Distance to cities (km)	18.67	40.91	0	51.44
SEIFA index	973.83	75.38	522.46	1178
Population[17] (numbers)	9989.75	6599.09	0	59032
Community income (AUD$ in thousands)	82.28	92.13	0	837.98
Green Vote (%)	8.62	5.23	0	45.6
Year (base=2011)	0.46	0.50	0	1
NSW dummy	0.26	0.44	0	1
NT dummy	0.02	0.13	0	1
SA dummy	0.10	0.30	0	1
TAS dummy	0.06	0.23	0	1
VIC dummy	0.22	0.42	0	1
WA dummy	0.11	0.31	0	1
QLD dummy	0.23	0.42	0	1
Observations (N)	2,134			

2.5 Results

The estimated coefficients of spatial lag dependence (ρ) – global spatial spill-over effect and spatial autocorrelation (λ) of the SDM and SDEM, respectively were statistically insignificant (results reported in Table B.7 and Table B.8 in the appendix B). Hence, the commentary

[17] There were 12 SA2s with no residential population, but there were agricultural land in those SA2s.

following is based on the results from the non-spatial tobit and SLX tobit model of share of organic area. The non-spatial and spatial model with dependent variable shares of organic area performed better than models with shares of organic businesses in terms of AIC, BIC and log-likelihood value. The marginal effects[18] of the random effect panel tobit[19] and SLX tobit model to explain OA diffusion in terms share of organic area and farm are reported in Table 2.3 (results with standard errors are reported in Table B.9 in the Appendix B). Additional sensitivity testing results using the balanced panel data models in terms of share of organic area and business and share of organic business with randomly generated average organic business and different specification of the spatial inverse distance matrix and sample observations without the SA2s that are located in the rangeland[20]to check the robustness of the estimates were reported in Table B.10 to Table B.15 in Appendix B). The estimated marginal effects of the non-spatial and spatial model does not vary that much (a few exceptions exist), despite the statistically significant local spill-over effects in the SLX tobit model.

2.5.1 Effects of farm structure, agricultural specialisation and intensity

The structural variables related to farming within a given area appears to be the most consistent ones in all model specifications in explaining the OA diffusion process. Higher concentration of OA is likely to be located in areas characterised by larger farms. A similar result has been found by Boncinelli et al. (2015) and Koesling et al. (2008). But contradicts the findings of Burton et al. (1999) and Läpple and Rensburg (2011) – suggesting that large farms are less likely to adopt. In case of Australia the finding is not surprising, given that large scale corporate farms other than the large pastoral farms located in the rangelands are converting to organic farming, farms are consolidated into larger units, and organic industry is becoming more corporate and larger in farm size like the conventional farming industry (Lawson et al. 2018; Lockie and Halpin 2005; Wheeler 2011). Also, Padel (2001) found that in the European countries the average organic farm size increased during the diffusion process and suggest that this may results from the structural change in the agricultural industry. In addition, given the greater accessibility of financial resources and information sources, large farms are quicker to adopt new innovation (Goddard et al. 1993). A systematic review by Sapbamrer and

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[18] The average marginal effects were estimated on the expected value of left and right censored outcome (E (y*|x)).

[19] The structural stability of the random effects tobit model was checked using Stata command *"quadchk"* (Stata). Following the rule of thumb, the relative difference of each coefficients was less than 0.001, which indicates the appropriateness of the quadrature integration point.

[20] One examiner suggested to check the robustness of the modelling results by dropping the SA2s located in the outback of the country. The digital boundaries of the SA2s were spatially joined with the digital rangeland boundaries (sourced from (ERIN 2005)) to identify which SA2s falls within the rangeland boundaries in different states and were dropped from the sample.

Thammachai (2021) also found inconclusive evidence in terms of farm size as one of the drivers of OA diffusion.

In addition, areas with a higher percentage of irrigated farm businesses positively influences the intensity of OA adoption and diffusion. As expected, areas with low stocking density benefits higher uptake of OA, which may be because of the low transition cost for these farms to convert to OA; this aligns with other findings (Läpple and Kelley 2014; Niedermayr et al. 2016; Schmidtner et al. 2012). Given that organic farming is more labour intensive (Finley et al. 2018; Jansen 2000; Lohr and Park 2009), especially in the early phases of conversion, it is not surprising that areas with increased availability of agricultural labour (both within the SA2 – direct effect and in neighbouring SA2s – spill-over effects) positively influence OA diffusion.

The statistically significant positive marginal effect of agricultural specialisation variables - the share of grazing and horticultural land within the SA2 - mirrors the findings of Wynen (2019) that higher shares of organic land (approximately 95%) were utilised for grazing modified and improved pastures in 2015/16. Lawson et al. (2018) found that the highest number of organic producers were involved in plant based horticultural activities (fruit growing) in 2018. Similarly, Gabriel et al. (2009) report that organic farms are concentrated in areas characterised by improved grassland and mixed/dairy farms in England. Although, the direct effect of increased horticultural land is positive (within its own SA2), the spill-over effects are negative, which indicates that neighbouring areas with similar type of farms hinder the diffusion process. This effect may be caused by increased competition for natural resources; land and water for irrigation and access to premium markets. It seems that the negative externalities outweigh the positive spill-over effects such as the reduced cost of learning alternative forms of farming through knowledge spill-over or agglomeration economics (Delbridge and Connolly 2017).

Table 2.3 Marginal effects of the tobit random-effects unbalanced panel models to explain the spatial diffusion of certified organic farming in Australia, 2010/11–2015/16 (N=2,134)

Variables	*Share of organic area (Model I)*			*Share of organic business (Model II)*		
	Tobit	*SLX Tobit*		*Tobit*	*SLX Tobit*	
	X	*X*	*WX*	*X*	*X*	*WX*
Farm size	0.032***	0.026***	-0.017	0.026***	0.019***	-0.022
Irrigated business	0.001***	0.001***	0.00	0.001***	0.001***	0.000
Livestock density	-0.018*	-0.022**	0.019	-0.017*	-0.021**	0.017
Agricultural labour	0.010***	0.008***	0.025**	0.010***	0.008***	0.031***
Crop (%)	0.000	0.000	-0.002	0.000	0.00	-0.003**
Grazing (%)	0.001*	0.001**	-0.002	0.000	0.000	-0.001
Horticulture (%)	0.001**	0.002**	-0.008**	0.001	0.001*	-0.009***
Aridity index	0.033	0.037		0.037	0.036	
Severe drought	0.191***	0.186***	0.534*	0.046	0.048	0.571**
NDVI	0.495***	0.426***		0.485***	0.412***	
Elevation	0.000***	0.000**		0.000***	0.000***	
Soil texture	0.000	-0.001		0.009	0.009	
Soil pH[21]	0.034***	0.030**		0.033**	0.025*	
Green vote	0.003	0.004**		0.004**	0.004**	
Conservation land	-0.001**	-0.001**	0.002	-0.001	-0.001*	0.003**
Distance to cities[22]	-0.000*	-0.000		-0.000**	-0.000*	
SEIFA	0.000	0.000		-0.000*	0.000	
Taxable income	0.000**	0.000*	0.000	0.000***	0.000**	0.000
Population	-0.000***	-0.000***		-0.000***	-0.000***	
Year (base=2011)	0.021*	0.053***		0.009	0.036**	
NSW (base=QLD)	0.031	0.023		0.032	0.014	
NT	0.118	0.168		0.114	0.154	
SA	0.080*	0.104*		0.107**	0.118*	
TAS	-0.081***	-0.100***		-0.084***	-0.114***	
VIC	0.107***	0.110**		0.114***	0.100*	
WA	0.039	0.041		0.049	0.042	
Left-censored	1,525			1,525		
Right-censored	3			4		
Uncensored	606			605		
Log likelihood	-2,662.234	-2,649.506		-2,685.788	-2,670.233	
Wald Chi2	213.060***	218.590***		217.310***	227.340***	
AIC	5,382.468	5,377.013		5,429.575	5,418.466	
BIC	5,546.775	5,597.978		5,593.882	5,693.430	

Notes: The outcome variable is the share of organic area in total area of agricultural holding in Model I and share of organic farm business in total agricultural business in Model II. Variables name started with W indicates explanatory variables with spatial lag. Asterisks *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

[21] Following one of the examiner's suggestion quadratic term of soil pH level was also tested in the model and it was statistically insignificant (results reported in **Table B.16** in Appendix B).

[22] Another specification of urban centres and localities with 5,000 or more population was also tested in the final models of share of organic area and farm and the results remain unchanged with this population cut-off.

2.5.2 Effects of natural and environmental factors

Farms located in areas that are affected by severe drought (both direct and spill-over effects) are more likely to convert to OA (direct effects only significant for Model I) as indicated by the significantly positive marginal effect for their own and neighbouring SA2s. Higher OA concentration in drought affected areas may be explained by the literature that organic farms perform better (in terms of higher yield) in dry conditions, which is argued to result from the greater soil water-holding capacity of organic farms and their soils' organic matter (Gomiero et al. 2011; Lotter et al. 2009; Patil et al. 2014). Also, areas characterised by higher plant density and increased greenness of plant canopy cover (as measure by the NDVI) are positively associated with a higher share of OA. In addition, organic farms are more likely to be present in areas characterised by high altitude (hilly terrain), which aligns with the finding of Gabriel et al. (2009) who suggested that the opportunity cost of transition may be lower for farms located in less favoured agricultural areas. Switching to organic management provides the opportunity to capture premium prices for products. In contrast to Gabriel et al's. (2009) and Schmidtner et al's. (2012) contention that farmers in England and Germany tend to convert to OA in areas that are less suitable for agricultural production (less fertile soil), higher share of organic area and of soil pH level are positively correlated and statistically significant indicating that a higher concentration of OA was more likely to occur in areas with good quality soil. Low and very high pH levels are harmful for agricultural production and the optimal level of soil pH for plant growth is 5.5 to 7 and the maximum pH level was 8 in our study area (reported in Table 2.2).

2.5.3 Effects of market accessibility and socio-economic factors

Social acceptance by the social networks in which farmers operate has been found to play a vital role in farmers' decisions to adopt alternative farming systems like organic agriculture (Marasteanu and Jaenicke 2015; Schmidtner et al. 2012; Wollni and Andersson 2014). The larger the share of the Green vote, which was used as a proxy indicator in support for organic farming, has a statistically significant positive effect on OA adoption and diffusion (except for the non-spatial tobit in Model I though the coefficient is still positive). In the context of Germany and the USA, it is perceived that in general voters of Green parties are more receptive to OA or other alternative farming systems (Marasteanu and Jaenicke 2015; Schmidtner et al. 2012), creating local markets. Unlike Schmidtner et al. (2012) who finds that the share of conservation land positively influences the spatial distribution of organic farming in Germany, the share of conservation and protection land in each SA2 (direct effect) constrains the diffusion process. As expected, market accessibility, as measured by the distance to major urban centres, has a positive statistically significant influence on a higher share of OA, though the effect is only significant in the spatial model. This finding also supports other OA adoption literature, which find organic farms are more likely to be located in close proximity to cities (Boncinelli et al. 2015; Koesling et al. 2008; Lewis et al. 2011). As expected, higher concentration of OA appears in areas with higher community income (proxy indicator of consumer demand). This supports Schmidtner et al. (2012), who used number of organic food stores at county level to measure organic food demand/market access and found a positive effect on OA. In contrast to the earlier results, regional population has a significant negative effect, implying higher concentration OA in areas characterised by low population density, which is in line with Gabriel et al.'s (2009) finding that rural areas with low population density (far from urban sprawl) has higher share of OA in England. The positive and significant year variable indicates the upward trend of OA diffusion in Australia (as depicted in Figure 2.1). Finally, the existence of regional heterogeneity was also confirmed by the significant regional variables. There are higher concentrations of OA in the states of South Australia and Victoria, whereas Tasmania has a lower share of OA.

2.6 Discussion

A spatially explicit dataset of structural, environmental and socio-economic variables was prepared to explain the role of these factors in the regional diffusion of OA in Australia across two years – 2010-11 and 2015-16. Overall, it was found that the spatial clusters of higher concentration of OA at a regional level were attributed to the local spatial spill-over effects arising from the neighbouring regional attributes rather than the intensity of OA diffusion in the neighbouring regions (e.g. no strong evidence of global spill-over effects). This contrasts with the general findings from European (Allaire et al. 2015; Bjørkhaug and Blekesaune 2013; Schmidtner et al. 2012) and American (Lewis et al. 2011; Marasteanu and Jaenicke 2016) literature. This literature has found that OA adoption was significantly influenced by the neighbouring farmers' and regions' (counties, micro-territories) adoption choices. The widespread and vast land resources and the large average size of the limited number of Australian organic farms (as shown in Figure 2.2) compared with that of other countries, and the lack of spatial proximity between them, may be one of the reasons for this contradictory finding. More research is warranted, depending on future availability of farm level panel datasets, to explore if the results of spatial dependence vary on the basis of spatial scale. However, in Germany Schmidtner et al. (2012, 2015) studied the spatial distribution of OA adoption at two spatial scales – county and municipality level - to assess if the results vary with changing spatial resolution and found no significant difference. At both spatial scales, OA adoption was induced by neighbouring regions' share of OA (global spill-over). In contrast, Boncinelli et al. (2015) and Boncinelli, Riccioli, and Casini (2017) identified significant differences in spatial dependence depending on the spatial scale and the farming industry in Italy. At regional (municipality) level, aggregated OA adoption was found to be influenced by the adoption intensity of nearby regions, whereas in the later study about farm level spatial structure of organic viticulture, neighbours' characteristics (local spill-over) were found to be more significant than neighbours' adoption choices.

In addition, in regions with certain physical structures - such as large irrigated farms with low stocking rates, plus increased availability of agricultural labour and grazing and horticultural land are more likely to have higher OA. The higher demand for labour may constrain the diffusion of OA if sufficient labour is not available. On the other hand it also creates employment opportunities (Jansen 2000). In terms of environmental conditions, drought affected regions and increased vegetation, as measured by the NDVI, were significantly associated with higher intensity of OA. In drought affected areas, it is possible that OA may serve as a climate change adaptation strategy for famers' (Scialabba and Müller-Lindenlauf 2010). Wheeler (2011) suggests government may provide support to farmers, in terms of increased access to credit during the organic transition period (like a government run drought relief fund), to overcome financial barriers that may hinder the diffusion of OA.

It has been argued that farming systems that produce ecosystem services, irrespective of whether they are conventional or organic, or any other form of sustainable agricultural innovations, should be supported through various market-based financial incentives such as: biodiversity offsets; carbon farming; auctions; tenders; and eco-taxes (Lockie 2013; Stolze and Lampkin 2009; Wheeler 2011). These ecosystem services provide diverse benefits above and beyond the ground: provisioning (food, fibre, bioenergy); supporting and regulating (climate regulation, pollination, natural pest control, water quality; soil formation, biodiversity, carbon sequestration, and nutrient retention); and cultural (aesthetic, recreational, spiritual) (Bryan 2013). If OA produces more benefits, farmers are likely to respond positively to the market signal of these incentives, which will further the adoption of sustainable innovations (Reganold and Wachter 2016). With respect to market forces, a knowledge-based policy, aimed to provide increased access to information sources, outreach programs to facilitate increased interaction between farmers and extension officials, increased public and private funding for agricultural

R&D and community awareness programs are recommended by Reganold and Wachter (2016), Lee (2005) and Wheeler (2011).

This study is not without limitations. The results were drawn from a census panel of farms over two years at a regional level, hence spatial heterogeneity among individual farms was not considered. These regional aggregates might mask the potential individual heterogeneity that operates at farm-scale, and therefore differ from results that obtained from an individual level interaction (Anselin 2002; Niedermayr et al. 2016; Storm et al. 2015). One promising avenue for future research involves in-depth analysis of the influence of spatial interaction at a finer spatial scale (farm level) by collecting detailed historical data about certified organic producers' physical locations, yields, margins and price premiums, etc. from the nationally accredited organic certifiers such as the Biodynamic Research Institute, the Australian Certified Organic and the National Association for Sustainable Agriculture Certified Organic, all of which were active in the initial phases of organic certification, and comparing the diffusion at the farm level over space and time.

2.7 Conclusion

The intensity of OA diffusion in Australia was studied using a panel dataset from the latest agricultural censuses (2010/11 and 2015/16) at regional level. The SLX tobit model was employed to separate the effects of local spatial spill-over in OA diffusion. The results show that higher concentration of OA in a region is not influenced by the share of OA in neighboring areas (termed global spill-over). Rather, regional collective capacities, as well as neighboring regions' characteristics (local spill-over), significantly influenced the diffusion process. The results are in line with the findings of sustainable technology adoption and diffusion literature both from developed and developing countries. Large extensively managed farms with grazing and horticultural land use, areas with more irrigated farms and higher tree density and green vegetation, drought affected regions, high altitude, and good soil quality are the physical and environmental factors that contribute to the higher concentration of OA within a region. Also, a higher share of green voters in an area, proximity to urban areas and higher community incomes in general seems to increase market potential, positively affecting the regional share of OA. In contrast, densely populated areas and higher percentage of nature conservation land hinders OA diffusion. Also, spatial heterogeneity was found. Regions located in the states of South Australia and Victoria have higher concentration, whereas Tasmania has lower share of OA.

Chapter 3 The spatial influences of organic farming and environmental heterogeneity on biodiversity in South Australian landscapes

Abstract

The beneficial effects of certified organic farming on biodiversity and conservation remains unexplored in Australia, despite it having the world's largest amount of certified organic farmland and unprecedented loss of biodiversity. This study explored the spatial effects of organic farming (intensity of local farming systems), environmental heterogeneity, and urbanisation on two widely studied taxa — vascular plant and bird species richness (surrogate measures of biodiversity) in the state of South Australia, using a unique organic certification postcode level dataset from 2001 to 2016 (N=5,440). The results of the spatial Durbin error model confirm the positive spatial congruence of the presence of organic farming with vascular plant species richness, whereas only weak to no statistically significant evidence was found for bird species richness. Landscape features (habitat heterogeneity) and green vegetation a proxy indicator of resource availability, rather than organic farming, appeared to be the prime drivers of bird species richness gradients. Hence, biodiversity conservation strategies that promote low intensity farming and increase landscape heterogeneity to provide quality habitat (a whole of landscape approach by incorporating private agricultural landholders) could be beneficial for biodiversity conservation because different taxa respond at different spatial scales.

Keywords: Organic farming; vascular plant and bird richness; environmental heterogeneity; spatial Durbin error model; South Australia

Statement of Authorship

Title of Paper	The spatial influences of organic farming and environmental heterogeneity on biodiversity in South Australian landscapes
Publication Status	☐ Published ☐ Accepted for Publication ☐ Submitted for Publication ☑ Unpublished and Unsubmitted work written in manuscript style
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Principal Author

Name of Principal Author (Candidate)	Maksuda Mannaf		
Contribution to the Paper	Conceptualisation and development of the study; undertook literature review; collected and prepared data for spatial econometric analysis and interpreted the results; wrote the manuscript.		
Overall percentage (%)	70%		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	1/12/2020

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);
ii. permission is granted for the candidate in include the publication in the thesis; and
iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Name of Co-Author	Sarah Ann Wheeler		
Contribution to the Paper	Supervised the conceptualisation and development of the study; provided organic (contacted the certifying organisations) and climate data; supervised and suggested econometric modelling; evaluated and edited manuscript.		
Signature		Date	3/12/20

Name of Co-Author	Alec Zuo		
Contribution to the Paper	Supervised the conceptualisation and development of the study; provided climate data; supervised and suggested econometric modelling; evaluated and edited manuscript.		
Signature		Date	3/12/20

3.1 Introduction

Australia is one of the seventeen megadiverse countries of the world and is home to an estimated 566,000 species, of which 84% of plants, 45% of birds and 87% of mammals are native (Bradshaw 2019; Chapman 2009; Haque et al. 2020). Like the rest of the world, Australia is facing unprecedented loss of biodiversity, despite current policy and management efforts (Bardsley et al. 2019; McDonald et al. 2015; Woinarski et al. 2015). Habitat loss due to agricultural expansion and intensification, climate change, invasive species and pathogens, governance issues, and changed fire regimes are documented as the major threats to continuing decline of the nation's native flora and fauna (Bradshaw 2012; Evans et al. 2011; Reside et al. 2013).

Since European settlement, the highest rate of species loss has been experienced in south-eastern Australia (Bradshaw 2012; Woinarski et al. 2015). Creating habitats only within reserves or protected areas has been suggested that it may not be enough to conserve biodiversity in the face of future climate change (Bardsley et al. 2019; Batáry et al. 2011). Less intensive farm management practices of private agricultural properties plays a significant role in biodiversity conservation (Chamberlain et al. 2010; Gonthier et al. 2014). Integration of private agricultural properties in the whole-of-landscape conservation policy is gaining increasing attention by policy-makers around the world (Andersson and Lindborg 2014; Bardsley et al. 2019; Gonthier et al. 2014; Tscharntke et al. 2005).

There is growing scientific evidence of the benefits of organic farming as a less intensive farming system that balances overall (economic, environmental and social welfare) sustainability goals (Meemken and Qaim 2018; Reganold and Wachter 2016; Rigby and Cáceres 2001; Sandhu et al. 2008; Seufert and Ramankutty 2017). In particular, biodiversity benefits of organic farming: findings from meta-analysis revealed overall 30% higher species richness for organic farming compared to conventional farming (Bengtsson et al. 2005; Tuck et al. 2014), though the effects vary among taxa, organism groups, spatial scales, and surrounding landscape features (Bengtsson et al. 2005; Benton et al. 2003; Fuller et al. 2005; Hole et al. 2005; Rahmann 2011; Stein-Bachinger et al. 2020; Tuck et al. 2014; Winqvist et al. 2012). Organic farming is a worldwide phenomenon, which is practiced in 186 countries by 2.8 million producers and it occupied 1.5% of total agricultural land (71.5 million hectares) globally in 2018 (Willer et al. 2020). Half of the world's 35.7 million hectares which is certified organic is in Australia and organic land accounted for 9.6% of Australian total agricultural land in 2018 (Williams et al. 2019) .

Although several studies have used annual vascular plant and bird species richness data from the Atlas of Living Australia (ALA) to address various questions (e.g. landscape biodiversity and respiratory heath (Liddicoat et al. 2018); influences on avian species (Coops et al. 2018; McKinney and Kark 2017); identification of refugia using species distribution models (Reside et al. 2013); and sampling biases in the digitalization of Australian flora (Haque et al. 2020), to date no study has considered the spatial correlation between organic farming presence and biodiversity outcomes measured by vascular plant and bird species richness using ALA data.

This study seeks to analyse the spatial association between certified organic farming and species richness (vascular plant and bird biodiversity were the surrogate measures) at postcode level. A unique dataset of certified organic farming, spanning 2001-2016, was assembled using databases of the two major Australian organic certifiers. The present study attempts to investigate the spatio-temporal association of the presence of organic farming on various biodiversity indicators, by controlling for biomass productivity, energy-water dynamics (e.g. rainfall, temperature, and evapotranspiration), habitat heterogeneity, and agricultural land use in a multifunctional agricultural landscape in South Australia.

In other words, this study sought to investigate answers to the question of whether the presence of organic farming is associated with increased plant and/or bird species prevalence in South Australia, using a spatial Durbin error model across sixteen years of data. Although the biodiversity benefits of organic farming have been reasonably widely explored in European countries and North America (Belfrage et al. 2005; Bengtsson et al. 2005; Chamberlain et al. 2010; Kirk et al. 2020; Puig-Montserrat et al. 2017; Rahmann 2011; Smith et al. 2010; Tuck et al. 2014), the spatial correlation between organic farming and biodiversity conservation outcomes remains unexplored in Australia.

3.2 Effects of organic farming, environmental heterogeneity, and urbanisation on biodiversity: summary of the literature

The spatial pattern of plant and bird species richness results from a complex process of interaction and synergy between various biotic and abiotic factors, such as: habitat heterogeneity (Kissling et al. 2008; Koh et al. 2006; Xu et al. 2016; Zhang et al. 2013); water-energy dynamics (Coops et al. 2018; Diniz-Filho and Bini 2005; Hawkins et al. 2005; Kreft and Jetz 2007; Tripathi et al. 2019); plant productivity (Coops et al. 2018; Jetz and Rahbek

2002; McKinney and Kark 2017; Parviainen et al. 2010; Xu et al. 2016); anthropogenic land use (Batáry et al. 2011; Piha et al. 2007); and human population footprint/urbanisation (Lee et al. 2004; Luck 2007; Luck et al. 2010; McKinney and Kark 2017). Hence, it is important to account for these factors in estimating the influence of organic farming on conserving biodiversity, otherwise the effects of organic farming may be overestimated (Chamberlain et al. 2010; Gabriel et al. 2010; Kirk et al. 2020; Piha et al. 2007).

There are several studies that have found positive effects of organic farming on biodiversity conservation in agricultural lands. This has included higher plant and bird species richness on organic: rice fields (Katayama et al. 2019); vineyards (Puig-Montserrat et al. 2017; Rollan et al. 2019); and apple farming (Katayama 2016). In addition, the heterogeneity of the agricultural landscape (amount of natural, semi-natural habitat) and agricultural land use (crop versus grass land), seems to positively influences species richness, even without organic farming or hedge management (Batáry et al. 2010; Benton et al. 2003; Fahrig et al. 2011; Fischer et al. 2011; Tscharntke et al. 2005; Weibull et al. 2003). In contrast, more pronounced effects of organic farming were found in simple landscapes. The biodiversity benefits of agri-environmental management schemes[23] have been found to be higher in simple landscapes (low proportion of semi-natural habitats) compared to complex landscapes (higher proportion of semi natural habitats; namely >20%) (Batáry et al. 2011; Hiron et al. 2013).

However, the benefits of organic farming vary among taxa, with more pronounced and consistent effects found for plant richness, as compared to bird richness (Bengtsson et al. 2005; Fuller et al. 2005; Tuck et al. 2014). Moreover, studies show little to no benefit of organic farming on bird biodiversity at various spatial scales (Hiron et al. 2013; Puig-Montserrat et al. 2017). Some found even more birds on conventional farms, despite higher availability of food resources on organic farms (Gabriel et al. 2010). No significant difference in plant richness was found between organic and conventional farms in semi-natural areas, despite organic farms having more semi-natural habitats (Gibson et al. 2007; Goded et al. 2019; Weibull et al. 2003). An overview of the literature's findings is presented in Table C.1 in Appendix C.

In addition, most of the earlier studies applied spatial autoregressive (SAR) and spatial error models (SEM) to account for spatial dependence, which is a common attribute of species distribution data. In response to the recent criticisms of the SAR model, due to the problem of

[23] These schemes provide economic incentives to farmers in European countries to conserve the environment and includes organic farming, reduced use of chemical fertilisers, low livestock density, low mowing frequency, etc. (Batáry et al. 2011)

identifying causal relationships (Gibbons and Overman 2012) and in growing recognition of the importance of local spatial spill-over effects (LeSage 2014) (i.e. neighbouring regions' natural and environmental attributes), this study employs a spatial Durbin error model (SDEM) to account for spatial dependence in the data.

3.3 Material and methods

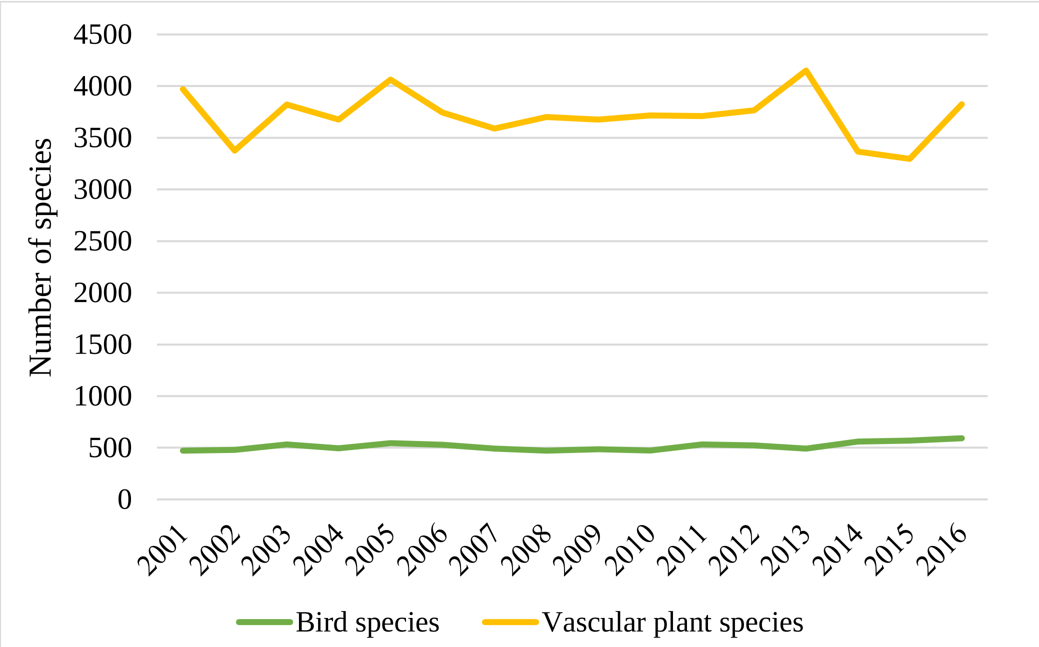
3.3.1 Study area

This study focused on the state of South Australia (SA), which covers approximately 983,300 km^2, of which 53% was utilised for agricultural production in 2016 (ABARES 2020a). The state represents an interesting case study area because of its diversified agricultural production, extent of organic lands and environmental heterogeneity. For example, in 2015/16, 22% of total agricultural land area was under certified organic management (ABS 2016i), and it also has strong specialisation in certified organic wine grape production and wine making (Lawson et al. 2018; Wheeler and Crisp 2011). The northern arid region of the state (87% of the state), where average annual rainfall varied between 0-200 mm in 2019 (BoM 2020f), is dominated by large pastoral farming, and has minimal clearance of native vegetation; about 96% vegetation remains, but it is degraded due to overgrazing (Bradshaw 2019). By contrast, the high rainfall zones — the southern regions of the state (with 200-900 mm average rainfall in 2019 (BoM 2020f)) — have been heavily modified since European colonization through intensive agricultural production and retain only about 4-26% of native vegetation (Bradshaw 2019; Evans 2016; Reside et al. 2017). Although SA was the first state to have legislative control (e.g. the *Native Vegetation Management Act 1985*) over native vegetation clearance, much of the land clearing had been done before 1975 (Marano 2001; Reside et al. 2017).

3.3.2 Dependent variables: vascular plant and bird species richness

ALA provides the largest free and open repository of Australian biodiversity data that are compiled annually from multiple sources (Belbin and Williams 2016). For the purposes of this study, the species richness of vascular plants and birds were sourced from ALA using the spatial portal tool - points to grid. In the points to grid tools there were various filtering options. The following filters were used to generate the annual grids of species richness layers: only spatially valid records with spatial coordinates; within a predefined annual date range of 1st January to 31st December each year over 16 years from 2001 to 2016; within the spatial boundaries of SA; and among the list of species – Aves (birds) (ALA 2020b) and SA vascular plants (ALA 2020a). The vascular plant and bird species richness girds provides the average number of species in a nine by nine moving pane window where each pane was 0.01^0 latitude/longitude which is approximately 1 km^2 (ALA 2020a, 2020b). Figure 3.1 shows the average annual species richness for vascular plants and birds in SA at postcode level over 16 years in SA.

Figure 3.1 Annual species richness and number of occurrences of vascular plants and birds in SA from 2001 to 2016



Own figure (Data sources: vascular plants (ALA 2020a) and birds (ALA 2020b))

3.3.3 Independent variables

3.3.3.1 Organic certification data

Data related to the certified organic farming businesses was collected from two major organic certifiers – NCO and ACO (out of six active certifying organizations) in Australia – which together account for almost 90% of the nation's organic certification (Williams et al. 2019). One of the certifying bodies, the NCO, operates from SA, whereas ACO operates from the state of Queensland, Australia. Information related to organic certification (business names, contact information, and types of products produced and processed by certified organic producers, processors, wholesalers, and retailers) are publicly available from the respective websites of the six certifying bodies, but only for active organic businesses. Information related the operators who cancelled their certification was not publicly available. In addition, the websites do not provide a farm's location, which is the prime factor in analysing any impacts of organic farming on biodiversity.

The organic farming dataset (organic producers only) that is used in this study is unique in the sense that the coverage of the dataset varies both spatially and temporally over 16 years: 2001 to 2016. It was put together by the study author: accessing databases at one of the certifiers and compiling historical information from both of the two certifiers. The NCO organic certification database provides detailed information about location of the farms, industry specific information (e.g. livestock, dairy, meat cattle, horticulture, viticulture, cereals, beekeeping and aquaculture), farm size (only for active farming businesses) and date of certification (entry and exit) starting from 1989 (there are only few records for earlier time periods). After 2001 representative amount of records were obtained. The ACO dataset provided location and commodity information only and only started in 2007. In both the NCO and ACO datasets there were different types of addresses (for example: home, company, delivery, postal, farm, and farms with multiple locations).

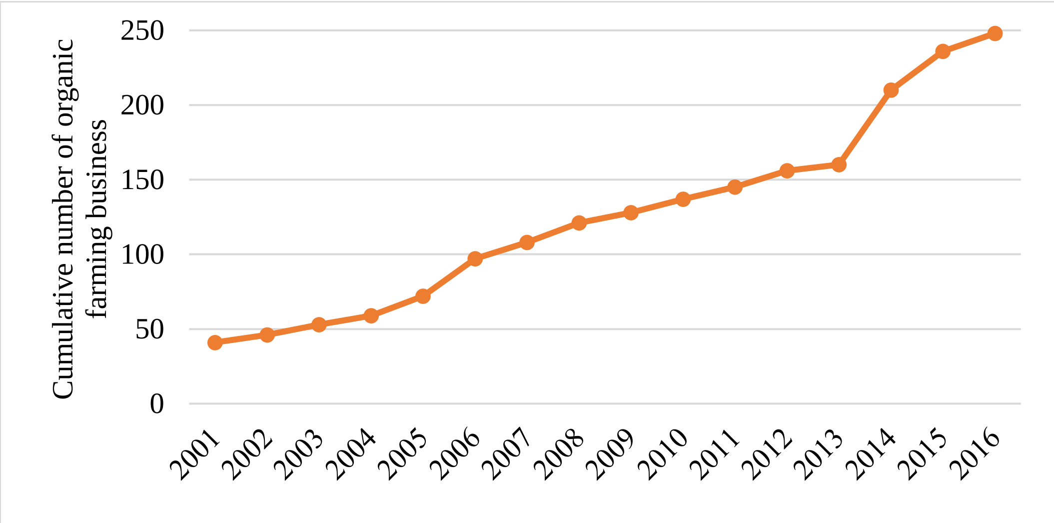
From the datasets, it was not possible to precisely identify the exact farm location, especially for farms that are located in rural areas and which no longer retained certification. Hence, all the locations of organic farming businesses (which also included businesses with multiple locations) were identified at postcode level. All the locations of farms were checked using satellite images in Google Maps. Businesses that are located in major urban centres, where there were no agricultural properties (checked using a historical land valuation dataset provided by the SA Office of the Registrar General; details of these data are provided in the independent variables section) were deleted from the sample.[24] Both the datasets also provide dates of certification - contract from, contract sent, service from and dis-certification – and the date when the business disabled their certification. Among the different dates, contract from date was selected as the date of adoption because this date was available for all observations. In addition, on the basis of an average organic in-conversion time period of three years, only farming businesses that were active for more than three years (on the basis of certification and dis-certification dates) were included in the study.

Finally, a panel dataset of certified organic farming businesses from 2001 to 2016, at postcode level, was compiled using both the NCO and ACO datasets. This dataset is a representative one for SA and was cross-checked with the organic commodity statistics compiled by the ABS for the first time in 2011 (ABS 2011a). There were 196 organic farming businesses in 2010/11 in SA noted by the ABS and the dataset compiled for this study contained 145 organic businesses

[24] The number of organic business that provided addresses which were located in major cities were very few (<1% of the sample).

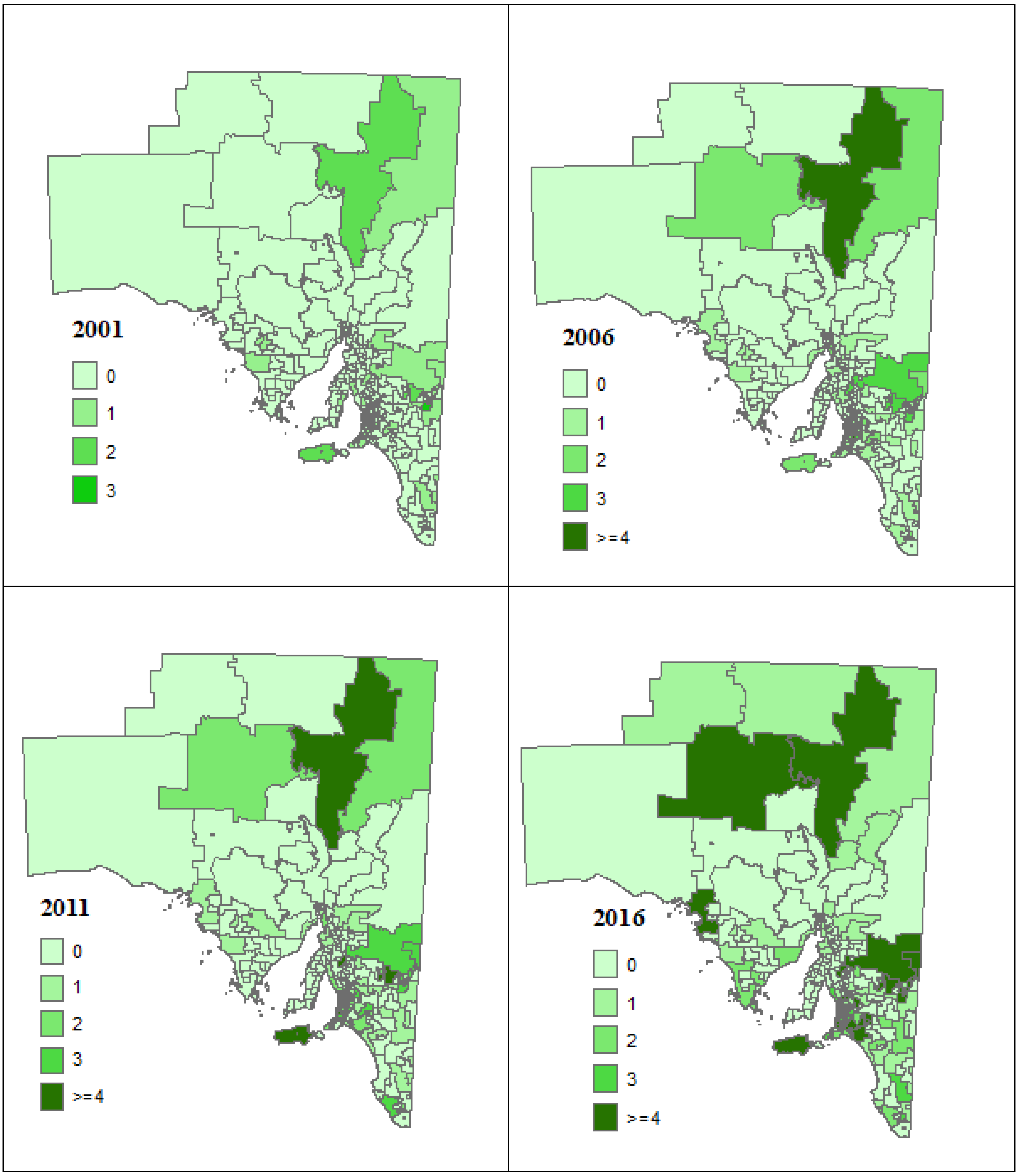
in 2011, which represents 74% of total observations. In 2016, 94% of total observations were represented (248 out of 265 organic farming businesses) (Lawson et al. 2018) in the organic dataset. Comparisons for time-periods earlier than 2011 were not possible because no published source is available that reports the total number of organic businesses at state level (annual data were only available for the whole of Australia from sources like (Willer et al. 2020; Williams et al. 2019). The cumulative number of organic farming businesses and spatial distribution at postcode areas, over the study period is depicted in Figure 3.2 and Figure 3.3, respectively. Figure 3.4 and Figure 3.5 depicts the spatial patterns of certified organic business by farm size, and agricultural industries, respectively.

Figure 3.2 Cumulative number of certified organic farming businesses with multiple locations in SA from 2001 to 2016



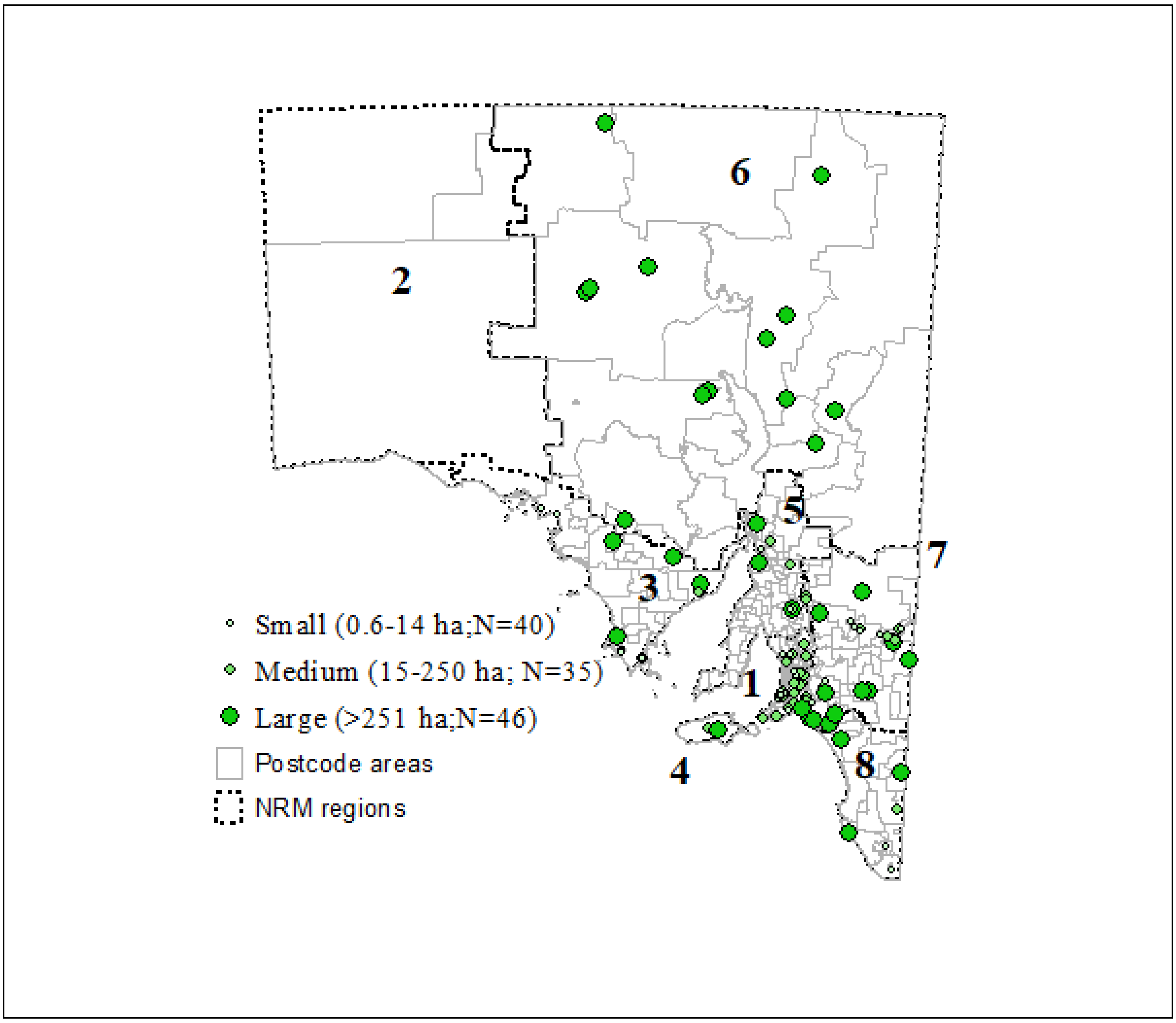
Own figure (data source: number of certified organic farming business – NCO and ACO personalised data request and database establishment)

Figure 3.3 Spatial distribution of certified organic farming businesses (numbers) over a 5 year period, 2001-2016 at postcode level in South Australia



Own maps (data sources: number of certified organic farming businesses – NCO and ACO personalised data request and database establishment, base map – postcode areas (ABS 2016j))

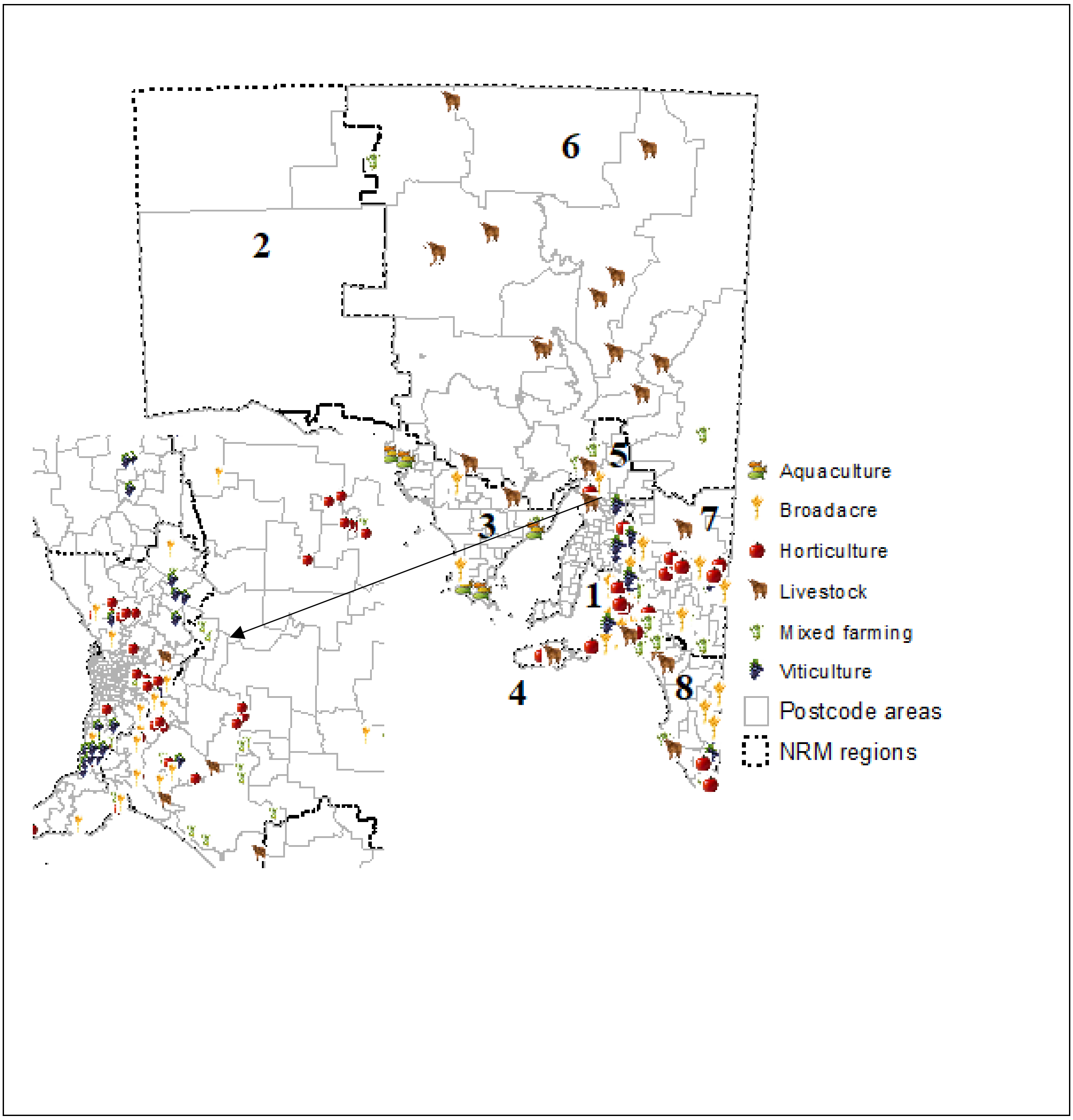
Figure 3.4 Spatial distribution of NCO* certified organic farming business (producers) by farm size in South Australia in 2018 (N=121)



Own map (data sources: base maps – postcodes areas (ABS 2016j) and NRM regions (ABS 2016g); locations and farm size of certified organic farming business – NCO personalised request)

Notes:*Farm size was only available for NCO certified organic farm businesses. The numbers in the map indicates NRM regions: 1- Adelaide and Mount Lofty Ranges (AMLR); 2 – Alinytjara Wilurara (AW); 3 – Eyre Peninsula (EP); 4 – Kangaroo Island (KI); 5 – Northern and Yorke (NY); 6 – South Australian Arid Lands (SAAL); 7 – South Australian Murray Darling Basin (SAMDB); 8 – South East (SE).

Figure 3.5 Spatial distribution of certified organic farming business (producers) by agricultural industries in South Australia in 2018 for NCO and ACO (N=197).



Own map (Sources: base maps – postcodes areas (ABS 2016j) and NRM regions (ABS 2016g); locations of certified organic farming business – NCO and ACO personalised request)

Notes: The numbers in the map indicates NRM regions: 1- Adelaide and Mount Lofty Ranges (AMLR); 2 – Alinytjara Wilurara (AW); 3 – Eyre Peninsula (EP); 4 – Kangaroo Island (KI); 5 – Northern and Yorke (NY); 6 – South Australian Arid Lands (SAAL); 7 – South Australian Murray Darling Basin (SAMDB); 8 – South East (SE).

3.3.3.2 Intensity of agricultural land use

The total number of land parcels used for agricultural production at postcode level was calculated as an indicator of regions with intensive agricultural practice by utilising a historical land valuation dataset, provided by the SA Office of the Registrar General. The agricultural land valuation dataset, which is used for rating and taxation purposes, contains records related to the location of all the land parcels, the date the record came into force and was cancelled, and other information related to their structural attributes. Because agricultural properties often contain multiple land parcels, counts of land parcels, rather than the number of farming businesses, were used in the empirical models. In the valuation system, land parcels were assessed together, and one unique property identifier number was provided if the land parcels were contiguous. In cases where land parcels owned by the same landholder were located in different regions (in this case, local government areas), a different identifier number was assigned for that parcel. The valuation records also changed if any portion of the land was sold over the time-period, or an amalgamation occurred with the adjoining land. In addition, where the whole of the land under one valuation record was sold, the records were retained and transferred to the new ownership. Using the locations of the land parcels, with the dates from which the property came into force and its cancellation date, an annual dataset for all the agricultural land parcels that were active and inactive after some years over the study time period (2001 to 2016) at postcode level was prepared.

The percentage of crop, grazing, and horticultural land use in each postcode was calculated using the ABARES's "Catchment Scale Land Use Data", at 250m resolution, as a measure of anthropogenic land use change. In addition, the percentage of waterbodies and nature conservation land at postcode level were also derived from this source. The dataset was only available for 2000-2001, 2001-2002, 2005-2006, 2010-2011, and 2016. The land use classes were calculated on the basis of the "Australian Land Use and Management's" secondary hierarchy level classification (details provided in Table B2 in appendix B). In addition, two proxy indicators of agricultural intensification — average content of nitrogen and phosphorus (%) in the soil — were calculated using "Soil Attribute Maps" (Viscarra Rossel et al. 2014f, 2014g).

3.3.3.3 Habitat heterogeneity

The biotic/habitat heterogeneity was modelled with three variables: the diversity of land cover, elevation, and soil diversity. A Shannon diversity index of 22 land cover classes[25] was calculated using the "Dynamic Land Cover Dataset", provided by Geoscience Australia at a resolution of 250m (temporal coverage: 2001 to 2015). The diversity index (H) was calculated as: $H = -\sum_{i=1}^{j} p_i \ln(p_i)$, where p_i is the proportion of i^{th} land cover and j is the total number of land cover types found within each postcode. Higher values of the index correspond to higher habitat heterogeneity. Mean elevation and elevation ranges (the difference between maximum and minimum elevation) were used to measure topographic heterogeneity by utilising the digital elevation model developed by Geoscience Australia, at a resolution of 25m. "Soil Attribute Maps", at a resolution of 90m and developed by the CSIRO, were utilised to calculate the Shannon diversity of soil types. Soil sand, clay, and silt content (%) in the < 2 mm fraction (0 to 5 cm) were used to measure soil diversity.

3.3.3.4 Climate and vegetation index

Three variables— annual rainfall, maximum temperature, and actual evapotranspiration— were used to represent climate factors. Annual climate data were obtained from the Bureau of Meteorology (BoM) at a resolution of 5km. The Normalised Difference Vegetation Index (NDVI) was used as a surrogate measure of vegetation productivity or resource availability. The 6-monthly gridded NDVI dataset was acquired from the BoM at a resolution of 5km. The NDVI index value ranges between -1 to +1 and higher values are associated with higher density and greater greenness of plant canopy cover (BoM 2020e).

3.3.3.5 Human activity

The effect of the human footprint on biodiversity was captured by population density, the urban accessibility index, distance to the nearest principal sealed highway, and distance to the nearest coast. The annual estimated residential population from 2001 to 2016 was sourced from the Australian Bureau of Statistics (ABS) at statistical area level 2 (SA2). This is the smallest geographic unit at which the ABS release annual population data. The population estimate at postcode level was obtained by spatially joining the physical boundaries of 2016 postcodes with the SA2 boundaries and then population density per km^2 was calculated for 2016's postcode areas. In addition, to capture the interaction effects of intensity of population and

[25] Details about the land cover classes is reported in Table C.2 in Appendix C

distance to urban centres,[26] an index of urban accessibility was calculated. The index was defined as the inverse distance between the centroids of each postcode and the nearest urban centres, weighted by the population of the urban centres. The population estimates and the physical boundaries of urban centres were sourced from the ABS, which were available for the census years (2001, 2006, 2011, and 2016). Therefore, linear interpolation was used to calculate the inter census annual change in the urban accessibility index.

In addition, Euclidean distance from the centroid of each postcode to the nearest sealed principal highway and coastline was calculated. The widely used Euclidean distance which is measured as a straight-line distance between two points was used in the study rather than the road network distance. The road network distance is considered to be more accurate and precise measures of geographic distance over the Euclidean distance which can only be considered as a proxy for the actual physical distance (Boscoe et al. 2012; Combes and Lafourcade 2005). But due to data limitation over the sixteen years study time period it was not possible to calculate the road network distance such as public, private transit distance and the associated travel time.

Finally, a continuous trend variable was included in the models to account for potential annual change in species richness over time and regional dummies were used to account for the unobservable omitted variables which may affect the models' empirical findings. SA is divided into eight natural resource management (NRM) regions and most of the biodiversity conservation policies and land care programmes are implemented at this level. From 2001 to 2016, the physical boundaries of the NRM regions did not change much. Hence, on the basis of 2016's NRM regions' boundaries (ABS 2016g), NRM dummies were included in the models.

Description of the variables with data sources and summary statistics of the variables used in the empirical models are provided in Table 3.1 and Table 3.2. In 2016, there were 342 postcode areas in SA; of these, two postcode areas were dropped (namely postcode 5005 because no occurrence of species was recorded over the study time-period and postcode 5960, which being an island did not have neighbouring areas that shared physical boundaries with this postcode in the specification of contiguity matrix). This left a total of 340 postcodes each year, over the 16 years from 2001 to 2016 and the final sample contained 5,440 observations. The robustness

[26] The urban centres were defined using two specifications: population of 1,000 or more and population of more than 5,000 or more, following (Haensch et al. 2019) in Australian context.

of the results from the empirical models were also verified using only postcodes that had some level of agricultural activity during the years studied (namely 298 postcodes areas (with total observations 4,768)). Size of the postcode area was also included in the models – but due to serious collinearity problems was not included in the final modelling.

Table 3.1 Variables description and data sources

Variables	Label	***Variables description***	***Source***
Dependent variables			
Vascular plant richness (numbers)	VPSR	Average vascular plant species richness in natural logarithm	(ALA 2020a)
Bird richness (numbers)	BSR	Average bird species richness in natural logarithm	(ALA 2020b)
Independent variables			
Organic farm business (numbers)	OFB	Numbers of organic farming businesses	NCO and ACO – personalised request
Agricultural land parcels (numbers)	ALP	Numbers of agricultural land parcels	SA Office of the Registrar general
Soil nitrogen content (%)	SNC	Percentage of nitrogen content in the top soil	(Viscarra Rossel et al. 2014f)
Soil phosphorous content (%)	SPC	Percentage of phosphorous content in the top soil	(Viscarra Rossel et al. 2014g)
Annual rainfall (mm)	Rain	Average annual total rainfall	BoM-specialised request
Annual temperature (^{0}C)	Temp	Average annual maximum temperature	
Actual evapotranspiration (mm)	AET	Indicates estimated total evapotranspiration (water removal) from soil, vegetation, and groundwater.	(BoM 2020a)
Land cover diversity index	LCDI	Shannon diversity index on the basis of 22 land cover classes. The higher value of the index indicates increased diversity	(Lymburner et al. 2015)
NDVI index	NDVI	Normalised difference vegetation index measures greenness of an area. Increased green vegetation is associated with the higher value of the index	(BoM 2020e)
Conservation land (%)	ConL	Percentage share of nature conservation and environmental protection land in the total land area of each postcode	(ABARES 2016b, 2020b)
Water bodies (%)	WB	Percentage share of waterbodies (rivers, lakes, wetland, etc.) in the total land area of each postcode	
Crop (%)	CL	Percentage share of irrigated and dryland cropping area in the total land area of each postcode	
Grazing (%)	GL	Percentage share of grazing land in the total land area of each postcode	
Horticulture (%)	HL	Percentage share of horticultural land in the total land area of each postcode	
Elevation (m)	Ele	Average elevation	

Elevation range(m)	ER	Average Elevation range (difference between maximum and minimum elevation)	(Geoscience Australia 2015)
Soil diversity index	SDI	Shannon diversity index of soil types (percentage of sand, silt, and clay content in the top soil)	(Viscarra Rossel et al. 2014d, 2014e, 2018)
Urban accessibility index	UAI	Inverse distance between the centroids of each postcode and the nearest urban centres, weighted by the population of the urban centres (in natural logarithm)	(ABS 2006b, 2011h, 2016o, 2018a)
Population density (numbers/km$^{2)}$	PD	Number of human population per square kilometre of the postcode areas	(ABS 2018b)
Distance to highway (km)	DR	Euclidean distance between the centroid of each of the postcode area to the nearest principle sealed highway	(DPTI 2013)
Distance to coast (km)	DC	Euclidean distance between the centroid of each of the postcode area to the coastline	(Geoscience Australia 2004)
Postcode areas (km^2)	POA	Geographic unit of analysis – postcode areas in 1000 square kilometres	(ABS 2006a, 2011d, 2016j, 2018a)
Trend	Tre	Trend (1=2001 to 16=2016)	
Adelaide and Mount Lofty Ranges (base)	AMLR	AMLR=0 if postcode areas fall within AMLR regions; 0=otherwise	(ABS 2016g)
Alinytjara Wilurara	AW	AW=0 if postcode areas fall within AW regions; 0=otherwise	
Eyre Peninsula	EP	EP=0 if postcode areas fall within EP regions; 0=otherwise	
Kangaroo Island	KI	KI=0 if postcode areas fall within KI regions; 0=otherwise	
Northern and Yorke	NY	NY=0 if postcode areas fall within NY regions; 0=otherwise	
SA Arid Land	SAAL	SAAL=0 if postcode areas fall within SAAL regions; 0=otherwise	
SA Murray Darling Basin	SAMDB	SAMDB=0 if postcode areas fall within SAMDB regions; 0=otherwise	
South East	SE	SE=0 if postcode areas fall within SE regions; 0=otherwise	

Table 3.2 Descriptive statistics of the variables included in the empirical models, 2001-2016 (N=5,440)

Variables	*Mean*	*Standard deviation*	*Minimum*	*Maximum*
Dependent variables				
Vascular plant richness (ln numbers)	2.84	1.94	-4.39	8.71
Bird richness (ln numbers)	2.54	1.78	-4.39	7.50
Independent variables				
Organic farm businesses (numbers)	0.37	0.96	0.00	14.00
Agricultural land parcels (numbers)	193.01	281.93	0.00	2612.00
Soil nitrogen content (%)	0.03	0.01	0.01	0.07
Soil phosphorous content (%)	0.00	0.00	0.01	0.02
Annual rainfall (mm)	446.16	191.23	37.36	1535.00
Annual temperature (^{0}C)	22.61	1.93	17.83	31.97
Actual evapotranspiration (mm)	485.48	122.17	66.00	787.77
Land cover diversity index	1.03	0.56	0.00	2.37
NDVI index	0.30	0.11	0.00	0.59
Conservation land (%)	12.43	16.91	0.00	100.00
Water bodies (%)	1.50	5.10	0.00	72.15
Crop land (%)	19.76	27.54	0.00	100.00
Grazing land (%)	32.75	29.23	0.00	100.00
Horticultural land (%)	3.77	10.27	0.00	100.00
Elevation (m)	151.24	143.94	4.65	570.42
Elevation range (m)	218.36	204.48	5.87	1100.93
Soil diversity index	0.73	0.12	0.33	0.91
Urban accessibility index (ln)	-9.83	4.13	-18.01	8.81
Population density (numbers/km^2)	486.04	808.56	0.00	3296.23
Distance to highway (km)	13.38	28.60	0.01	299.99
Distance to coast (km)	48.21	77.63	0.57	616.54
Postcode areas (in1,000 km^2)	2.65	13.71	0.02	191.16
Trend	8.50	4.61	1.00	16.00
AMLR dummy (base)	0.46	0.50	0.00	1.00
AW dummy	0.00	0.05	0.00	1.00
EP dummy	0.08	0.27	0.00	1.00
KI dummy	0.01	0.11	0.00	1.00
NY dummy	0.17	0.38	0.00	1.00
SAAL dummy	0.06	0.24	0.00	1.00
SAMDB dummy	0.16	0.37	0.00	1.00
SE dummy	0.06	0.24	0.00	1.00

3.4 Econometric method and model estimation

Due to a number of time-invariant independent variables (elevation range, soil diversity index, distance to highway, distance to coast and NRM dummies) that would be dropped in fixed effects panel models, the empirical modelling starts with random effects non-spatial panel and Ordinary Least Square (OLS) regression models to explore the effects of organic farming and environmental heterogeneity on biodiversity in the South Australian landscape from 2001 to 2016. Previous research (Ma and Swinton 2011; Ma and Swinton 2012; Polyakov et al. 2013, 2015; Tapsuwan et al. 2012; Tapsuwan and Polyakov 2016) also used the random effects models to address this issue. In the second step, to account for the spatial dependence (i.e. observations at one location *i* depends on the observations at another location *j*), which is a common attribute of species distribution and natural and environmental datasets (Diniz-Filho et al. 2003; Hawkins et al. 2007; Kissling and Carl 2008; Legendre 1993), three specifications of spatial models were estimated: spatial lag of explanatory variables (SLX); spatial Durbin error (SDEM); and spatial Durbin (SDM). Ignoring spatial dependence violates the basic assumption of OLS regression models that observations are independent of each other and hence may lead to inefficient and biased estimates of the parameters and cause inflation of type I errors (Jetz and Rahbek 2002; Kissling and Carl 2008; Kreft and Jetz 2007; Xu et al. 2015). As prior knowledge about the true nature of spatial dependence structure is not known, these three spatial models were estimated and compared.

The SLX model is an extension of the standard OLS model. But it has an additional term that captures the exogenous interaction effects by acknowledging that the outcome (species richness) at location *i* is not only a function of the explanatory variables at location *i* but is also influenced by the covariates in location *j*. It is viewed as the most parsimonious model and is often suggested as the point of departure in the specification of spatial models (Gibbons and Overman 2012; Halleck Vega and Elhorst 2015; LeSage and Pace 2009). The SDEM augments the SLX model by incorporating a spatially auto-correlated error term (Elhorst 2014) and the SDM model captures the mixed effects of endogenous interaction (species richness at location *i* impacted by the level of species richness at location *j*) and exogenous interaction (LeSage 2014). The OLS regression, SLX, SDM, and SDEM models are specified below in equations (1), (2), (3), and (4), respectively:

$$y = X\beta + \varepsilon \qquad (1)$$

$$y = X\beta + WX\theta + \varepsilon \qquad (2)$$

$$y = \rho Wy + X\beta + WX\theta + \varepsilon \qquad (3)$$

$$y = X\beta + WX\theta + u;\ u = \lambda Wu + \varepsilon \qquad (4)$$

where *y* is the dependent variable, measured by the average number of species per postcode area (vascular plant and bird richness), *X* is a vector of explanatory variables; β is a vector of estimated response parameters and ε is the error term, assumed to be independently and identically distributed; *W* is the *n* by *n* spatial weight matrix (defined in the subsequent section), which indicates the structure of spatial interdependence among the *n* observations; θ is the parameter of the exogenous interaction effect to be estimated; *WX* represents the indirect effects of spatially lagged exogenous variables; ρ is the scaler parameter, which indicates the strength of spatial lag dependence; *Wy* indicates endogenous interaction effects; and λ is the scaler parameter of spatial auto-correlated error.

To explore the structure of spatial interdependence in the observations, two specifications of a spatial weight matrix were utilised in the empirical models: a) contiguity[27] (postcode areas that share a boundary and are neighbours) and b) k- nearest neighbour[28] (the closest k postcodes [i.e. k=5] were specified as neighbours). Euclidean distance was used in the specification of the matrices. Anselin (1988) and Elhorst (2001), suggested that a row normalised spatial weight matrix may become asymmetric and cause the remote and central regions (in this case postcodes) to have the same impact, hence the two matrixes was normalised using the procedure described in Elhorst (2014). For example, suppose W_0 is the contiguity matrix before normalisation and *D* is the diagonal matrix consisting of the row sums of matrix W_0. The normalised contiguity matrix was specified as: $W = D^{-1/2} W_0 D^{-1/2}$.

All the spatial models were estimated using the maximum likelihood technique using the package "spxtregress", available in StataMP 16 software (StataCorp 2019). In the empirical models $\log_e$, transformed dependent variables (average vascular plant and bird species richness) and one of the explanatory variables, the urban accessibility index, were used to improve the model's fit following Polyakov et al. (2015). In addition, the spatial lag for distance based variables, (urban accessibility index, distance to highways, and distance to coastlines) and time invariant variables, (elevation range and soil diversity indexes), were not incorporated in the empirical models because the distance based variables are the attributes of locations rather than

[27] Percentage of spatial connectivity for the matrix was 1.60 with average 5.43 neighbours. The minimum number of neighbours was 1 and the maximum was 14.

[28] Percentage of spatial connectivity for the matrix was 1.47 for the 5 nearest neighbour matrix specification.

being features of individual observations (Polyakov et al. 2015) and are highly correlated with the respective non-spatial specifications. To reduce the risk of multicollinearity, variance inflation factors (VIF) and pairwise correlation among the explanatory variables was checked using Spearman's correlation and reported in Table C.3-Table C.7 in appendix C, respectively. The variables for which the correlation coefficient (>0.7) and VIF (>10) are very high were not included in the empirical models (Jetz and Rahbek 2002; Kreft and Jetz 2007; Xu et al. 2015). Among the variables that are highly correlated and have high VIF value, the variable that explains more deviance (using univariate regression) was retained (Xu et al. 2016). Following this procedure, eight variables — annual average rainfall, maximum temperature, elevation, soil nitrogen contents, soil phosphorus contents, population density, urban accessibility index with a population of 5,000 or more, and area of the geographical unit (postcode) — were not incorporated in empirical models. However, additional sensitivity testing was conducted to make sure the inclusion of these variables did not change the key results. The key findings of the study remained unchanged with the inclusion of postcode area which was used to control for the size effects of the spatial units, confirming the robustness of the final models results (Table C.9 in Appendix C shows the results of the sensitivity test by including postcode area as one of the explanatory variables). Finally, vascular plant species richness was included as a covariate only in models of bird richness because of results from other studies that found an impact of plant richness on bird species richness (Kissling et al. 2008; Liang et al. 2018; Zhang et al. 2013).

3.5 Results and discussion

The results from the empirical models of vascular plant and bird species richness in South Australia's landscape from 2001 to 2016 are presented in this section. Four different model specifications—non-spatial OLS regression, SLX, SDM, and SDEM—were estimated. They were compared for the two taxonomic groups—vascular plants and birds—using two different spatial weight matrixes; contiguity and the five nearest neighbours for the full sample (including all the postcodes with and without primary production, (N= 5,440) and a reduced sample which only included postcodes with primary production, (N=4,768)).

The performance of these spatial and non-spatial models was assessed using three criteria: minimisation of spatial dependence; higher value of pseudo R^2 (calculated as the squared correlation coefficient between observed and predicted outcome variable (Xu et al. 2016)); and the lowest Akaike Information Criteria (AIC) value, widely used in the empirical literature

(Jetz and Rahbek 2002; Kreft and Jetz 2007; Piha et al. 2007; Xu et al. 2016). The results of comparing the spatial models are reported in Table 3.3. Of the models, the SDEM model, with contiguity matrix, performed better, although the difference between SDM and SDEM models was marginal. Despite the slight differences in the performance of the models, the effects of the explanatory variables do not vary much with few exceptions, which indicates the robustness of the results. Hence, the following commentary is based on the estimated marginal effects (direct, indirect, and total) from the SDEM with contiguity matrix model of vascular plant and bird species richness and is reported in Table 3.4. The significant positive value of the spatial dependence (λ=0.645 – vascular plant; and λ=0.533 - bird) indicates that the species richness gradient in one postcode is spatially correlated with the neighbouring postcode's species richness. The results of the non-spatial OLS model (reported in Table C.8) and the spatial models (SDEM, SDM, and SLX) with contiguity and nearest neighbour matrix for full and reduced samples, as a sensitivity check, were reported in Table C.10-Table C.20 in Appendix C.

The three types of effects from the SDEM were interpreted as: a) a direct effect showing the change in a response variable (species richness) in location *i* (own postcode) due to the change in the explanatory variable in own area *i* (within postcode); b) an indirect effect/ spatial spill-over, which measures the change in an outcome variable as a result of change in the covariates of all the neighbours; for example *j*, *k*, and *l* in case of only three neighbours (defined by the spatial weight matrix); and c) the total effect is the sum of direct and indirect effects.

Table 3.3 Comparison of various spatial models performance

		Bird species richness				**Vascular plant species richness**			
		Full sample*[*] *(N=5,440)		***Reduced*[**] *sample (N=4,768)***		***Full sample (N=5,440)***		***Reduced sample (N=4,768)***	
		Contiguity	***Nearest neighbour***	***Contiguity***	***Nearest neighbour***	***Contiguity***	***Nearest neighbour***	***Contiguity***	***Nearest neighbour***
SDM	**ρ**	0.518	0.526	0.495	0.509	0.624	0.609	0.594	0.599
	R^2	0.646	0.630	0.654	0.645	0.476	0.436	0.468	0.437
	AIC	14331.740	14323.000	12633.230	12608.580	15828.940	15889.440	14397.840	14402.050
SDEM	**λ**	0.533	0.541	0.506	0.521	0.645	0.629	0.614	0.619
	R^2	0.650	0.639	0.657	0.651	0.507	0.477	0.492	0.467
	AIC	14372.650	14352.710	12671.090	12638.860	15843.410	15882.290	14405.950	14386.770
SLX	**ρ/λ**	-	-	-	-	-	-	-	-
	R^2	0.643	0.634	0.654	0.645	0.495	0.470	0.483	0.460
	AIC	15243.810	15259.070	13397.490	13401.030	17344.230	17377.840	15619.580	15646.850

Notes:[*] Full sample includes all the postcodes with and without primary production.
[**] Reduced sample only includes postcodes with primary production.

3.5.1 Effects of certified organic farming

As expected, the direct, indirect, and total effects of the presence of certified organic farming businesses at postcode level are positive and statistically significantly associated with vascular plant richness. Identification of a causal relationship between organic farming and species richness is beyond the scope of this study. The above findings supports that at a broader scale the presence of organic farming is spatially associated with enhanced vascular plant richness as noted in various studies focused at varying spatial scales; field, farm, and regional (Jonason et al. 2011; Katayama et al. 2019; Rundlöf et al. 2010; Tuck et al. 2014; Winqvist et al. 2011). On the other hand, the spatial association was insignificant for bird richness. The result is not surprising, given that among various taxa (such as plants, vertebrates, and invertebrates), birds showed mixed results and the most inconsistent effects for organic farming (Bengtsson et al. 2005; Fuller et al. 2005; Tuck et al. 2014). Although there are studies that found a positive impact of organic farming on bird richness (Batáry et al. 2010; Belfrage et al. 2005; Katayama 2016; Rollan et al. 2019; Winqvist et al. 2011), there are also studies that found no statistically significant effects of organic farming on bird richness, after controlling for landscape complexity and spatial dependence in their empirical models (Gabriel et al. 2010; Hiron et al. 2013; Piha et al. 2007; Puig-Montserrat et al. 2017).

3.5.2 Effects of environmental heterogeneity

All the variables that were used to explain habitat diversity in the empirical model have statistically significant direct effects (except conservation land for plants) and are positively associated with species richness of both vascular plants and birds, confirming that habitat heterogeneity is one of the universal drivers of species richness gradients (Benton et al. 2003; Stein et al. 2014). These findings — increased land cover diversity and range of elevation enhanced species richness of plant and birds in Australia — supports similar results found in elsewhere in the world (Hawkins et al. 2005; Kissling et al. 2008; Koh et al. 2006; McKinney and Kark 2017; Xu et al. 2016). In addition, an increased proportion of conservation land and water bodies (rivers, lakes, wetland, etc.) at postcode levels positively influenced biodiversity, which indicates the important role of conservation and protected areas and water sources. Such areas provide increased food webs, nesting and foraging for different species in biodiversity conservation at landscape levels (Luck et al. 2010; Piha et al. 2007). In terms of soil condition, increased diversity of soil types (sand, silt, and clay) in an area significantly reduced both plant and bird richness.

The direct marginal effect of actual evapotranspiration was statistically significantly negative for bird richness, implying that more bird species were found in areas with lower value of actual evapotranspiration corresponds with increased environmental stress and low levels of ambient energy (Hawkins et al. 2003; Wright 1983). This contradicts findings in the literature in an Australian context, where actual evapotranspiration was positively correlated with increased bird species richness and was found to be the strongest positive determinant of bird richness (Coops et al. 2018; Hawkins et al. 2005; Symonds and Johnson 2008). One reason for this disparity may arise from the spatial scales of the study areas and the application of spatial models (results from various sensitivity tests – focusing on only postcode areas with at least some level of agricultural activities, alternative model specifications – SDEM, SDM, and SLX models with different matrix specification (nearest neighbours) were reported in Table C.10, Table C.12, Table C.13, Table C.16, and Table C.18 in Appendix C where actual evapotranspiration was not statistically significant). This study focuses on postcode areas in SA from 2001 to 2016, whereas the geographic scope was the whole of Australia in the studies by Coops et al. (2018); Hawkins et al. (2005); Symonds and Johnson (2008) and their results were based on static modelling of species richness at a single point in time. On the other hand, for vascular plant richness, all the three effects (direct, indirect, and total) were positive and statistically significant as expected (except for the direct effect, which was not statistically significant).

Vascular plant species richness—a surrogate indicator of resource availability and aboveground biomass (only included in the bird richness model)—is statistically significantly (in direct and total effects) and positively correlated with bird richness, which aligns with findings that highlight the positive association of woody plant richness and bird species distribution (Kissling et al. 2008; Liang et al. 2018; Zhang et al. 2013). Another measure of vegetation productivity, NDVI (which measures the greenness of vegetation), is not statistically significant for bird richness after controlling for the positive effects of vascular plants' richness on birds. Whereas, as expected, the marginal effects (direct and total) of NDVI are positive and statistically significant (except the indirect effect which is not significant) for plant richness; this compliments the findings that measures of productivity are a global prime driver of plant richness (Parviainen et al. 2010; Xu et al. 2016).

3.5.3 Effects of agricultural land use intensity

The direct, indirect (only significant for birds) and total effects of the number of agricultural land parcels, (which was used as a proxy indicator of agricultural land use intensity at postcode level), were statistically significant and positively associated with increased species richness of vascular plants and birds. This is in line with the findings of Schneider et al. (2014) and Tuck et al. (2014) that intensive agricultural landscapes with higher percentages of arable fields have higher species richness of both plants and birds. Another study by Kirk et al. (2020) in Canada also suggests that the positive effects of organic farming on bird abundance depends on agricultural land use intensification at a regional scale and that the effect reduces with decreasing agricultural intensification.

In contrast, the direct effects of (own postcode) increased proportion of agricultural land use for cropping and horticulture was negative and statistically significant for both plants and birds, but an increased proportion of grazing land has mixed effects. It is negatively correlated with bird richness (direct effect), whereas for vascular plants direct, indirect (neighbouring areas influence), and total (addition of direct and indirect) effects were positive and statistically significant except the direct effect, where the association is still positive, but not significant. A meta-analysis by Batáry et al. (2011) found higher species richness in grassland compared to cropland because grasslands are less intensively managed. However, the negative correlation with bird richness contradicts the findings of Piha et al. (2007) who suggest beneficial effects of grasslands on bird richness in a Boral agricultural landscape in Finland.

3.5.4 Effects of urbanisation and geographic distance

Among the three surrogate variables which were used to assess the influence of human disturbance on biodiversity only one variable, distance to coast, was statistically significant and positively correlated with both plant and bird richness, implying postcode areas that are further away from coasts have higher species richness, which indirectly indicates the negative effects of human activity on species richness (Koh et al. 2006; Lee et al. 2004) by reducing the resource availability, loss and degradation of natural habitat in the lowlands due to land clearing. The highest rate of land clearance (only about 4-26% of native vegetation has remained (Bradshaw 2019; Evans 2016; Reside et al. 2017)) for human settlement and agricultural development in SA had occurred in the southern regions near the coast. Although, Luck et al. (2010) and McKinney and Kark (2017) found that human population density was positively associated with bird richness in Australia. The effects of the urban accessibility index, which measures the interaction effects of population density and distances to urban centres and to highways, have no statistically significant influence on vascular plant and bird richness in this study.

Table 3.4 Results of SDEM (contiguity matrix) of bird and vascular plant species richness in South Australia, 2001–2016 (N=5,440)

	Bird Species Richness (Model I)						Vascular plant species richness (Model II)					
	Direct effect	*Std. Err.*	*Indirect effect*	*Std. Err.*	*Total effect*	*Std. Err.*	*Direct effect*	*Std. Err.*	*Indirect effect*	*Std. Err.*	*Total effect*	*Std. Err.*
Organic farming businesses	-0.013	0.021	-0.015	0.046	-0.028	0.056	0.058**	0.025	0.099*	0.058	0.157**	0.071
Land cover diversity index	0.296***	0.072	-0.024	0.125	0.272**	0.123	0.460***	0.101	-0.168	0.175	0.293	0.178
Elevation range	0.001***	0.000	-	-	0.001***	0.000	0.002***	0.000	-	-	0.002***	0.000
Conservation land	0.002***	0.002	0.007**	0.003	0.009***	0.003	0.003	0.002	0.013***	0.004	0.015***	0.005
Water bodies	0.016***	0.005	0.052***	0.013	0.068***	0.013	0.021***	0.007	0.056***	0.017	0.077***	0.018
Soil diversity index	-1.624***	0.365	-	-	-1.624***	0.365	-1.717***	0.548	-	-	-1.717***	0.548
Actual evapotranspiration	-0.001***	0.000	0.000	0.000	-0.001	0.000	0.000	0.000	0.001***	0.000	0.001**	0.000
Vascular plant richness	0.358***	0.012	-0.030	0.023	0.328***	0.025	-	-	-	-	-	-
NDVI	0.173	0.462	0.724	0.593	0.897*	0.543	1.318**	0.571	0.082	0.773	1.400*	0.758
Agricultural land parcels	0.001***	0.000	0.001***	0.000	0.002***	0.000	0.001***	0.000	0.000	0.000	0.001***	0.000
Crop land	-0.005**	0.002	0.002	0.003	-0.003	0.002	-0.005**	0.002	0.005	0.004	0.000	0.004
Grazing land	-0.001***	0.002	0.003	0.002	0.002	0.003	0.001	0.002	0.009***	0.003	0.009***	0.004
Horticultural land	-0.005*	0.003	-0.004	0.005	-0.008	0.005	-0.007**	0.003	0.001	0.007	-0.006	0.007
Urban accessibility index	0.001	0.011	-	-	0.001	0.011	-0.007	0.015	-	-	-0.007	0.015
Distance to road	0.001	0.002	-	-	0.001	0.002	-0.001	0.003	-	-	-0.001	0.003
Distance to coast	0.001*	0.001	-	-	0.001*	0.001	0.005***	0.001	-	-	0.005***	0.001
Trend	0.040***	0.006	-	-	0.040***	0.006	0.018**	0.007	-	-	0.018**	0.007
AW (base=AMLR)	2.357***	0.905	-	-	2.357***	0.905	0.797	0.604	-	-	0.797	0.604
EP	-0.775***	0.265	-	-	-0.775***	0.265	-0.348*	0.178	-	-	-0.348*	0.178
KI	-1.579***	0.542	-	-	-1.579***	0.542	-0.690*	0.358	-	-	-0.690*	0.358
NY	-0.818***	0.236	-	-	-0.818***	0.236	0.080	0.158	-	-	0.080	0.158
SAAL	-0.467	0.398	-	-	-0.467	0.398	0.138	0.268	-	-	0.138	0.268
SAMDB	-0.086	0.230	-	-	-0.086	0.230	0.088	0.154	-	-	0.088	0.154
SE	-0.659**	0.322	-	-	-0.659**	0.322	-0.442**	0.217	-	-	-0.442**	0.217
Spatial error (λ)	**0.533*** **						**0.645*** **					
Pseudo R^2	0.650						0.507					
AIC	14372.650						15843.410					

Notes: The outcome variable is the average bird and vascular plant species richness in *Model I* and *Model II*, respectively. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

3.6 Discussion

Overall, both vascular plant and bird species richness are statistically significantly associated with the same sets of covariates with few exceptions, which is not surprising given that the same result was found in other studies that explored the spatial drivers of both taxonomic groups (Katayama et al. 2019). The positive spatial congruence of the presence of organic farming at postcode level with vascular plant species richness confirms the findings of existing literature that organic farming effects are more pronounced and consistent for plant richness, whereas little to no statistically significant evidence was found for bird species richness. Findings from the studies by Bengtsson et al. (2005); Gabriel et al. (2010); Gonthier et al. (2014); Winqvist et al. (2012); Schneider et al. (2014) focusing on various spatial scales – field, farm, and landscape/regional level suggests that the beneficial impacts of organic farming for plants are mostly attributed to the prohibited use of chemical fertilisers, insecticides, and herbicides and the beneficial effects of organic farming are weaker at broad scale. The difference in the effects of organic farming on plant and bird richness is not surprising given that there are studies that found no evidence to support the positive effects of organic farming on bird species at a local scale (Hiron et al. 2013). Also, Puig-Montserrat et al. (2017) found no evidence to support the beneficial effects of organic vineyard management on bird richness and more birds were found on conventional farms despite higher availability of food resources on organic farms (Gabriel et al. 2010). Landscape features such as increased semi-natural habitats, field margins, proximity to water sources, and grasslands seem to have more pronounced impacts on bird richness (Chamberlain et al. 2010; Piha et al. 2007).

Plants and birds have different functional traits such as: mobility, range size, dispersal ability and sensitivity to intensified agricultural land management (Gonthier et al. 2014) which may explain their varying response to organic farming. Birds are more mobile and have larger range size than plants, hence those species are not limited only to organic fields or farms for the availability of foods, habitat, nesting, and foraging (Piha et al. 2007; Winqvist et al. 2012). They may therefore not respond well to local scale farm management (Gonthier et al. 2014).

Among the explanatory variables: the direct effects of increased habitat heterogeneity (land cover diversity and elevation range), plant productivity (NDVI), and proportion of conservation land and water bodies at own postcode area were statistically significantly and positively correlated with species richness for both birds and plants. However, increased anthropogenic land use for cropping and horticultural farming, soil type diversity, and proximity to coast significantly reduced species richness of both taxa at a minimum of 10% level of significance. Contrary to expectation, actual evapotranspiration was negatively associated with bird richness (direct effect) and its direct effect was not significant (but positive as expected) for vascular plants.

This study is not without limitations. The results were drawn from ALA's species richness datasets and this does not differentiate between native and non-native species[29] over the study time-period and is limited to the geographic boundaries of SA and operates only at postcode level. It may be more beneficial to model at a smaller scale at which agricultural decision-making operates; that is, the farm-scale. However, broader scale studies have implications for biodiversity conservation as most of the conservation strategies are implemented at landscape scale. While this study analysed the long-term effects of certified organic farming by modelling the spatial association in terms of the numbers of organic farming businesses (numbers) at postcode level; intensity of certified organic management – proportion of organic area in total arable land - may have been a better indicator. This measure was used by Piha et al. (2007) to determine the effects of certified organic farming on bird richness in a boral mosaic landscape in Finland. In addition, this study does not differentiate between the levels of farming intensity in conventional farming. Given there are many farms that are conventionally managed but with little to no chemical fertiliser use and those that set aside larger portions of natural and semi-natural habitats, such actions also increase species richness.

The above findings have important implications for biodiversity conservation policies in SA. Biodiversity conservation alone in conservation reserves and protected areas may not be enough to combat the widespread loss of terrestrial biodiversity (Bardsley et al. 2019). Agricultural landscapes, which host many important farmland species, need to be incorporated in conservation policies. A multi-scale biodiversity conservation strategy that promotes low intensive farming systems and increases landscape heterogeneity to provide quality habitat (a whole of landscape approach by incorporating private agricultural landholders) could be beneficial for biodiversity conservation as different taxa respond at different scales (Batáry et al. 2011; Gabriel et al. 2010; Gonthier et al. 2014; Piha et al. 2007).

[29] Vascular plant species richness and bird (aves) richness for SA was acquired from ALA's spatial portal using ALA created SA vascular plant species and Aves species list. Hence the chance of inclusion of weed and invasive species in the plant and bird species richness dataset is low, given that there are separate list of weed and invasive species created in the website.

Given the important role of organic farming in conserving natural and environmental resources such as soil, biodiversity and climate change mitigation (Lori et al. 2017; Squalli and Adamkiewicz 2018; Tuck et al. 2014; Tuomisto et al. 2012) future research should investigate the potential influences of organic farming on other tradable ecosystem services, such as GHG emissions and carbon sequestration – while controlling for spatial dependence and other contextual factors in the face increased government initiatives for the sustainable management of natural and environmental resources such as biodiversity offsets, carbon pricing, environmental planting (afforestation and reforestation) and sustainable financing (Ascui and Cojoianu 2019; Best et al. 2020; Bradshaw et al. 2013; Reside et al. 2017).

3.7 Conclusion

The biodiversity impact of organic farming in SA was studied using a novel panel organic certifications dataset, combined with vascular plant and bird richness and environmental complexity gradients data, compiled from multiple sources from 2001 to 2016 at postcode level (the geographic unit of analysis for which the organic data were available). In addition, spatial dependence, which is a common attribute of inherently spatially structured species distribution data, was accounted for by estimating three types of spatial econometric models. The results revealed significant spatial dependence - species richness in one postcode was positively associated with neighbouring postcode area's species richness for both vascular plants and birds. These findings confirm that the effects of organic farming vary among taxa and are strongly influenced by landscape complexity and agricultural land use intensification. Vascular plants respond positively to the extent of organic farming at postcode level, whereas bird richness was mostly positively influenced (spatially correlated) by landscape heterogeneity, conservation land, and waterbodies (wetland, lakes, rivers etc.) rather than by organic farming. Over the time-period, both bird and vascular plant richness showed increasing trends in SA. However, results from this study suggest important implications for biodiversity conservation policies in SA, and there may need to be increased focus on multi-scale biodiversity conservation strategies to promote low intensive farming systems and increases landscape heterogeneity to provide quality habitat.

Chapter 4 Estimating the value of native vegetation on South Australian agricultural property values

Abstract

Understanding how private land-holders value on-farm natural and environmental resources is essential for the conservation and sustainable management of the natural resources. This study seeks to determine the value of on-farm natural capital, and in particular native woody vegetation, in South Australia, Australia, using sales and valuation price of agricultural properties over the time-period of 1998-2013. Findings from the spatio-temporal Durbin model revealed that the presence of native woody vegetation on agricultural properties significantly increased the per hectare market price (i.e. price sold in the market), but at a decreasing rate as the proportion of vegetation increased. The marginal return of vegetation was highest for small size properties and lowest for larger properties. In addition, the direct effects of increased annual rainfall, increased soil natural productivity, increased market accessibility, proximity to locational amenities, smaller size properties, availability of irrigation, and higher commodity price were also positively capitalised into sales prices. On the other hand, increased drought and high soil erodibility significantly reduced per hectare sales prices. Comparing valuation price models with sales price models, it was found that the valuation prices seem to undervalue the presence of native vegetation on agricultural properties and hence provide weaker evidence of the value of on-farm natural capital in South Australian context.

Keywords: Drought, ecosystem services, native woody vegetation, natural capital, spatio-temporal Durbin model.

Statement of Authorship

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Principal Author

Name of Principal Author (Candidate)	Maksuda Mannaf		
Contribution to the Paper	Conceptualisation and development of the study; undertook literature review; collected and prepared data for spatial econometric analysis and interpreted the results; wrote the manuscript.		
Overall percentage (%)	70%		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	1/12/2020

Co-Author Contributions. By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);
ii. permission is granted for the candidate in include the publication in the thesis; and
iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

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4.1 Introduction

Native vegetation is an important natural capital and plays a vital role in the health and prosperity of agricultural ecosystem services in the heavily-cleared landscape of Australia where approximately 44% of forest and woodland have been cleared since European settlement and the remaining vegetation is degraded and highly fragmented (Bradshaw 2012, 2019; EPA 2013; Evans 2016; Reside et al. 2017). As a natural capital stock, native vegetation provides public and private benefits through ecosystem services such as: shade and shelter areas for crops and livestock (notably newborn lamb survival in extreme climatic conditions); biodiversity benefits; climate regulation; soil erosion and salinity control; cultural and spiritual benefits; and conservation, recreational and aesthetics amenity values (Chancellor et al. 2019; Marano 2001; Polyakov et al. 2015; Smith and Sullivan 2014). In 2016-17, Australian farmers managed 51% of the total land area of Australia (ABS 2016f). Therefore, incorporating natural capital considerations into private landholder decision-making is fundamental, given they are the primary stewards of natural and environmental resources.

Indeed, buyers of properties are increasingly taking into account the value of inherent natural capital stocks (Polyakov et al. 2015; Samarasinghe and Greenhalgh 2013), and financial institutions in Australia are increasingly considering on-farm natural capital stocks as a buffer against credit risks for agricultural lending (Ascui and Cojoianu 2019; Azad and Ancev 2020). However, given that natural capital on a farm has many externality impacts, and provides both public and private benefits, it is usually under-valued within the valuation, agricultural lending and insurance markets (Marais et al. 2019); although it has been suggested that the economic value of natural capital types can be captured indirectly through the related market agricultural land price (Ma and Swinton 2011).

South Australia (SA) is the driest state in the driest inhabited continent – Australia, in the world. It suffers regularly from droughts and reduced rainfalls, and has a diversity of agriculture and rainfall zones, with most rain falling in the south of the state (EPA 2013). The Millennium drought was one of the most severe droughts on record experienced from 2001-02 to 2009-10 (Banerjee and Bark 2013; Mishra and Singh 2010). The southern regions in particular have experienced widespread clearing, with 75% of native vegetation cleared since European colonization for agricultural development and urbanisation (Bradshaw 2012; Evans 2016; Marano 2001). SA was the first state in Australia to have legislative (*Native Vegetation Management Act 1985*) control over clearing of native vegetation, and in the years following this act, if land clearing was denied, compensation was paid to landowners, with the *Native Vegetation Act 1991* introducing a clause to draw compensation to a close. Further legislation in 2017 now requires any modifications to native vegetation in SA requiring landowners to produce a significant environmental benefit to offset any negative clearance impacts. This study applies hedonic valuation to two rare databases (historical sales and valuation price[30] of agricultural properties) obtained from the SA Office of the Registrar General, to estimate the capitalised amenity value of native vegetation to different agricultural industries. It also seeks to understand how inter-annual climate variability and drought impacts agricultural land values across a range of different farm-scales, using both a) sales, and b) valuation prices of properties.

4.2 Valuing natural capital on agricultural properties

Hedonic pricing – a revealed preference valuation method – has been widely used to assess the value of natural and environmental resources on which agriculture depends. Some examples include the valuation of: water trading restrictions (Bigelow et al. 2019; Ifft et al. 2018); water rights (Brent 2016; Petrie and Taylor 2007); irrigation (Buck et al. 2014; Faux and Perry 1999; Grimes and Aitken 2008; Mukherjee and Schwabe 2014; Sampson et al. 2019); climate change (Mendelsohn and Dinar 2003; Mendelsohn et al. 1994; Quaye et al. 2018; Schlenker et al. 2005); soil attributes (Palmquist and Danielson 1989; Samarasinghe and Greenhalgh 2013; Xu et al. 1993); wetlands (Shultz and Taff 2004; Tapsuwan et al. 2009); and natural and environmental amenities and dis-amenities (Bastian et al. 2002; Marano 2001; Polyakov et al. 2013, 2015; Ready and Abdalla 2005; Sengupta and Osgood 2003; Tapsuwan et al. 2012; Walpole and Lockwood 1999; Wasson et al. 2013). A more detailed overview of the agricultural land valuation literature is provided in Table D.1 in Appendix D.

The literature suggests that environmental amenities such as agricultural open space, scenic views, elk and fish habitat, and hunting, recreation and angling opportunities command premium prices for agricultural land (Bastian et al. 2002; Fleischer and Tsur 2000; Henderson and Moore 2006; Wasson et al. 2013); whereas large-scale production has been found to reduce property prices (Ready and Abdalla 2005). A study conducted by Uematsu et al. (2013) in the USA showed that composite natural amenity index (based on climate, topography and water area at county level) was positively associated with the per unit farmland price – with the effects more pronounced in the higher-price quantile of per unit farmland value. Tapsuwan et al.

[30] Property valuation is estimated by the Registrar General by comparing individual property values with recently sold similar types of properties in the same area or comparable locations, with relevant adjustments made according to market fluctuations. This valuation is used for rating and tax assessment purposes.

(2012) found a positive influence of recreational amenity value (using site proximity and recreational attractiveness index for rivers and parks on rural property values) on rural property sales price in the Murray-Darling Basin region, SA. Ma and Swinton (2011) found the value of ecosystem services from agricultural farms and surrounding landscapes was capitalised into farmland value in terms of increase in per hectare sales price.

There are only a handful of studies that have specifically explored the value of native vegetation on agricultural property values. Sengupta and Osgood (2003) found that 'greenness' (measured by a vegetation index) increased the price of small recreation-oriented ranches in the USA. Another study by Borchers et al. (2014) explored the relationship between agricultural land value using farm operator reported per unit land and rental value by farming industries (crop and pasture land) with its use and amenity value using nation-wide survey data for the USA. In Australian context, Walpole and Lockwood (1999) assessed the influence of remnant native vegetation clearance regulation on rural property sale price from 1987-1997 in Victoria and New South Wales, and found no statistically significant influence on per hectare sales price when the proportion of native vegetation was less than 50% of the property, but significantly reduced property value if the vegetation exceeded 50% of the properties. Whereas for selected agricultural regions of SA from 1983-1997, Marano (2001) analysed the market value of remnant native vegetation with and without heritage agreement, and found both neutral and negative effects on property price without and with heritage agreements, respectively. In addition, Polyakov et al. (2013) estimated the marginal value of native vegetation for rural lifestyle properties ranging between 1-20 hectares using the per hectare sale price of properties located in central Victoria from 2001-2011. The findings revealed diminishing marginal property sale value benefits of native vegetation as the proportion of vegetation of the property increased. They also suggested that an increase in the proportion of vegetation to 40% from the current median proportion of 15%, could optimise ecosystem service benefits from native vegetation. Another study conducted by Polyakov et al. (2015) in Victoria from 1991-2011 found that the marginal value of native vegetation changes with the primary scope and size of the properties. The per hectare sale price of properties increases as the proportion of native vegetation increases, but at a diminishing rate. The marginal private benefit of native vegetation was greater for small and medium size properties and smaller for large farms.

Most of the studies estimating the impact of environmental amenities on agricultural property price at the farm-level often involve smaller geographic areas, shorter time periods, aggregated data at a regional/county level, or a specific type of land use – often ignoring the differential effects of impacts across different agricultural industries and farm sizes. Exceptions include Ma and Swinton (2011); Polyakov et al. (2015); Walpole and Lockwood (1999), where the value of ecosystem services (provisioning, supporting, regulating and cultural) across different types of agricultural properties (small lifestyle, hobby/medium and large farms) has been estimated and Borchers et al. (2014) compared per unit land and rental value by cropping and grazing industry.

The contribution of this study is threefold: firstly, to the best of the authors' knowledge, this is the first study to estimate the property value of native vegetation as a natural capital stock using both market value (sale price) and valuation price; secondly, the study estimated value across various farm sizes and agricultural industry (cropping, grazing and horticulture); and finally, the study controlled for inter-annual climate variability and extreme events such as drought which may impact agricultural land price.

In particular, the study uses a spatio-temporal hedonic pricing model to estimate the impact of various forms of natural capital on South Australian agricultural properties from 1998-2013 and determine whether the valuation price (VP) and sale price (SP) differ in their ability to determine the price premium. It used two databases of property valuation: SA Office of the Registrar General annual VP and actual SP of rural properties over time, and also puts together large-scale databases to capture physical, socio-economic and soil natural capital attributes of the farm and local area. It was hypothesised that the impacts of native vegetation, as a prime driver of farmland price premium, change with farm size and industry.

4.3 Econometric method and model estimation

The empirical model estimates the value of natural capital for agricultural properties based on a state-wide parcel-level pooled dataset of both government valuation and actual sales data over time from 1998 to 2013,[31] using a spatio-temporal Hedonic price model. Hedonic pricing is one of the most commonly used revealed preference non-market valuation methods used for differentiated market goods based on the theoretical framework of Rosen (1974), which was later extended by Palmquist and Danielson (1989) for agricultural land use. A complex set of factors influence farmland values, which are broadly categorised as productive and consumptive use of land, locational factors and potential for urban development (for example: Ma and Swinton 2011; Maddison 2009; Polyakov et al. 2015). The productive and consumptive

[31] 2013 was the latest year for agricultural properties sales price provided by the SA Office of the Registrar General at the time of data request.

attributes are further divided into built-in and environmental features of the property. Total economic value of the natural capital in the form of ecosystem services presented in Table D.2 in appendix D. Consider the following benchmark specification for the value of farmland:

$$Y = \alpha + \beta X + \varepsilon \qquad (1)$$

Y is measured in two forms in this study (namely per hectare real sale price, the SP model and government valuation, the VP model); α is the intercept; β is a vector of parameters to be estimated; X is the vector of explanatory variables including natural and environmental amenities; and ε is the error term, assumed to be independently and identically distributed.

Inherently spatial datasets, such as property transaction data, mostly suffer from issues of spatial dependence and spatial heterogeneity in a cross-sectional or pooled dimension. Ignoring the spatial relationship in the estimation of empirical models using ordinary least square (OLS) methods could lead to inefficient and biased estimates of the parameters. Manski (1993) identified three types of interaction effects to explain the spatial dependence. Firstly, the endogenous interaction, which in the context of this study is likely to be present if the property price depends on the price of nearby properties, which is also termed as the global spill-over effect due to the endogenous feedback effect. Secondly, the exogenous interaction effect arises when the price of one property is not only influenced by its own attributes, but also the characteristics of neighbouring properties (water availability, native vegetation, soil attributes, etc.), also termed as the local spill-over effect. Finally, correlated effects stem from the spatially auto-correlated omitted variables that determine the price of the properties. A general-to-specific approach of model specification (Elhorst 2014) was followed and a non-spatial linear model was first estimated, prior to the diagnostic tests, to see whether the benchmark model needed to incorporate the spatial interaction effects or not.

The Global Moran' *I* test[32] rejects the null hypothesis of no spatial autocorrelation in the agricultural property price (sale and valuation price). Also, the Lagrange Multiplier[33] (LM) and Robust Lagrange Multiplier[34] (RLM) tests for spatial error and spatial lag dependence rejects the null hypothesis of no spatial autocorrelation in the error term, and no spatial lag dependence, respectively. Hence, the Model diagnostic tests suggest the Spatial Durbin Model (SDM) is an appropriate model specification due to the existence of both spatial error and lag

[32] For the SP model (statistic=0.04, p value=0.00) and VP model (statistic=0.22, p value=0.00)
[33] For the SP model (statistic=5028.80, p value=0.00) and VP model (statistic=3152.94, p value=0.00)
[34] For the SP model (statistic=8073.46, p value=0.00) and VP model (statistic=6197.59, p value=0.00)

dependence (LeSage and Pace 2009). Furthermore, Elhorst (2010) and LeSage and Pace (2009) argued that the SDM produces unbiased estimates of the coefficients in uncertainty regarding model specification in case of existence of both spatial lag and error dependence. The SDM can also nest other spatial model specifications by putting restrictions on one or more parameters (see Elhorst 2010, p. 10). The SDM is specified in equation (2) and the corresponding data generating process in equation (3):

$$Y = \rho WY + \alpha + \beta X + WX\theta + \varepsilon \qquad (2)$$

$$Y = (I_n - \rho W)^{-1} (\alpha + \beta X + WX\theta + \varepsilon) \qquad (3)$$

Here, ρ is the scaler parameter, which indicates the strength of spatial dependence; W is the *n by n* spatio-temporal weight matrix (defined in the subsequent section), which indicates the structure of spatial interdependence among the observations; θ is the parameter of the exogenous interaction effect to be estimated; WY indicates endogenous interaction effect and implies that farmland value in the sample depends on the weighted average prices of the neighbouring farms; WX represents the spill-over effects of spatio-temporally lagged exogenous variables (for example on-farm native vegetation of neighbouring properties may have aesthetic amenity value) on farmland values.

4.3.1 Interpretation of direct, indirect and total effects

The results of the SDM model need to be interpreted differently than the OLS model. Use of point estimates to explore the effects of spatial spill-over may lead to erroneous conclusions (LeSage and Pace 2009). The equation (3) in the form of matrix of partial derivatives of Y termed as E(Y) with respect to K^{th} explanatory variable of X in unit 1 up to unit N can be written as:

$$\begin{bmatrix} \frac{\partial E(Y)}{\partial x_{1k}} & . & \frac{\partial E(Y)}{\partial x_{Nk}} \end{bmatrix} = \begin{bmatrix} \frac{\partial E(y_1)}{\partial x_{1k}} & . & \frac{\partial E(y_1)}{\partial x_{Nk}} \\ . & . & . \\ \frac{\partial E(y_N)}{\partial x_{1k}} & . & \frac{\partial E(y_N)}{\partial x_{Nk}} \end{bmatrix}$$

$$= (I - \partial W)^{-1} \begin{bmatrix} \beta_K & w_{12}\,\theta_k & . & w_{1N}\theta_k \\ w_{21}\theta_k & \beta_K & . & w_{2N}\theta_k \\ . & . & . & . \\ w_{N1}\,\theta_k & w_{N2}\,\theta_k & . & \beta_K \end{bmatrix}$$

Each of the diagonal and off-diagonal elements of the matrix measures the direct and indirect effects for each of the observations in the sample, respectively. Therefore, LeSage and Pace (2009) proposed using one summary indicator of direct effects, measured as the average of the diagonal elements and mean of either row or column sums of the off-diagonal elements of the matrix as the average indirect effect, for the ease of interpretation. Three types of effects can be derived from the SDM model: 1) direct effect measures the change in the dependent variable of the i^{th} observation because of a one-unit change in any explanatory variable of the i^{th} observation; 2) indirect row effect indicates how a one-unit change in specific independent variable of all neighbours (defined by the spatial weight matrix) leads to a change in the dependent variable of the i^{th} observation; and 3) total effects is the sum of direct and indirect effects (Läpple et al. 2017).

4.3.2 Spatio-temporal weight matrix

To explore the structure of spatial dependence in the observations of farmland value a spatial weight matrix was specified. Specification of the weight matrix is often arbitrary as there are little to no theoretical guidelines to follow in spatial econometrics – which is the major drawback of the application of spatial models in applied research (Bell and Dalton 2007). In the field of environmental and resource economics the most frequently used matrices are contiguity, inverse distance (with or without a cut-off point) and k-nearest neighbour (Elhorst 2014). In the dataset, the majority of land parcels are not immediate neighbours – which does not allow the construction of a contiguity matrix. For the purposes of this study an inverse distance spatio-temporal weight matrix was specified, at a threshold distance of 22km[35], to ensure at least one neighbour for each observation in the sample. However, the inverse distance matrix was chosen over k-nearest neighbour as the former allows the strength of spatial influence to decrease as the distance increases, which is not possible for the nearest neighbour approach.

Using a spatial weight matrix, while ignoring the temporal dimension that is present in the dataset, assumes farmland values simultaneously influence each other. In other words, farmland value at any moment in time is influenced by the spatially-weighted average price of neighbouring properties previously sold, along with future prices of properties yet to be sold. However, the actual agricultural property market does not operate this way and it is more

[35] Alternative specification of the matrix with 11km cut-off distance was also specified to check sensitivity of the spatial models results. Empirical findings with the alternative specification of spatial weight matrix were similar, supporting the robustness of the key findings.

rational to consider the effects of past observations only on current farmland value. Hence, the observations are ordered chronologically so that the first row corresponds to the earliest observation, to create a spatial and temporal matrix with conditions of at least one neighbour and two years of temporal lag.[36] The spatial matrix was specified as: $W^S_{ij} = 1/d_{ij}$, where d_{ij} measures the Euclidian distance between land parcels *i* and *j*. Following Maddison (2009) and Dubé and Legros (2013), the spatio-temporal matrix (W) was defined as the Hadamard product of inverse distance matrix (W^S), and temporal matrix (W^T) of the same *n by n* dimension. The temporal matrix W^T is a lower triangular matrix, so that only past observations influence current decisions and was defined as the inverse function of the time elapsed between the properties that were sold previously:

$$W^T = \begin{cases} 1 & if\ 0 < d_i - d_j \leq 2 \\ 0 & otherwise \end{cases}$$

Where d_i and d_j are sale dates (year) of properties *i* and *j*, respectively.

Following the line of argument by Anselin (1988) and Elhorst (2001) that row normalised inverse distance spatial matrix may become asymmetric and cause the remote and central observations to have same impact, the spatio-temporal inverse distance weight matrix W was normalised using the procedure described in Elhorst (2014). Suppose, W_0 is the inverse distance matrix before normalisation and D is the diagonal matrix consisting of the row sums of matrix W_0. The normalised inverse distance matrix is specified as: $W = D^{-1/2}\, W_0\, D^{-1/2}$.

To control for unobserved variables that may cause spatial dependence and the effects of regional property sub-markets on farmland value, regional dummy variables (based on Natural Resource Management (NRM) regions[37]) were incorporated into the empirical model. The model diagnostic tests was carried out using Stata code developed by Shehata and Mickaiel (2014) to identify the presence of spatial dependence. The SDM was estimated based on maximum likelihood function, and robust standard errors were used in the empirical model to minimise heteroscedasticity issues.

[36] Three different spatio-temporal matrix (2, 3 and 5 years lag) were constructed to check the robustness of the model specification. The results revealed no sensitivity due to the spatio-temporal matrix specification. Two years temporal lag with 22 km cut-off distance was chosen on the basis of higher R^2 value and following Polyakov et al. (2015) in a similar Australian context.
[37] Spatial boundaries of the NRM regions were only available for census years starting from 2011. Hence, NRM specification for 2011 was used for the whole time-period (1998-2013) in the empirical models.

To determine the functional form of the hedonic model (equation 2) linear, log-linear and log-log transformation were used, and respective models (sale and valuation) were estimated and compared with the model performance on the basis of goodness of fit (R^2). A spatio-temporal SDM model, with natural log transformed dependent variable, produces best fit of the data.[38] Following Polyakov et al. (2015), natural logarithm of explanatory variables namely: property size and distance, based locational amenity variables, was incorporated in the empirical model to improve the model's goodness of fit. The variance inflation factors (VIF) and pairwise correlation between independent variables were checked (reported in Table D.4 and Table D.5 in appendix D). For all the explanatory variables the correlation coefficient was below 0.7 (except rainfall and temperature) and VIF was less than 10. Issues were identified with annual rainfall and temperature, and it was decided to leave both in the model given the large observations and the fact that both rainfall and temperature are important predictors of land value and including/excluding on or the other did not affect the model performance nor the signs or significance of those variables, hence both were included in the empirical SDM models.

4.4 Study area and data

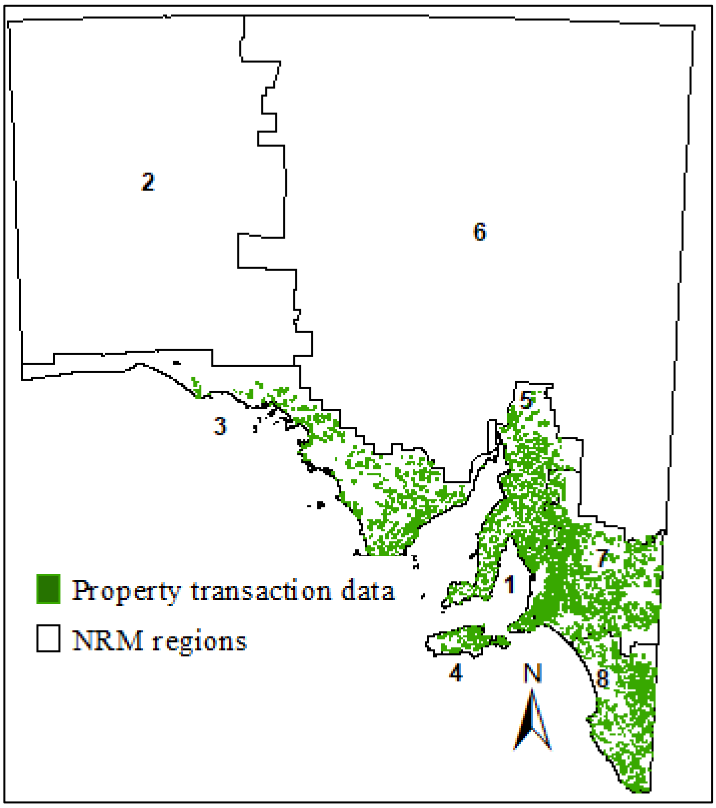
4.4.1 Construction of dependent variables – sale and valuation price of agricultural properties

Figure 4.1 shows the map of the study area with property transaction data. Two South Australian datasets were utilised to estimate the marginal values of natural capital on property values: 1) geo-referenced parcel-level cadastre rural property sales database: contains detailed sales information (sale price, date, owner type, sales type) of all property types from 1985 to 2013; and 2) SA Office of the Registrar General agricultural land valuation: the annual valuation price for all rural agricultural properties from 1985 to 2017. Details about the annual property valuation data was provided in Chapter 3. Both datasets contained information about the basic physical attributes such as lot size, water availability, number of rooms, land use code, etc. and had a unique property identifier "valuation number". The annual panel land valuation dataset contains valuation price of all sold and un-sold agricultural properties located in SA, but the sales dataset only contains observations of sold properties. To achieve the objective of the study (which was to determine if the sale and valuation price differ in capturing the value

[38] The robustness of both SP and VP model specifications was checked using CPI-adjusted total sale and valuation price as dependent variable in the SDM model and the models findings were identical to per hectare model specifications with intuitive sign for lot size (positively associated with sale and valuation price).

of on-farm natural capital) the valuation dataset was rearranged in a pooled data format like the sales dataset using the property identifier numbers that was present in both datasets and the sold properties were matched with the properties from the valuation dataset to identify the sold properties and obtain the valuation price of the respective sold properties for that respective year. Records related to open-market transactions that are considered for “full transfer’’ of private properties used for agricultural activities were selected. In the case of repeated sales,[39] the latest record was utilised to avoid the complexity in creation of spatial weight matrix, which is utilised later in the estimation of empirical models.

Figure 4.1 Map of the study area and agricultural property transaction (geographic boundaries of agricultural lots) data



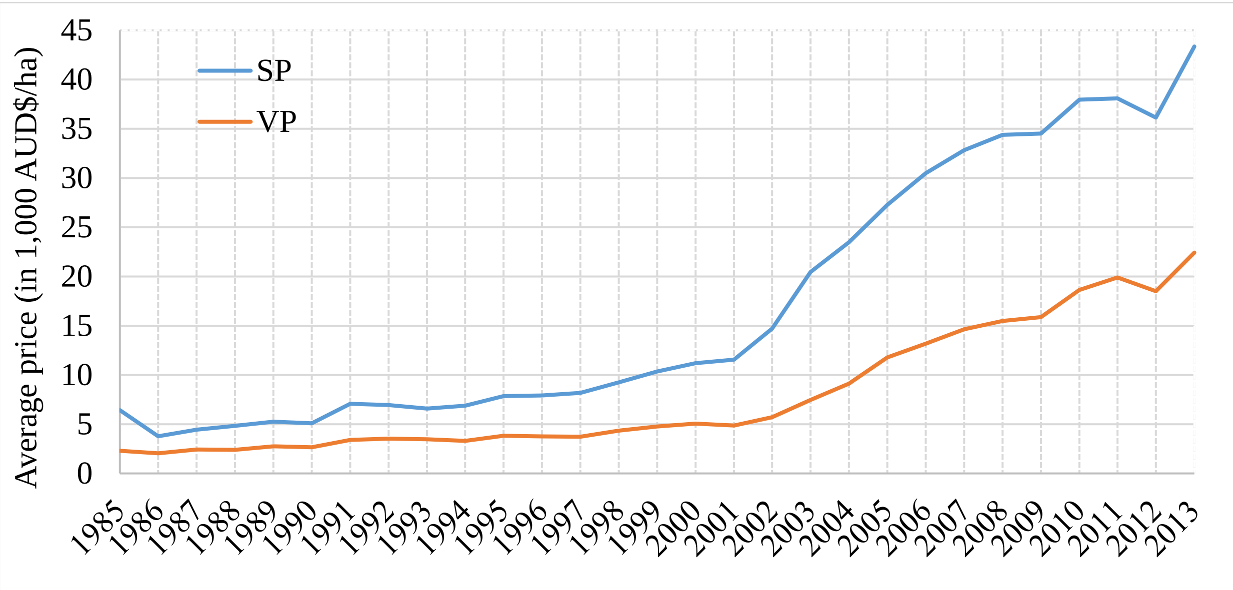
Own maps (data sources: base map – NRM regions (ABS 2011c); customised property transaction datasets (sales and valuation price) - SA Office of the Registrar General)

Note: The numbers in the map indicates NRM regions: 1- Adelaide and Mount Lofty Ranges (AMLR); 2 – Alinytjara Wilurara (AW); 3 – Eyre Peninsula (EP); 4 – Kangaroo Island (KI); 5 – Northern and Yorke (NY); 6 – South Australian Arid Lands (SAAL); 7 – South Australian Murray Darling Basin (SAMDB); 8 – South East (SE).

[39] The number of observations for repeated sales were very small (<1% of total observations).

There were a number of observations with either missing or extremely low/high sale and valuation prices in the dataset. Agricultural properties that were less than two hectares in size with a price per hectare (sale and valuation) of less than AUD$50 were removed. In addition, agricultural properties located in major cities and SA arid land (NRM region) were excluded from the final sample. Property transaction data commencing from 1998 was used in the empirical model, as some of the geo-referenced explanatory variables used in the study were not available during earlier time-period. The 1,256 observations of the first two years (1998 and 1999) were used to create the spatio-temporal matrix. The final datasets used in the empirical spatio-temporal model of SP (N=10,513) and VP (N=10,513) contained equal number of observations of sales and valuation price of agricultural properties from 1998-2013 for the whole of the state's intensive agricultural zone[40] "Southern South Australia". Per hectare sale and valuation price were constructed using farm size, and both prices were converted to real price using the consumer price index (CPI) using 2004 as the base year – sourced from ATO (2020). The CPI adjusted per hectare sale and valuation prices are presented in Figure 4.2.

Figure 4.2 CPI-adjusted (base year=2004) average per hectare sales and valuation of agricultural properties in South Australia from 1985-2013

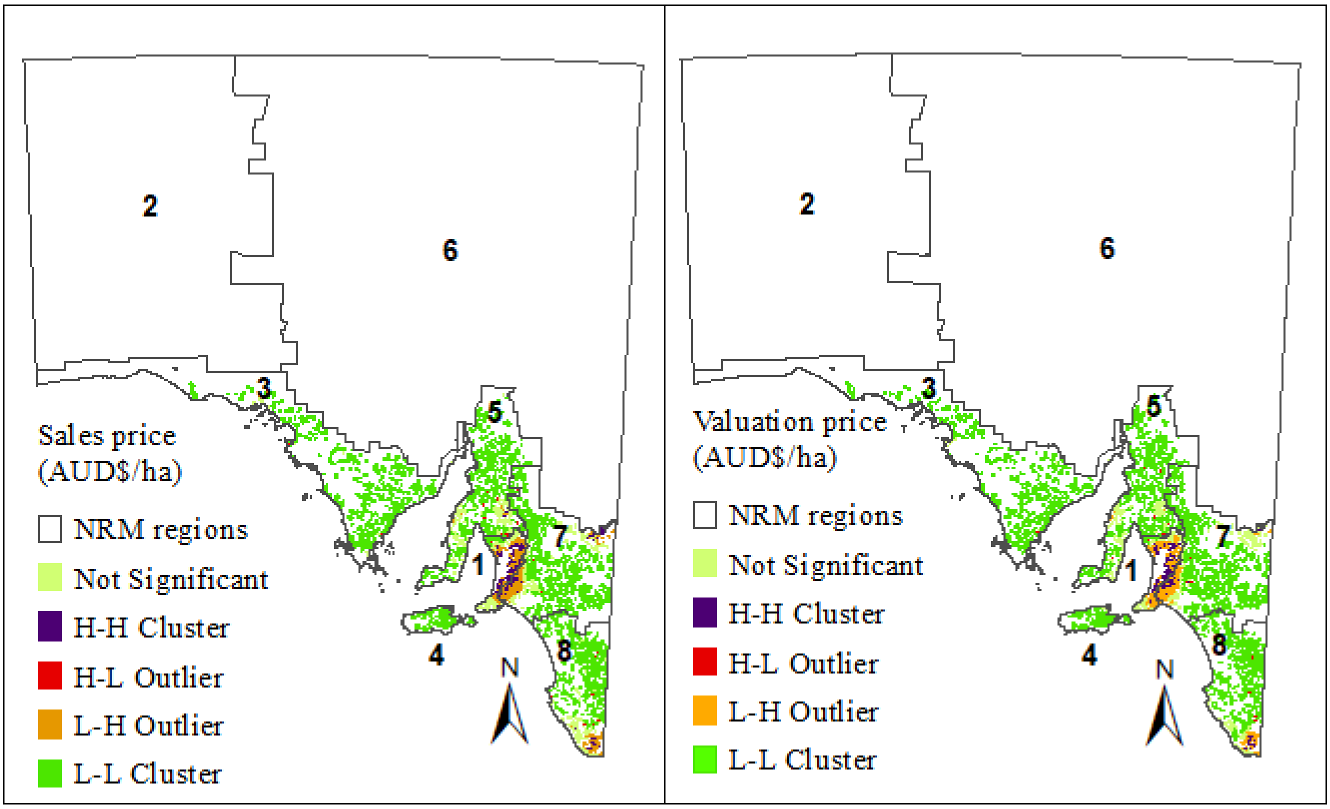


Own figure (data source: customised property transaction and valuation data from the SA Office of the Registrar General)

[40] The northern arid regions covering 87% of SA are dominated by a few large pastoral industries, conservation and protected land. Southern temperate regions represents the agricultural zone of the state.

Clusters and outliers of agricultural properties in terms of per hectare sales and valuation price are presented in Figure 4.3 (clusters and outliers with 11km inverse distance matrix are reported in Figure D.1 in appendix D).

Figure 4.3 Cluster and outliers of agricultural properties per hectare real (base year 2004) sales and valuation price in SA at 22 km threshold inverse distance, 2000-2013



Own maps (data sources: base map – NRM regions (ABS 2011c); customised property transaction datasets (sales and valuation price) - SA Office of the Registrar General)

Notes: H-H (high-high clusters) indicates statistically significant high valued land surrounded by lands with high value; L-L (low-low clusters) means statistically significant low valued land neighboured with farm lands with low value; H-L (high-low outliers) shows statistically significant high valued land bordered by lands with low value; L-H (low-high outliers) indicates statistically significant low valued land encircled by lands with high value.

The numbers in the map indicates NRM regions: 1- Adelaide and Mount Lofty Ranges (AMLR); 2 – Alinytjara Wilurara (AW); 3 – Eyre Peninsula (EP); 4 – Kangaroo Island (KI); 5 – Northern and Yorke (NY); 6 – South Australian Arid Lands (SAAL); 7 – South Australian Murray Darling Basin (SAMDB); 8 – South East (SE).

The full sample was subdivided into three groups to explore the differential impact of native woody vegetation on per hectare sale and valuation price by farm size and agricultural industry. Stata code *"xtile"* was utilised to subdivide the data into three groups according to farm size to indicate small (2-12.23 ha; N=3,475), medium (12.24-64.48 ha; N=3,523) and large (64.49-4944.87 ha; N=3,515) farms. Property land use description attached to the SP and VP datasets was utilised to create the three broad categories of industry subsamples following OVG (2019)[41]: cropping (N=4,041), grazing (N=5,320) and horticulture (N=1,152).

4.4.2 Independent variables

The literature in Table D.1 in appendix D illustrated the many variables that have been found to influence rural property values. These findings were used as a basis to collect information on a range of different capitals.

4.4.2.1 Physical capital

Information about lot size and lot characteristics (building presence and the number of main rooms was available) from the land valuation dataset. To control for the structural attributes per unit of land, the total number of main rooms was divided by the lot (farm) size – following Maddison (2009). Dummy variables separately controlled for sheds, agricultural industry, irrigation, and groundwater bores. Location of groundwater bores used for irrigation purposes was obtained from the Bureau of Meteorology's (BoM) Australian groundwater explorer (BoM 2019a). Bore location was spatially matched with the geocoded property database to identify location on the property. All physical capital attributes were expected to have positive influence on farmland value, other than the lot size variable. Previous literature has found mixed results regarding farm size: in the majority of cases per unit sale price of agricultural properties reduces with increasing farm size (Ready and Abdalla 2005; Sengupta and Osgood 2003; Sheng et al. 2018; Bastian et al. 2002; Wasson et al. 2013; Zhang et al. 2020). However, in some studies the total sale price increases as the property size increases (Grimes and Aitken 2008; Ifft et al. 2018), while others found diminishing effects of farm size (Maddison 2000; Polyakov et al. 2015).

4.4.2.2 Natural and environmental capital

The proportion of native woody vegetation (generally >1m tall) on each property was calculated using the SA Land Cover Layers, developed by Department for Environment and

[41] The land use categories that were included in final observations for the empirical analysis were reported in Table D.3 in appendix D.

Water (DEW). The datasets provide spatial and temporal summaries of 17 categories of land classes for 6 epochs from 1987-2015 (1987-1990, 1990-1995, 1995-2000, 2000-2005, 2005-2010 and 2010-2015) based on the Landsat satellite images and local calibration data at a scale of 1:50,000 (DEW 2017a). As the dataset provided a five-yearly average condition of native vegetation, linear interpolation was used to calculate the annual change in vegetation rather than using the same value for the epochs.

The impact of native vegetation on farmland value can vary between different regions and production types (Chancellor et al. 2019; Marano 2001). For example, woody vegetation in cropping land may reduce productivity by competing for soil nutrients and therefore hinder the application of machinery in planting and harvesting on a wide-scale. Grazing land with excessive woody vegetation may reduce pasture production and increase herd management costs, but at the same time tree cover provides shade and shelter for livestock. Woody vegetation also offers a source of cultural, recreational and aesthetic amenities, and provides benefits to combat the effects of climate change, improve water quality, act as a carbon sink, boost the biodiversity by providing habitat, and reduce soil erosion and salinity.

In addition, the price structure of broadacre farms is different to irrigated horticulture or livestock farms. Horticultural farm prices tend to be higher because of the associated high capital cost of perennial fruits and nuts, trees, and viticulture. Similarly, a higher proportion of fixed capital costs increases grazing farmland values relative to broadacre (Chancellor et al. 2019). Given literature findings of the impact of vegetation on various farm industries, it is also expected that native vegetation is expected to have differential impacts on land values by industry, which is something that has not been explored in-depth in the existing literature.

To capture the influence of climate variability on farmland value, a one-year lagged rainfall and temperature variable was included in the empirical model. The annual climate data (average maximum temperature and total rainfall grids) were obtained from BoM at a resolution of 5km, and extracted at farm-level by spatially matching properties with climate grids. Although drought can be measured in many ways (e.g. meteorological, hydrological and socio-economic (Bastin et al. 2014)), this study uses BoM's (2019b) definition, where: a region is affected by serious drought if the recorded rainfall lies between the bottom 5th and 10th percentiles over an extended period of three months or more; while a severe drought occurs when recorded rainfall sits within the lowest 5th percentile for the area over a period of three months or more. Annual rainfall percentile grids (5th – severe drought and 10th – serious drought) were sourced from BoM. Rainfall percentile grids and property cadastre layers were overlayed to extract rainfall deficiency at the property level, and a dummy "Drought" was created.

To capture the difference in natural productivity of the land different soil attributes such as percentage of sand, silt, clay, soil organic carbon content, plant available water holding capacity of the soil and pH ($cacl_2$) in the top soil (0-5cm) were calculated. CSIRO-developed "Soil Attribute Maps" at a resolution of approximately 90m were used. A dummy variable for soil pH (basic soil) was created to indicate the optimal rate for the growth of most of the plants ranging between 5.5 and 7. Soil erosion data was sourced from DEW "Soil Erosion Max Potential-Wind or Water" at a 50m resolution. This resource measures the erosion potential in the event of removal of vegetation and other ground-cover, due to fire, overgrazing or land clearance. A soil erosion index was created ranging from low, moderately low, moderate, moderately high, high, very high and extreme values (1-7), where high value was associated with higher erosion risk. A digital elevation model developed by Geoscience Australia, at a resolution of 25m, was used to derive the average property elevation.

Euclidean distance to the nearest source of surface-water from the property was included in the model to serve as a proxy for recreational amenity and direct views (expected to increase property values).

4.4.2.3 Social, human and economic capital

To measure the urban development potential and population pressure, remoteness index, and distance to nearest urban centres were incorporated given previous literature findings (e.g. Maddison 2009; Polyakov et al. 2013; Polyakov et al. 2015). Australia is divided into five classes of remoteness on the basis of the accessibility/remoteness index of Australia by the ABS, with scores ranging from 0 (high accessibility) to 15 (high remoteness). The index measures the relative accessibility to the widest range of goods, services and opportunities for social interaction, by calculating the road distance from a point to the nearest urban centre and localities (ABS 2016l). A remoteness index (1-4) was generated for the four classes as properties in the major cities were not included in the sample: inner regional, outer regional, remote and very remote Australia, to indicate the relative accessibility for each property by spatially matching both datasets. Remoteness was hypothesised to have a negative effect on land value. To capture the interaction effects of intensity of population (population density of major cities) and distance to urban centres with a population 1,000 or more, an index "urban accessibility" was created (Borchers et al. 2014; Maddison 2009; Polyakov et al. 2015). This index was defined as the inverse distance between each property and nearest urban area, weighted by population, and was expected to have a positive effect on property price. The relative locational quality of the properties and access to amenities were included in the empirical model by calculating the Euclidean distance from the centroid of each of the properties to the nearest urban centres and localities (UCL) with population 1,000 or more, nearest surface water source, sealed principle road, coastline, and national conservation reserve.

Regional socio-economic conditions indicated by population density, average area income, employment opportunities, and accessibility to wider economic resources, were expected to positively influence property values. Higher population density raises property values by creating more demand (and increased conversation of rural to urban land (Wheeler et al. 2020)), while higher income increases the willingness to pay higher prices. The Socio-Economic Index for Areas (SEIFA) by ABS of relative disadvantage for postcodes, based on five-yearly census data, measures the relative advantages and disadvantages of an area in terms of income, employment, education, occupation, housing and other miscellaneous variables. A high score of the SEIFA index is associated with a relatively low incidence of disadvantage and vice versa (Haensch et al. 2019; Wheeler and Zuo 2017). The property data was spatially merged with SEIFA scores at postcode levels. As the data was only available at five-yearly intervals, such as 1996, 2001, 2006 and 2011, the same values were used for the intra-census years to avoid reverse causality (Wheeler et al. 2020). The same treatment was given to other census year-based variables.

Agricultural profitability is an important determinant of farmland value and was expected to influence both sale and valuation prices. The annual real value of commodity price index (base year 1998) was sourced from (ABARES 2019a) for broadacre, livestock, fruits, vegetables, and grapes. This price variable was assigned to each property by temporally matching its primary production focus.

Finally, a continuous trend variable was included in the model to account for the annual change in prices over time. Table 4.1 presents the summary statistics used in the empirical model.

Table 4.1 Summary statistics of the variables used in spatial Hedonic pricing model (N=10,513)

Variable definition	***Source***	***Mean***	***Std. Dev.***	***Min.***	***Max.***
Dependent variables					
Per hectare mean sale price in real prices in natural logarithm ($/ha)	SA Office of the Registrar General – specialised request and (ATO 2020)	8.83	1.77	4.04	13.66
Per hectare mean valuation price in real prices[a] and natural logarithm ($/ha)		8.22	1.62	3.92	12.25
Independent variables: Physical capital					
Lot (farm) size in natural logarithm (ha)		3.50	1.67	0.69	8.51
Number of main rooms per hectare (rooms/ha)		0.29	0.64	0	5.24
Structure dummy (1=presence of structure; 0=otherwise)		0.75	0.43	0	1
Irrigation dummy (1=irrigated land; 0=non-irrigated)		0.06	0.24	0	1
Cropping dummy		0.38	0.49	0	1
Livestock (base) dummy		0.50	0.50	0	1
Horticulture dummy		0.04	0.20	0	1
Market gardening dummy		0.01	0.11	0	1
Mixed farming dummy		0.01	0.07	0	1
Viticulture dummy		0.05	0.22	0	1
Groundwater bore dummy (1=bore/s on the property; 0=otherwise)	(BoM 2019a)	0.12	0.33	0	1
Natural and environmental capital					
Annual average maximum temperature (^oC)	BoM – specialised request	21.90	1.72	17.84	26.30
Annual rainfall (mm)		501.56	193.13	99.60	1116.34
Drought dummy (1=drought; 0=otherwise)[b]		0.06	0.24	0	1
Proportion of native woody vegetation	(DEW 2017a)	0.20	0.23	0	1
Elevation (metres)	(Geoscience Australia 2015)	167.95	155.57	0.22	693.61
Silt (%)	(Viscarra Rossel et al. 2014e)	2.82	1.73	0.01	10.06
Sand (%)	(Viscarra Rossel et al. 2014d)	49.44	9.85	8.49	91.67

Clay (%)	(Viscarra Rossel et al. 2018)	21.12	8.77	2.00	49.58
Organic carbon (%)	(Viscarra Rossel et al. 2014b)	0.85	0.34	0.15	2.16
Soil water holding capacity (%)	(Viscarra Rossel et al. 2014a)	5.34	1.28	0.04	11.43
Soil pH dummy (1=basic soil; 0=otherwise)	(Viscarra Rossel et al. 2014c)	0.51	0.50	0	1
Soil erosion index (1=low, 2=moderately low, 3=moderate, 4=moderately high, 5=high, 6=very high, 7=extreme)	(DEW 2017b)	2.76	1.17	1	7
Human, social and economic capital					
Distance to principle sealed highway (metres) in natural logarithm	(DPTI 2013)	8.47	1.32	1.41	11.13
Distance to national conservation reserve (metres) in natural logarithm	(DEW 2013)	8.84	0.99	0	10.78
Distance to coast (metres) in natural logarithm	(Geoscience Australia 2004)	10.26	1.17	4.61	12.34
Socio-economic index for areas (SEIFA)	(ABS 2012)	972.95	55.59	712.46	1116.59
Urban accessibility in natural logarithm	(ABS 2006b, 2011h, 2018a)	-11.08	2.23	-16.77	-1.95
Adelaide and Mount Lofty ranges	(ABS 2011c)	0.21	0.411	0	1
SA Murray-Darling Basin (base)		0.32	0.47	0	1
Kangaroo Island		0.03	0.16	0	1
Eyre Peninsula		0.08	0.27	0	1
Northern and Yorke Peninsula		0.19	0.39	0	1
South East		0.17	0.38	0	1
Real commodity price index	(ABARES 2019a)	118.71	22.43	51.30	184.04
Trend (1=2000 to 14=2013)		7.34	3.90	1	14

Notes: [a] In the conversion of real per hectare sale and valuation of agricultural properties 2004 was used as base year.

[b] Two specifications of meteorological drought measured by rainfall deficiency was tested in the empirical model. Serious drought occurs when rainfall lies between the bottom 5th and 10th percentiles over an extended period of three months or more; while a severe drought occurs when recorded rainfall sits within the lowest 5th percentile for the area over a period of three months or more.

4.5 Results and discussion

The estimation results from the spatio-temporal SDM for sale price (SP) and valuation price (VP) are presented in Table 4.2 (see Table D.6-Table D.8 in appendix D, respectively for full sample non-spatial OLS and SDM results with standard errors); while the overview of the effects of native vegetation by farm size and types are reported in Table 4.3. Findings from various sensitivity tests confirmed the robustness of the key findings of the empirical model. The results from SP and VP models for linear and log-linear transformation of the variables, total sales and valuation price, farm size (small, medium, and large) and industries (crop, grazing, and horticulture) sub-samples in details, alternative specification of inverse distance (11km cut-off) in the 2 years spatio-temporal matrix, and 3 and 5 years spatio-temporal (22km inverse distance) matrix were reported in Table D.9-Table D.32 in appendix D.

The statistically significant and positive coefficient of the spatial lag dependence confirms the existence of spatial effects in both SP and VP models and the magnitude of the dependence is much higher in the VP model. The Likelihood Ratio (LR) test of SDM vs. SAR of the null hypothesis (θ =0) revealed SDM was preferred over SAR and LR test of SDM vs. SEM of the null hypothesis ($\theta+\rho\beta= 0$) indicates SDM was preferred over SEM (test statistic reported in Table 4.2) and was the best fit. Which infers agricultural property prices are influenced by neighbouring property prices and characteristics. Hence, the following section focuses on the marginal value of the direct and indirect effects from the SDM model of SP and VP for the full sample (farm size and industry subsample model results are discussed where relevant).

Overall, the SP model had a slightly higher goodness of fit (R^2) value compared to the VP model. The SP model explains 87% of variation, whereas the VP model explains 84% of variation within the model. Although all five categories of capital are significantly associated with both the SP and VP models, and the signs are generally consistent with the non-spatial OLS regression results. However, native vegetation as a natural capital stock is valued differently across both models and varies according to farm size and types.

4.5.1 Natural and environmental capital

4.5.1.1 Native woody vegetation

The direct effect of the proportion of native woody vegetation on the property highlight a significant difference in the sale and valuation price models. Overall, for the full sample valuation model, the relationship between proportion of native vegetation percentage and valuation price per hectare is U-shaped, with the minimal valuation estimated at native vegetation percentage being 72%, everything else being equal. Contrary to the valuation model results, the relationship between native vegetation percentage and sale price per hectare is inversely U-shaped, with the maximum valuation estimated at native vegetation percentage being 32%, everything else being equal. These sales price findings reflect similar results of Polyakov et al. (2013), Polyakov et al. (2015), Sengupta and Osgood (2003) and Tapsuwan and Polyakov (2016). The inverse effects of native vegetation on valuation price per hectare may be due to the fact that land valuers generally put more emphasis on physical and agricultural production-related attributes of properties such as: number of buildings and their condition, improvements on the property, location, slope, elevation, nearby land use, land use classification, zoning area, property size, heritage restrictions, rainfall, water availability, and highest and best use of the land (DPTI 2019). Also, as stated by GA (2019), land valuers and financial institutions tend to consider on-farm natural resources like native vegetation to have "zero productive value." Ma and Swinton (2012) also reported that appraised values tend to understate environmental amenity values within the market transaction price of the property. Another study conducted by Nind (2002) found that environmental resources are only taken into account within land valuation when they have beneficial or detrimental effects, and are reflected by the market price. Unless the benefits of environmental management systems within agriculture are captured by the market price, they are unlikely to be reflected in the property valuation price. Land-valuation process could serve as an incentive for the wider adoption of environmental management systems in agriculture (Nind 2002).

The model results from the farm-size quantiles in Table 4.3 are of particular interest and provide more explanation of the potential reasons for the impact of native vegetation on sales and valuation prices. The results highlight that the marginal value of native vegetation was positively capitalised into both market and valuation price per hectare of the small size properties (up to 12.23 hectares), however the marginal return decreases as the proportion of vegetation increases past a threshold. Race et al. (2010) found that small-size lifestyle property owners' value native vegetation for non-economic activities, such as aesthetic and recreational purposes, and spend more time planting and maintaining the vegetation. Medium-size properties (12.24 to 64.5 hectares) acquire a significant premium sales market price per hectare with an increase in native vegetation (which decreases after a certain point), but the direct effect on valuation price was not statistically significant. In contrast, increased vegetation areas on large-size (64.6-4945 hectares), production oriented, statistically significantly decrease agricultural property prices per hectare (both sale and valuation) (and the squared term is not significant for the SP model). The negative effects for large farms are unsurprising given that, for large commercial agricultural farms, the annual income generated from farming activities is of prime importance – as opposed to non-economic returns such as amenity values (Slee 1998). Other studies such as Deaton and Vyn (2010), along with Vyn (2012), also found that an increase in the proportion of woody area reduced agricultural properties sales prices in the Ontario province of Canada.

At the industry level subsamples, the sales price per hectare of cropping (weakly significant), grazing and horticultural properties significantly increased from an increase in native woody vegetation (and decreased past a certain threshold point). In contrast, there was no significant results found for the valuation price per hectare for grazing and horticulture, although an increase in proportion of native vegetation was a negative statistically significant impact on valuation prices per hectare for cropping farms. The results support the hypothesis that native vegetation is valued differently among industries and varying farm sizes.

Although the direct price effect of native vegetation is opposite in the SP and VP models, the indirect and total effects are significantly positive in both models and has the largest effect on property prices. An increased proportion of native woody vegetation within neighbouring agricultural properties (off-site) raises own property sale and valuation price, and the magnitude of this effect is almost double in the VP compared to SP model. These results align with the findings of Ma and Swinton (2011) and Polyakov et al. (2013) suggesting the indirect benefits in the form of recreational and aesthetics ecosystem services from the presence of natural capital such as native woody vegetation, rivers, and lakes in surrounding agricultural properties are also positively capitalised into property price. Furthermore – as supported by Pandit et al. (2014) – urban tree canopy cover located in public spaces increased residential property value.

Table 4.2 Comparison of full sample SDM results between sale (SP) and valuation price (VP) per hectare model of South Australian agricultural properties (N=10,513), 1998-2013

	Sales price (SP)			*Valuation Price (VP)*		
	Direct	***Indirect***	***Total***	***Direct***	***Indirect***	***Total effect***
Drought	-0.066*	0.901**	0.835*	-0.025	3.062	3.036
Native woody vegetation	0.399***	14.277***	14.676***	-0.666***	124.350***	123.684***
Native woody vegetation square	-0.625***	-2.699***	-3.324***	0.460***	11.898**	12.358**
Annual rainfall	0.001***	-0.003***	-0.002***	0.002***	-0.016**	-0.014**
Annual temperature	0.013	-0.852***	-0.839***	0.018	-6.066**	-6.048**
Soil organic carbon	0.037	2.928	2.965	0.066**	0.045	0.111
Silt	0.022***	1.926**	1.947**	0.034***	13.224**	13.258**
Sand	0.001	-0.165*	-0.164*	0.002**	0.197	0.198
Clay	0.000	0.341***	0.340***	0.002*	2.943***	2.945***
Soil water holding capacity	0.069***	-2.016***	-1.947***	0.087***	-8.576**	-8.488**
Soil erosion index	-0.012*	2.650***	2.637***	-0.010	15.472**	15.462**
Basic soil	0.076***	-1.088	-1.011	0.060***	-11.294	-11.235
Elevation	0.000	-0.042***	-0.042***	0.000	-0.293***	-0.293***
Distance to coast	-0.023**	-0.097*	-0.120**	-0.055***	-1.416**	-1.471**
Distance to conservation reserve	0.033***	0.142***	0.174***	0.019***	0.498*	0.517**
Distance to surface-water	-0.025**	-0.108**	-0.133**	0.004	0.091	0.094
Distance to road	-0.009*	-0.041*	-0.050*	0.004	0.109	0.113
Lot size	-0.616***	1.388***	0.771	-0.497***	6.662**	6.165*
Main rooms per hectare	0.290***	2.430*	2.720*	0.209***	4.190	4.399
Structural improvements	0.483***	-2.816	-2.333	0.149***	-46.183**	-46.034**
Irrigation	0.257***	25.008***	25.265***	0.261***	128.786***	129.047***
Groundwater bore	0.082***	-1.084	-1.002	0.042**	13.720	13.763
Cropping	0.025	0.109	0.135	0.068***	1.759**	1.827**
Horticulture	0.220***	0.949***	1.169***	0.268***	6.942**	7.210***
Market garden	0.311***	1.342***	1.653***	0.446***	11.531**	11.977***
Mixed farming	0.124	0.536	0.660	0.152**	3.922	4.074
Viticulture	0.122***	0.528**	0.650**	0.221***	5.718**	5.939**
SEIFA	0.002***	-0.008***	-0.007**	0.002***	-0.036**	-0.034**
Real commodity price index	0.001**	-0.011**	-0.010**	0.002***	-0.112***	-0.110***
Urban accessibility index	0.077***	0.332***	0.409***	0.094***	2.434***	2.528***
Remoteness areas index	0.008	0.033	0.040	0.056***	1.453*	1.510*
Trend	0.022***	0.097***	0.120***	0.011**	0.283***	0.294***
EP	0.499***	2.156***	2.655***	0.513***	13.262	13.774**
KI	-0.009	-0.037	-0.045	-0.097*	-2.518	-2.615
AMLR	0.275***	1.189***	1.464***	0.301***	7.791***	8.092***
SE	0.281***	1.212***	1.493***	0.133**	3.447*	3.581*
NY	0.426***	1.839***	2.265***	0.378***	9.771***	10.149***
Spatio-temporal lag (ρ)	0.649***			0.776***		
Pseudo R^2	0.874			0.849		
AIC	19681.650			17735.300		

Notes: The outcome variable is the per hectare real price of agricultural properties. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table 4.3 Comparison of the capitalisation of native woody vegetation as a stock of natural capital and drought in real per hectare agricultural property value (sales and valuation price) by farm size and type

		Model	*Variable*	*Direct effect*	*Indirect effect*	*Total effect*
Farm size	Small (2-12.23ha; N=3,475)	SP	Drought	-0.065	1.706**	1.641**
			Native woody vegetation	1.271***	3.841	5.112
			Vegetation squared	-1.193***	-4.265***	-5.458***
		VP	Drought	-0.023	0.566	0.544
			Native woody vegetation	0.342***	10.427***	10.769***
			Vegetation squared	-0.254*	-0.817*	-1.072*
	Medium (12.24-64.48ha; N=3,523)	SP	Drought	-0.027	0.271	0.244
			Native woody vegetation	0.978***	3.206**	4.185***
			Vegetation squared	-1.228***	-0.639**	-1.867***
		VP	Drought	0.036	0.370**	0.406**
			Native woody vegetation	0.166	6.822***	6.988***
			Vegetation squared	-0.336**	-0.232*	-0.568**
	Large (64.49-4944.87 ha; N=3,515)	SP	Drought	-0.110**	3.504***	3.394***
			Native woody vegetation	-0.983***	-9.811**	-10.794**
			Vegetation squared	0.065	0.261	0.326
		VP	Drought	-0.089*	6.376***	6.287***
			Native woody vegetation	-1.459***	-32.082***	-33.541***
			Vegetation squared	0.528***	4.049**	4.577**
Farming industry	Cropping (N=4,041)	SP	Drought	-0.110**	1.184*	1.074
			Native woody vegetation	0.336*	-2.563	-2.227
			Vegetation squared	-0.914***	-2.627**	-3.542***
		VP	Drought	-0.038	2.222	2.184
			Native woody vegetation	-1.199***	-22.656	-23.855
			Vegetation squared	0.772***	7.540*	8.312**
	Grazing (N=5,320)	SP	Drought	-0.026	0.514	0.489
			Native woody vegetation	0.677***	4.242	4.919
			Vegetation squared	-0.816***	-2.289***	-3.105***
		VP	Drought	0.013	2.207**	2.220**
			Native woody vegetation	0.028	18.381**	18.409**
			Vegetation squared	-0.149	-1.138	-1.287
	Horticulture (N=1,152)	SP	Drought	0.012	-0.835*	-0.823**
			Native woody vegetation	0.580**	1.387	1.968
			Vegetation squared	-0.805**	-0.461	-1.266**
		VP	Drought	-0.155	0.294	0.139
			Native woody vegetation	-0.096	0.670	0.575
			Vegetation squared	0.109	0.049	0.157

<u>Notes</u>: *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively

4.5.1.2 Drought and climate

Figure D.2 and Figure D.3 in Appendix D provides information on the percentage of properties in SA (by industry and farm size) in severe drought over the time-period studied. Severe drought for an extended period of 12 months had a weak statistically significant negative direct effect on South Australian agricultural property sale prices per hectare (the effect is not statistically significant for valuation price; although the coefficient is still negative) in the total time-period model in Table 4.2. The direct impact of drought is also consistent in the farm size quantiles and industry subsample models, though it is most significant (and largest) for large farms and those in the cropping industry. These results suggest that persistent drought reduces the demand for agricultural property – due to lower operating profits (reduced crop and livestock production). The findings also align with the existing literature, which suggests: farms located in natural disaster prone areas (drought, flood and earthquakes) receive significantly lower rent/valuation compared to other areas (Quaye et al. 2018; Samarasinghe and Greenhalgh 2013); drought significantly reduces crop yield (Hughes et al. 2019; Kuwayama et al. 2018); and poorly performing farms, in terms of rate of return and higher debt, are more likely to exit farm business during drought (Wheeler and Zuo 2017).

Conversely, the spill-over (indirect) effects of severe drought is significantly positive for the SP model for the full sample, which suggests neighbouring agricultural properties impacted by drought increases own property price (similar to results found in Wheeler et al. (2020) for spatial impacts of higher temperature). One reason for this positive effect may be that, during drought, reduced on-farm production (reduction in crop yield, area planted) decreases grain supply – leading to an increase in grain price, which partially offsets the producers who are less affected by drought and able to produce some crops (Eslake 2018). Also, the effects of drought are disproportional and the economic impact of drought on agriculture depends on its frequency and duration, with the effects varying across regions and farming type. The intensity of indirect effect is much higher than the direct effect, which makes the total effect of drought significantly positive.

As expected, increases in average annual precipitation was statistically significant and positively capitalised into farmland value for all model specifications aligning with both national (Chancellor et al. 2019; Marano 2001; Samarasinghe and Greenhalgh 2013) and international literature (Uematsu et al. 2013; Barnard et al. 1997; Schlenker et al. 2006;

Mukherjee and Schwabe 2014; Van Passel et al. 2017). Annual average maximum temperature had no statistically significant direct effect on property values in full sample models.

4.5.2 Other natural and physical capital influences

The direct effects of most of the soil attributes were generally highly significant and had expected effects on both SP and VP models. Farmland with fertile soils – as indicated by the higher contents of silt, plant available water in the soil, soil with optimal pH range for crop growth, and lower risk of soil erosion – obtains a premium in both sale and valuation prices, consistent with other farmland valuation studies (Huang et al. 2006; Uematsu et al. 2013; Barnard et al. 1997; Xu et al. 1993).

Proximity to a coastline statistically significantly increased property values in both models; while proximity to the closest source of surface-water is only capitalised into farmland sale price per hectare for the full sample. This effect varied among farm size and farming types: large and cropping farm prices (SP and VP) increase with greater accessibility to water resources. Proximity to water resources can create opportunities for recreation through swimming, fishing and scenic views – and provides potential greater accessibility to surface-water for irrigation, which is beneficial for farming activities (Ma and Swinton 2011; Sengupta and Osgood 2003). Agricultural properties that are further away from national conservation parks command a higher price, with this finding similar to Tapsuwan et al. (2012).

The direct effects of variables related to the built-in production and consumption attributes of land parcel, are all positive and statistically significant and generally consistent across all full and subsample models of per hectare sale and valuation prices. Smaller-size properties, greater number of rooms, structural improvements, irrigated farmland and groundwater bores all command significantly higher prices per hectare in both models. Furthermore, farmland used for cropping (e.g. cereals, small seeds and fodder crops), horticulture (namely citrus, stone fruits, pome fruits, olives and almonds and other fruit tress), viticulture, market gardening and mixed farming (e.g. vines and stocks, dairy and pigs, cereals, stock, and horticulture) are valued higher when compared to grazing lands (e.g. cattle-beef and dairy, sheep, pig, goat, etc.) This result generally was found in both the SP and VP models. These findings are consistent with previous literature regarding hedonic pricing per unit of land (e.g. Borchers et al. 2014; Palmquist and Danielson 1989; Zhang et al. 2020; Mukherjee and Schwabe 2014; Sampson et al. 2019, Buck et al. 2014; Barnard et al. 1997; Sheng et al. 2018).

Agricultural properties located in natural resource management regions of Eyre Peninsula, Adelaide and Mount lofty ranges, Southeast, Northern and Yorke Peninsula command a premium price, whereas Kangaroo Island's agricultural properties are cheaper (only significant for the VP model) considering South Australian Murray-Darling region as the base. The annual trend variable is positive and highly significant, indicating an increase in the CPI-adjusted per hectare sale and valuation price of farmland over the study period – which mirrors the long-term increasing trend in the median price of national agricultural properties (RB 2019).

4.5.3 Social, human and economic capital influences

As anticipated, the effects of urban accessibility index (and the closer the distance to urban centres) is positive and statistically significant on property values in all model specifications. The other proxy variable, for measuring the effects of market access and urban development potential on farmland value-distance to the nearest urban centre, shows significantly negative effects across all model specifications. These result supports the findings from a wide range of farmland valuation literature examining urbanisation effects (Bastian et al. 2002; Borchers et al. 2014; Deaton and Vyn 2010; Delbecq et al. 2014; Henneberry and Barrows 1990; Maddison 2009). After controlling for urban proximity and interaction between geographic distance and population intensity, the coefficient of remoteness index is no longer significant for the SP model and contrary to expectations, properties located in remote areas command a significantly higher valuation price.

The direct effect of regional socio-economic condition (SEIFA index) is positively and significantly associated with both the sale and valuation price of agricultural properties and consistent across all model specifications. Properties that are located in more advantageous areas capture a higher price. This result supports the argument that higher regional population density, education level and median household income increases property price by boosting the demand for agricultural properties (Borchers et al. 2014; Huang et al. 2006; Quaye et al. 2018; Deaton and Vyn 2010; Delbecq et al. 2014; Henderson and Moore 2006). Neighbouring properties that are located in advantageous areas (high score of the SEIFA disadvantage index) significantly reduces own property sale and valuation price (indirect effect).

The direct effect of favourable output markets, as indicated by higher commodity prices for the industry in question, was statistically significantly positively associated with both sale and valuation per hectare prices. Positive changes in economic conditions encourages the continuation of farming and creates more demand for farmland (Marano 2001; Wang 2018;

Henderson and Moore 2006; Wheeler et al. 2020). Contrary to the positive direct effect, increasing real commodity price has a significantly negative indirect effect on both VP and SP models.

4.6 Summary

The above findings suggest that buyers of small and medium sized rural properties do value the presence of native woody vegetation. On the other hand, land valuation authorities do not seem to be placing value on such vegetation. The results suggest that VP is not a good substitute of SP while estimating the value of on-farm natural and environmental capital assets in this case native woody vegetation as the former price seems to undervalue these attribute of agricultural properties. The difference in estimating the value of native woody vegetation in SP and VP is also consistent with the observations of Bigelow et al. (2020) that market price of agricultural properties better capture the locational amenity values than self-reported farmland value in the USA; Ma and Swinton (2012) which also affirm that farmland appraisal price is not a reasonable proxy of sale price in the estimation of environmental amenity values in the USA; and Grimes and Aitken (2008) also suggest that value of irrigation was undervalued in farmland appraisal value compared to sale price in New Zealand.

The difference between a valuation and sales price (with sales being higher than valuation) is one key reason (see Figure 4.2): sales prices capture a range of amenity values that are not covered by valuation. In addition the valuation price reflects the market adjusted price not the actual price at which properties are transacted in the market (Ma and Swinton 2012). Whereas, sales price are more accurate indicators of farmers willingness to pay for various attributes of properties (Bigelow et al. 2020). Although the land valuation system provides incentives for conservation of on-farm natural resources through zoning, conservation/heritage agreement (provide notional value for the property), rebates in rating and tax exemptions, these incentives are much lower than the opportunity cost associated with the management of natural resources (Nind 2002; Marano 2001). The other determinants of farmland value such as the physical, social and human capital are almost identical and capitalised into both sale and valuation price. These findings reveal that the use of either sale or valuation price in the hedonic pricing of agricultural properties relies on the research goal. The availability and accessibility of annual valuation price for properties makes it a reasonable proxy but it should be used with caution.

The major incentive-based programs like biodiversity offset, carbon market and conservation agreements are often inadequate in their capacity to scale up and involve higher opportunity cost (loss of agricultural income) for landholders to participate. In addition, there are possibility that most of the participants of public conservation programs are those who are already conservation oriented and doing something to improve their on-farm natural capital (Evans 2016). Hence, this may not change the environmental attitudes of the landholders who are involved in large-scale land clearance (Evans 2016), who may need significantly more economic incentives to participate. Also, most of the public incentive programs tends to provide equal level of financial support without evaluating individual participants' benefits/costs (Polyakov et al. 2015). The results of the study revealed that private benefits of native vegetation vary across range of property size and farming industries in the study area, which may provide avenue for better targeting of public payments for ecosystem services-based programs, and evaluation of environmental projects. In the absence of a formal efficient and robust market for natural capital and ecosystem services a policy reform of a mix of long-term policies comprising legislative control, economic incentives and educational policies to raise the environmental awareness at community level is recommended to halt the land clearance, effective implementation ecological restoration and revegetation programs (Evans 2016; Reside et al. 2017).

Due to the unavailability of spatial data limitations, this present study covered 16 years (1998-2013) of agricultural property sale transactions and valuation assessments to estimate the value of native woody vegetation by farm size and type. Future work could consider the impact of various legislation and droughts on irrigated properties in SA, such as the separation of water use rights from land in the 2000s in South Australia. In addition, research on the effects of long-term climate risks on farmland value should be beneficial in the face of predicted more frequent and intense drought and bushfire in Australia.

4.7 Conclusion

Given the importance of effective management of natural resources – on which the productivity and profitability of the agricultural sector relies on heavily – this study estimated the marginal value of on-farm natural capital stocks on agricultural properties using sales and valuation price in the intensive agricultural zone of SA from 1998-2013 (N=10,513). A spatio-temporal hedonic pricing model controlled for spatial dependence, and independent variables across a set of five categories of capitals (physical, natural and environmental, human, social and economic), across both agricultural industries (cropping, grazing and horticulture), and farm size (small, medium and large farms). The findings of the study revealed that although all five categories of capital were significantly associated with both sale and valuation price of agricultural properties, the marginal value of native woody vegetation differed across industry and farm size.

While cleared land (decreasing vegetation) commanded a premium price per hectare in the valuation price model, increased native woody vegetation area captured a premium market price within the sales model – indicating private landholder willingness to pay for greater native vegetation area. However, the marginal value of native vegetation decreased as the property size increased, indicating that for large farms the short-term monetary return from agricultural production outweighed the ecosystem services from native vegetation which are realised in long-run. At the industry level, private landholders are willing to pay (reflected by the premium sale price) for native vegetation for broadacre crops, grazing and horticultural properties – but the marginal return diminishes as the proportion of native vegetation increased and the marginal value is lowest in cropping. Furthermore, severe drought of more than 12 months reduced the market price of agricultural properties, although this result varied among farm sizes (large farms prices were significantly reduced compared to small and medium farms) and industry (cropping was the most susceptible to drought impacts). The other important drivers of agricultural property values (sale and valuation price per hectare) were physical capital (house and structural improvements, irrigation presence, groundwater bores), rainfall, soil natural productivity attributes, proximity to urban areas and locational environmental amenities, and regional socio-economic capital.

The findings of this study in regards to valuation of natural capital through property sale and valuation price can be used in several ways: firstly, pave the way to reconcile economic and environmental returns from agricultural properties; secondly, provide incentives for the wider adoption of on-farm environmental management practices via premium land prices; thirdly, ensure better decision-making in sustainable financial investment for agricultural lending, property valuation and insurance; and finally, to encourage the development of mature environmental market/ecosystem service payment system.

Chapter 5 Conclusions and policy implications

5.1 Summary of the thesis and key findings

Australia provides a valuable case study for this thesis as it is a country of immense biodiversity, while at the same time has one of the highest rate of land clearing (Hansen et al. 2013) and has been identified as one of the world's deforestation hot spots (Reside et al. 2017; Simmonds et al. 2019). It contains an important flow of ecosystem services such as provision of habitats, soil erosion control, and climate change mitigation generated from natural capital stock of native woody vegetation on agricultural properties – which exhibits public good attributes and often lacks an efficient market. The purpose of this thesis is to understand the role of various types of natural capital on the agricultural landscape in more detail. It does so by analysing three case studies over space and time to explore the environmental and economic influences and outcomes of on-farm natural capital in the Australian agricultural landscape. Specifically, the thesis examined: 1) the spatial influences on the diffusion of certified organic farming (which is used as a proxy indicator of natural capital conservation innovations) at the SA2 level; 2) the association between the presence of certified organic farming and regional biodiversity at the postcode level in SA; and 3) the association between native woody vegetation coverage and climate (which are used as various forms of natural capital) and the land value of SA farms.

Chapter 1 discussed the critical impact and dependence of agriculture on natural capital in the world and the benefits and costs of organic farming as agricultural innovation in conserving natural capital. This chapter also provides an overview of the existing literature findings regarding the potential spatial influences on the diffusion of organic farming and its environmental outcomes and identified gaps in the empirical literature, and questions asked by the current thesis.

Chapter 2 considered the spatial spill-over effects on the regional intensity of certified organic farming diffusion in Australia, using organics as a proxy case study to better understand the diffusion of other clean and green technologies that aim to conserve/improve the stock of natural capital in farming businesses. The intensity of organic diffusion was measured as both: a) the proportion of total agricultural land holding that was certified organic within an SA2; and b) the proportion of total agricultural businesses that were certified organic within an SA2. This area-based measure at the SA2 level in Australia was similar to area-based measures in the international literature analysing spatial distribution of organic farming – such as county level in Germany (Schmidtner et al. (2012) and municipality level in France (Allaire et al. (2015). The empirical findings were derived using five-yearly national Australian agricultural census data – namely the 2010/11 and 2015/16 censuses (given that for censuses earlier than 2010/11 questions related to organic farming were not included) – and modelled using random effect panel SLX tobit models and non-spatial tobit models. Furthermore, to distinguish between global and local spatial spill-over influences on the diffusion process, SDM and SDEM models were also estimated.

The findings from the empirical spatial models revealed that local spatial spill-overs have statistically significant (both positive and negative) influences on regional organic diffusion intensity – with little to no statistically significant evidence to support the global spatial spill-over effects in an Australian context. In other words, the regional diffusion of organic farming was not influenced by neighbouring regions intensity of organic farming adoption. This finding aligns somewhat with the work of Lapple and Kelley (2015), whose models also took into account both global and local spill-over effects by estimating a SDM model, where they found statistically significant influences of both types of spatial spill-overs on organic farming adoption in Ireland. Most other studies in the literature have only assessed global spill-over effects. They have generally found that at both farm (Lapple and Kelley 2015; Lewis et al. 2011; Wollni and Andersson 2014) and regional (Allaire et al. 2015; Bjørkhaug and Blekesaune 2013; Marasteanu and Jaenicke 2016; Schmidtner et al. 2012) spatial scales, the adoption and diffusion of organic agriculture was statistically significantly impacted by the adoption choice or intensity of diffusion within neighbouring farms or regions, supporting a finding of a global spatial spill-over effect. One reason why this study did not find evidence for a global spatial spill-over effect may be associated with the fact that unlike this study, most studies are cross-sectional in nature with only a few exceptions (Allaire et al. 2015; Lewis et al. 2011). In addition, the widespread land resources and the larger average size of the limited number of Australian organic farms – compared with those of other countries – and the lack of spatial proximity between them, may be another explanation for this contradictory finding.

Another key finding from **Chapter 2** was that intensive agricultural SA2s – such as larger farm sizes, higher share of irrigated businesses, increased availability of labour force involved in agriculture, higher share of grazing and horticultural lands, and low livestock densities – were associated with higher intensity of organic diffusion. This result is supported by findings from previous studies (Boncinelli et al. 2015; Finley et al. 2018; Gabriel et al. 2009; Jansen 2000; Koesling et al. 2008; Lohr and Park 2009). Furthermore, SA2s characterised by increased green vegetation (measured by the regional average NDVI value), hilly areas (high elevation), high soil pH (optimal level for production is 5.5-7) were more likely to have a higher concentration of certified organic farming. Finally, a higher social acceptability for alternative forms of farming or environmental attitudes – as measured by the proxy indicator of regional share of vote for Green party - and higher community income (proxy indicator of demand) and low population density had a statistically significant positive influence on organic diffusion intensity in SA2s Australia. This result is supported by previous literature findings (Gabriel et al. 2009; Marasteanu and Jaenicke 2015; Wollni and Andersson 2014).

The role of organic farming in conserving natural and environmental resources such as soil, biodiversity and climate change mitigation has been widely studied in the literature (Lori et al. 2017; Squalli and Adamkiewicz 2018; Tuck et al. 2014; Tuomisto et al. 2012). However, many of these studies did not control for other significant confounding factors such as landscape heterogeneity, climatic conditions, anthropogenic land use, and urbanisation effects (Meemken and Qaim 2018). Rather, the majority used cross-sectional data and compared organic and conventional farms within matched landscapes, without accounting for spatial dependences that are inherent features of species distribution data in analysing the environmental effects of organic farming. There has also been no research in this area in Australia. To address this research gap, **Chapter 3** investigated the spatial influences from the presence of certified organic farming on biodiversity – measured by the average species richness of vascular plant and bird species - at the postcode level in South Australia between 2001 and 2016 using SDEM models. A spatially-explicit novel dataset of certified organic farming was used, collected via a personalised data request from the two major organic certifiers in Australia.

The results from the SDEM models for vascular plant and bird richness confirmed the presence of spatial dependence: the species richness of plants and birds at one postcode area was positively significantly associated with the level of species richness in neighbouring areas (Jetz and Rahbek 2002; Kreft and Jetz 2007; Xu et al. 2016). In addition, controlling for all other confounding factors, a positive statistically significant spatial association from the presence of organic farming at postcode level was found with vascular plant species richness, confirming previous literature findings (Bengtsson et al. 2005; Gonthier et al. 2014; Tuck et al. 2014; Winqvist et al. 2012). The beneficial impacts of organic farming for plants are mostly attributed to the prohibited use of chemical fertilisers, insecticides, and herbicides (Gonthier et al. 2014; Tuck et al. 2014; Winqvist et al. 2012). On the other hand, in the SDEM models little to no statistically significant evidence was found for the association of organic presence with bird species richness. The difference in the effects of certified organic farming presence on bird richness is not surprising, given a number of previous studies have also found no evidence (Chamberlain et al. 2010; Gabriel et al. 2010; Hiron et al. 2013; Piha et al. 2007; Puig-Montserrat et al. 2017; Tuck et al. 2014).

The spatial influences of the other key explanatory variables on both bird and vascular plant richness were consistent with the literature findings that estimated the determinants of plant and bird richness using spatial econometric models (Jetz and Rahbek 2002; Kissling et al. 2008; Kreft and Jetz 2007; Piha et al. 2007; Xu et al. 2016). The results in this study found that increased provision of natural habitats – as measured by increased land cover diversity, elevation range, and higher share of conservation land and water bodies – were statistically significantly and positively correlated with greater species richness for both birds and plants. Whereas, higher share of agricultural land use for cropping and horticulture reduced both species' richness.

One of the main questions that this thesis set out to answer was: what is the value of trees (vegetation) on agricultural properties, and does the presence of vegetation capitalise into property values? Does this capitalisation differ by industry and farm size? **Chapter 4** explored the association between the presence of on-farm native woody vegetation and economic returns in the form of market price and valuation price of agricultural properties in South Australia, between 1998 and 2013. A spatially-explicit unique pooled dataset was prepared using the sales (e.g. prices from properties sold on the market) and valuation (e.g. prices from annual valuation of farm properties for rate purposes) prices of agricultural properties obtained from the South Australian Office of Registrar General. A spatio-temporal hedonic pricing model SDM was employed to assess the correlation – using both per hectare sales and valuation price – with various natural capital features of the farm property. Features of the property included farm size (small, medium, and large); type of agricultural industry (cropping, grazing, and horticulture); climate and vegetation capital, along with other physical, natural, environmental, social, economic, and human capitals. Unfortunately, there was not enough organic farm sales in the database for it to be modelled as a form of natural capital, hence was not included in the modelling.

The results from the empirical models showed that, although the same set of covariates (five forms of capital assets) capitalised into both the sales and valuation price models and confirmed findings from previous literature, per unit sale and valuation price of agricultural properties differed significantly in capturing the value of native woody vegetation. Native woody vegetation was positively capitalised into per hectare sales price, but had diminishing marginal effects – as the proportion of vegetation increased the sales price also increased; but after reaching a peak it started to decrease. This result supports the earlier findings of Polyakov et al. (2015, 2013) in that buyers and sellers of agricultural properties positively value the presence of on-farm native woody vegetation within an Australian context (but only up to a certain point, where after this, the marginal benefits decline). In contrast, the valuation price model found a different result, where the increased presence of native woody vegetation decreased the per hectare property valuation price, however this effect was reduced as the proportion of native vegetation increased. More research is needed to confirm these findings given that, to date, no studies have employed both sales and valuation prices to estimate the value of native woody vegetation. Other key estimates of the impact of natural capital on agricultural property prices found that severe drought for an extended period of time (measured by 5th percentile rainfall deficiency) had a negative statistically significant direct spatial association with per hectare sales price. Agricultural properties located in severely drought-affected regions commanded significantly lower sales prices per hectare, however no significant influence was found in the valuation price model.

5.2 Policy implications

On the basis of this thesis results, a range of policy implications are discussed. The findings of the thesis largely support the existing natural resource conservation policies, such as biodiversity offsets, carbon pricing, environmental planting (afforestation and reforestation) and sustainable financing. Commentary is broken down into two sub-sections: organic specific farming policies and natural capital farming policies in general.

5.2.1 Organic farming policies in Australia

Although Australia has the largest share of absolute organic farm land in the world, some have argued that the growth of the organic sector is below industry expectations and much slower than European countries (Daugbjerg and Halpin 2010). Lack of government direct and indirect policy support for organic farming has been highlighted as one of the main reasons for the slow growth rate compared to European countries, where governments are actively involved in the organic sector (as well as market forces) by providing financial incentives such as organic conversion subsidies and other market incentives (Daugbjerg and Halpin 2010; Lohr and Salomonsson 2000; Stolze and Lampkin 2009; Wheeler 2011).

Traditionally, it has been the market side and private farmer action that has driven the growth of organic adoption in Australia (Wheeler 2011, 2008a; 2008b). For example, one of the largest Australian supermarkets – Woolworths – currently plans to spend up to AUD$30 million to promote adoption of organic farming over a five-year period to meet the growing consumer demand for organic fruits and vegetables (Marshall 2020). Organic farming exhibits some characteristics of public goods and faces market failure issues resulting from, among other factors, positive environmental externalities and information provision constraints (Wheeler 2011).

Given that there is growing international evidence that there are positive environmental externalities associated with organic farming (Sandhu et al. 2008; Schneider et al. 2014; Squalli and Adamkiewicz 2018; Winqvist et al. 2012; Winqvist et al. 2011), plus the fact that this thesis has provided some evidence of Australian positive environmental externalities, there may be a case for government support. In particular, government involvement in establishing property rights for environmental resources, increased information provision through funding for agricultural research and development, and addressing institutional biases – have all been cited as drivers of adopted innovation to sustain the natural and environmental resources (Daugbjerg and Halpin 2010; Wheeler 2011; Wheeler 2008a). Others emphasise the importance of market-based incentives for organic in particular – such as conversion support (Daugbjerg and Halpin 2010). It has also been argued that farming systems producing ecosystem services – irrespective of whether they are conventional, organic or any other form of sustainable agricultural innovation – should be supported through various market-based financial incentives such as: biodiversity offsets; carbon farming; auctions; tenders; and eco-taxes (Lockie 2013; Stolze and Lampkin 2009; Wheeler 2011). These ecosystem services provide diverse benefits above and beyond the ground: provisioning (food, fibre, bioenergy); supporting and regulating (climate regulation, pollination, natural pest control, water quality, soil formation, biodiversity, carbon sequestration, nutrient retention); and cultural (aesthetic, recreational, spiritual) (Bryan 2013). If organic agriculture produces more benefits, farmers are more likely to respond positively to the market signal of these incentives, which will further the adoption of sustainable innovations (Reganold and Wachter 2016). In addition, clearer property rights for organic and other alternative forms of sustainable farming is much needed to protect organic farmers from chemical trespass and drift from genetically modified crops seeds or pollen from neighbouring conventional farmlands and crops (NCO 2020; Wheeler 2011).

In addition to the above factor constraints, limited knowledge about the benefits and costs of alternative forms of farming – due to lack of research and funding into agro-ecological and sustainable forms of farming practices – has negatively impacted agricultural professionals' attitudes towards organic farming (Wheeler 2011; Wheeler 2008a, 2008b; Wheeler and Marning 2019). Agricultural professionals who have knowledge and experience in organic farming are more likely to have favourable attitudes towards the practice (Wheeler 2008b).

The results from **Chapter 2** showed that – in addition to regional farm structural variables – environmental factors such as regions with increased green vegetation; drought affected areas; increased social acceptance measured by proxy indicator - share of vote for Green party; market accessibility indicated by distance to major cities; and community income, were all more likely to result in a higher concentration of organic farming. These findings support that knowledge-based policies aimed at providing increased access to information sources, outreach programs to facilitate increased interaction between farmers and extension officials, increased public and private funding for agricultural research, and development and community awareness programs, all have beneficial effects on the diffusion of organic farming – as highlighted by Reganold and Wachter (2016), Lee (2005) and Wheeler (2011).

5.2.2 Spatially explicit policies for biodiversity conservation

Biodiversity conservation alone in conservation reserves and protected areas may not be enough to combat the widespread loss of terrestrial biodiversity (Bardsley et al. 2019; Gonthier et al. 2014). Agricultural landscapes, which host many important farmland species, need to be incorporated within conservation policies. A multi-scale spatially refined biodiversity conservation strategy, with spatial targeting that promotes low intensive farming systems and increases landscape heterogeneity to provide quality habitat (a whole of landscape approach by incorporating private agricultural landholders), could be beneficial for biodiversity conservation as different species respond at different scales (Batáry et al. 2011; Gabriel et al. 2010; Gonthier et al. 2014; Piha et al. 2007). This approach is reinforced by the findings from **Chapter 3**.

As part of the Australian government's commitment to the *Paris Agreement*, to reduce greenhouse gas emissions 26-28% by 2030 compared the 2005 level, the *Carbon Farming Initiative* – implemented from 2011 – provides financial support to land managers and farmers to reduce GHG emissions and sequester carbon in the soil and adopt biomass solutions (Power 2017). The Australian carbon credit unit earned by landholders and farmers for their modified business activities in reducing GHG emissions and storing carbon can be sold to the organisations that were obligated or agreed to offset emissions (Bradshaw et al. 2013). Others argue strongly that there is a need for a reinstatement of a carbon tax in Australia, to provide more incentives for carbon soil markets and credits (Best et al. 2020).

These financial incentives create opportunities for alternative agro-ecological farming practices that balance the dual goals of sustainable production and biodiversity conservation, to acquire benefits for generated ecosystem services and thereby encourage wider adoption of such clean energy efficient technologies. Environmental planting (afforestation – planting trees in naturally cleared land; reforestation – planting trees in human induced cleared land) of native woody vegetation has potential benefits for biodiversity conservation, climate change mitigation, and hydrological flows (Bradshaw 2019). The findings from **Chapter 4** in regards to valuation of on-farm natural capital stock of native woody vegetation – through property sale and valuation price – may be useful for policy-makers to improve decision-making around sustainable financial investment for agricultural lending, property valuation and insurance. This in turn would encourage the development of mature environmental market/ecosystem service payment systems, to reconcile economic and environmental returns from agricultural properties and to provide incentives for the wider adoption of on-farm environmental management practices, via premium land prices.

As mentioned above, the major incentive-based programs, such as biodiversity offsets, carbon market and conservation agreements are often inadequate in their capacity to scale up and achieve higher opportunity costs (loss of agricultural income) for landholders to participate (Bradshaw et al. 2013; Yang et al. 2010). Furthermore, potentially most participants of public conservation programs are those who are already conservation oriented and doing something to improve their on-farm natural capital (Evans 2016). Hence, this may not change the environmental attitudes of the landholders who are involved in large-scale land clearance (Evans 2016) and may need significantly more economic incentives to participate. Also, most of the public conservation incentive programs tend to provide an equal level of financial support without evaluating benefits and/or costs to individual participants (Polyakov et al. 2015). These programs have limited spatial targeting, thereby resulting in underpayment or overpayment in many cases, when compared to the net environmental outcomes (Yang et al. 2010). The results from **Chapter 4** revealed that private benefits of native vegetation vary across differing property sizes and farming industries in the study area, and greater biodiversity benefits (increased species richness) occur in landscapes with increased habitat diversity -

which may provide an avenue for better targeting of public payments for ecosystem services-based programs, and evaluation of environmental projects. In the absence of a formal efficient and robust market for natural capital and ecosystem services, a mix of long-term policies comprising legislative control, economic incentives and educational policies to raise environmental awareness at the community level is recommended to halt land clearance and implement ecological restoration and revegetation programs (Evans 2016; Reside et al. 2017).

5.3 Limitations and recommendation for future research

5.3.1 Limitations

The challenges and limitations associated with the secondary spatial panel datasets that were encountered during the data preparation and spatial econometric modellings (in terms of spatial currency, resolution, and temporal coverage), and how they were dealt with, are summarised in this section – along with their potential influence on the research findings.

Spatially explicit panel (**Chapters 2 and 3**) and pooled datasets (**Chapter 4**) were used in this thesis to address the research questions. Some of the explanatory variables used in the final spatial econometric models – soil texture index; various soil attributes (sand, silt, clay, pH level, organic carbon content, water holding capacity, soil erosion index); locations of groundwater bores; locational amenities (principle highway, surface water sources, conservation reserve) – were only available at a point in time, together with time invariant characteristics such as elevation and coastal location). Hence, constraining the scope to compare the estimates of fixed and random effect models. Following previous studies by Ma and Swinton (2011); Ma and Swinton (2012); Maddison (2009); Polyakov et al. (2013, 2015); random effects models were used in this thesis. In all the spatial models – SLX tobit, SDEM, and SDM – correlation or associations were identified rather than exact causality effects.

In **Chapters 2** and **3** the dependent variables were aggregated at a broad spatial scale – regional and landscape level (the finest spatial scale at which data were available) defined by the administrative boundaries of SA2 level and postcode areas, respectively. These regional aggregates might mask the potential individual heterogeneity that operates at farm-scale, and therefore differ from results that obtained from an individual level interaction (Niedermayr et al. 2016; Storm et al. 2015). Although a regional-level study has limitations, it also has important implications in identifying general patterns over a longer time period (Wheeler et al. 2020). There are studies that also used these types of artificial administrative boundaries to address various research questions such as: organic adoption – municipality level (Allaire et al. 2015; Bjørkhaug and Blekesaune 2013; Schmidtner et al. 2015); county level (Marasteanu and Jaenicke 2015; Schmidtner et al. 2012); organic farming and GHS emissions studies – state level (McGee 2015; Squalli and Adamkiewicz 2018); effects of pesticides on biodiversity – county level (Li et al. 2020); and farm exit decisions – regional scale (defined by the administrative boundaries of statistical local area) (Wheeler et al. 2020).

Several challenges were faced during the cleaning of the organic certification database that was employed in **Chapter 3**. In the organic certifier NCO and ACO databases there were different types of addresses (for example: home, company, delivery, post box, postal, farm, and farms with multiple locations). From the datasets, it was not possible to precisely identify the exact farm location, especially for farms that were located in highly remote areas or which no longer retained certification. In addition, one farm may have multiple lots, and it was not possible to identify all the lots under one farm business. Hence, all the locations of organic farming businesses (which also included businesses with multiple locations) were identified at postcode level and geocoded at postcode levels only for the purposes of empirical modelling. In the case of maps showing the spatial distribution of organic farm businesses, only from 2018 they were geocoded at multiple levels (exact farm location level, street level, town level, and postcode level) depending on the accuracy of the farm address. Furthermore, for the most recent years, more precise locations were available from the certifiers.

The research objective in **Chapter 3** did not differentiate between native and non-native vascular plant and bird species when investigating the spatial influence of organic farming on biodiversity. It was also limited to the geographic boundaries of SA, and operated only at the postcode level. While this study analysed the long-term effects of certified organic farming by modelling the spatial association in terms of the numbers of organic farming businesses at postcode level; the intensity of certified organic management – that is the proportion of organic area in total arable land – may have been a better indicator. This measure was used by Piha et al. (2007) to determine the effects of certified organic farming on bird richness in Finland. Furthermore, this study does not differentiate between the levels of farming intensity within conventional farming. Given there are many farms that are conventionally managed, but with little to no chemical fertiliser use and those that set aside larger portions of natural and semi-natural habitats, such actions may also increase species richness.

5.3.2 Future research

There are several avenues for future research that can be drawn from this thesis.

Firstly, subject to future panel data availability, the empirical models regarding spatial diffusion of organic farming could be examined at a finer spatial scale (farm level). There is also scope to further explore the organic dataset employed in **Chapter 3** (examining biodiversity impact) to analyse spatial diffusion at the postcode level, while limiting the geographic coverage to SA, but at smaller spatial scale – postcode level is much smaller than the SA2 that was used in **Chapter 2**. Furthermore, future studies could focus on a particular industry such as: broadacre crops, livestock, viticulture, or horticulture to understand if spatial dependence exists among farmers who are involved in similar types of farming activities.

In **Chapter 3** spatial correlation of organic farming with only vascular plant and bird richness was analysed at the landscape level (defined by postcode areas), leaving scope to expand the analysis at a smaller spatial scale (such as farm scale given that species richness data can be extracted at farm level using the ALA database) and other indicators of biodiversity such land mammals, reptiles, and arthropod species richness from ALA, depending on the future farm level organic certification data availability. Given the unprecedented loss of biodiversity nationally and globally and the impact on associated ecosystem services (Bradshaw 2019; Bryan 2013; Costanza et al. 2007; IPCC 2019), this may prove to be important research. In addition to measuring the impact on the average number of species, the spatial association of organic farming on diversity of species and evenness will provide further insights when assessing the impact of organic farming in conserving natural and environmental resources.

As an extension of the empirical methods used under **Chapter 3** for biodiversity, future research could investigate the potential influences of organic farming on other tradable ecosystem services, such as GHG emissions and carbon sequestration – while controlling for spatial dependence and other contextual factors. While regression analyses have been conducted in the USA using state-level longitudinal data of GHG emissions (McGee 2015; Squalli and Adamkiewicz 2018) – these studies did not account for spatial dependence, creating a further opportunity to address this research gap.

Finally, there is scope for future research using the spatially explicit dataset developed under **Chapter 4** to estimate the value of other natural capital, such as irrigation water. This could be achieved by exploring the spatial impact of various water legislation and droughts on irrigated properties, such as the unbundling – or separation – of water use rights from land, in the South

Australian context. In addition, following Wheeler et al. (2020), this thesis could be expanded to explore the effects of long-term climate risks (measured by a coefficient of variation, skewness and kurtosis of rainfall and temperature) on farmland value in the face of predicted more frequent and intense drought and bushfires in Australia. Moreover, there is scope to explore the effects of organic certification status on farmland value, given that the supply of organic farmland cannot be increased immediately with rising organic food demand, as organic conversion takes on average three years, along with differences between soil structure and fertility levels of organic farmland compared to conventional. Identification of farms that were sold after obtaining organic certification was not possible using the current organic dataset (used in **Chapter 3**) and property transaction dataset (sales price used in **Chapter 4**). In future, depending on availability, updating the sales dataset (the dataset used in Chapter 4 covers until 2013) combined with an updated organic certification dataset may provide an avenue to address this research question.

5.4 Conclusion

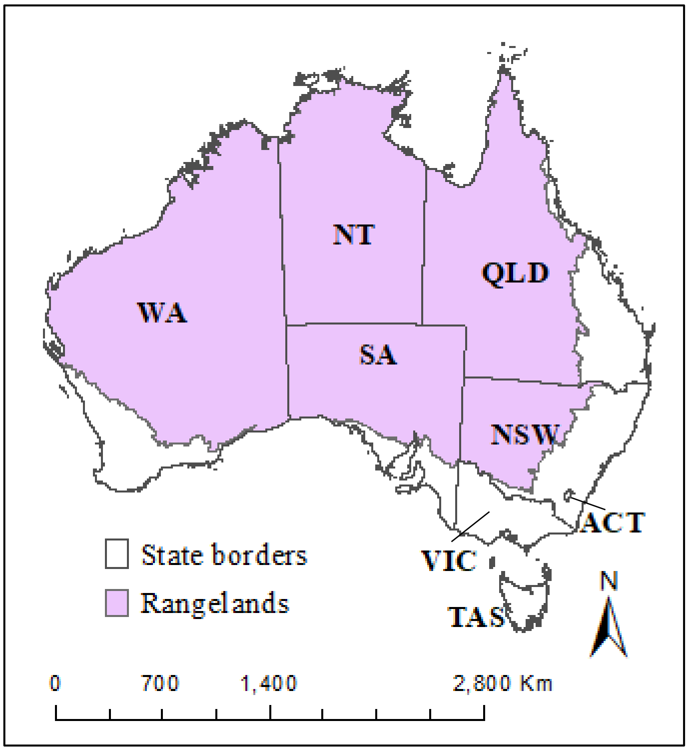
This study has provided a comprehensive analysis on the spatial diffusion of organic farming in Australia. It established new databases[42]; provided insights into the extent and type of organic farming across Australia; employed highly sophisticated spatial modelling; and highlighted the significant value that natural capital brings to the agricultural landscape.

Overall, there is a clear need for future research to fully understand the interdependence between agriculture, natural capital and the associated flows of ecosystem services. This includes analysing the influences of alternative forms of farming (such as organic farming) on other marketed and non-marketed ecosystem services, from a spatial perspective. This would enable a better understanding of the synergies and trade-offs between the dual goals of maximising production and conserving the stocks and flows of natural capital – ultimately assisting in the cost-effective management of increasingly scarce natural resources.

[42] As part of data agreement with the respective authorities the organic certification, property transaction and valuation databases that were build up for the thesis will not be made publicly available. The author and supervisors will utilise these databases for future research collaboration, and are open to collaboration with other researchers.

Appendix A Supplementary materials for Chapter 1

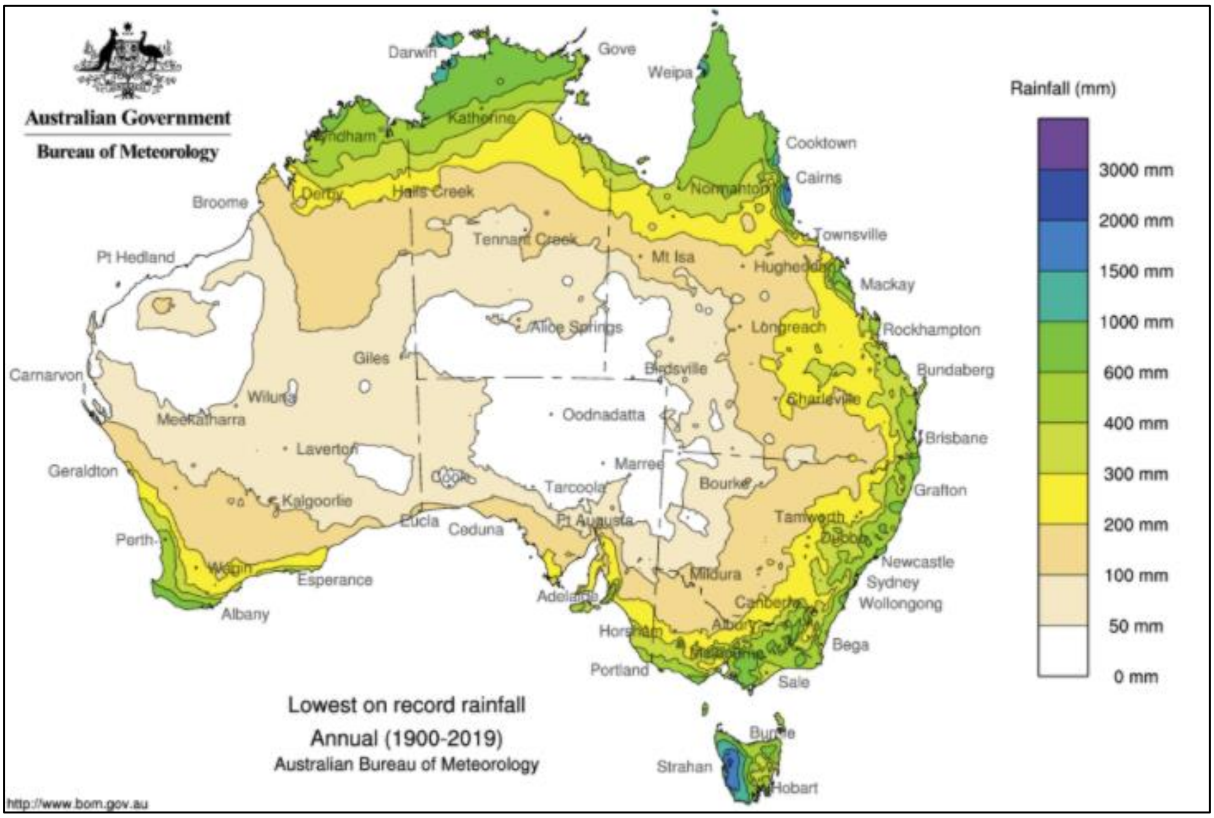
Figure A.1 Map of the study area (Australia with states, territory, and rangeland)



Own map (data sources: state borders (ABS 2016m); rangelands (ERIN 2005)

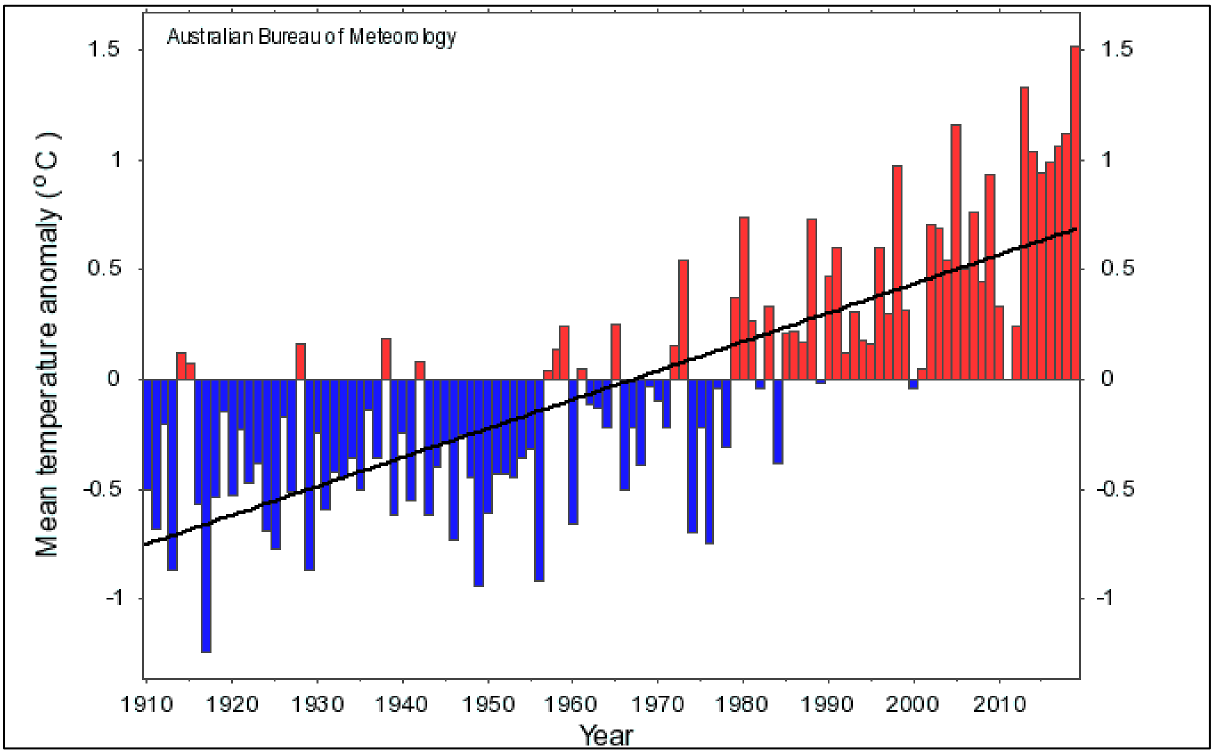
Notes: States and territories are shown as: ACT = Australian Capital Territory; NSW – New South Wales; NT – Northern Territory; QLD = Queensland; SA – South Australia; TAS – Tasmania; VIC – Victoria; WA – Western Australia

Figure A.2 Severe drought (5th percentile rainfall deficiency) in Australia (1900-2019)



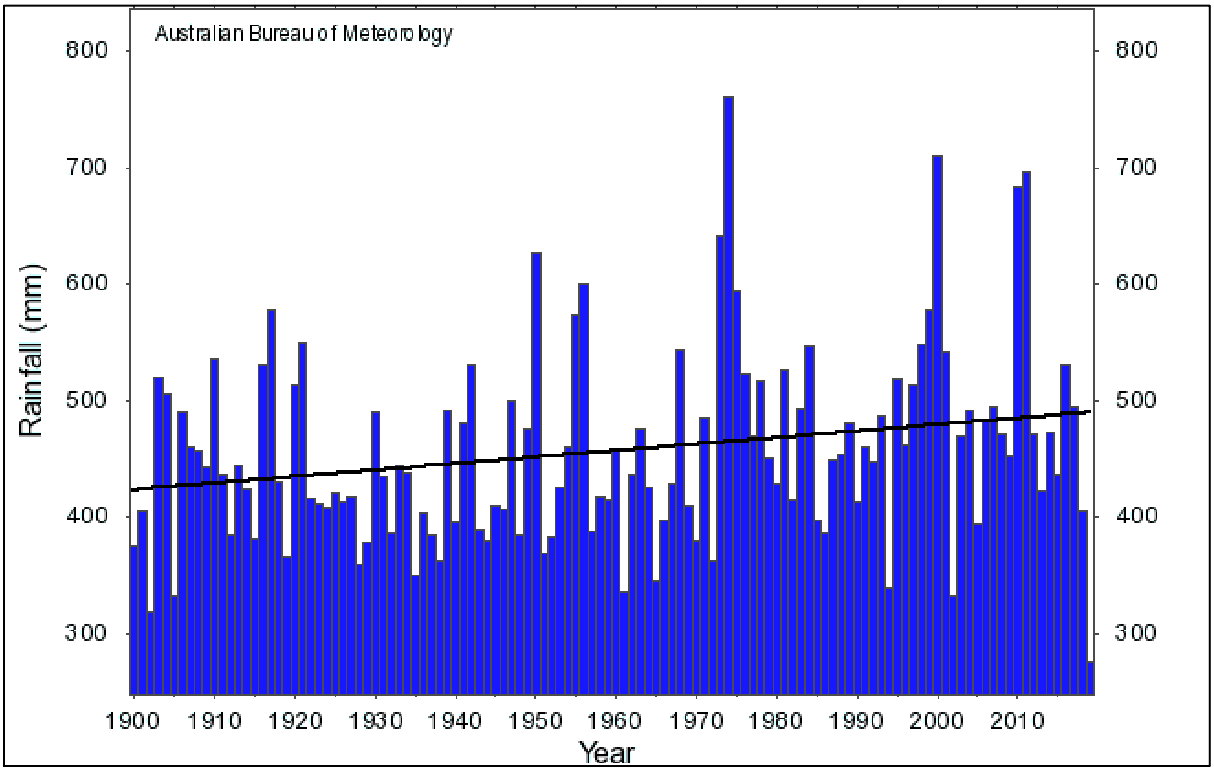
Source: (BoM 2020d)

Figure A.3 Annual mean temperature in Australia (1910-2019)



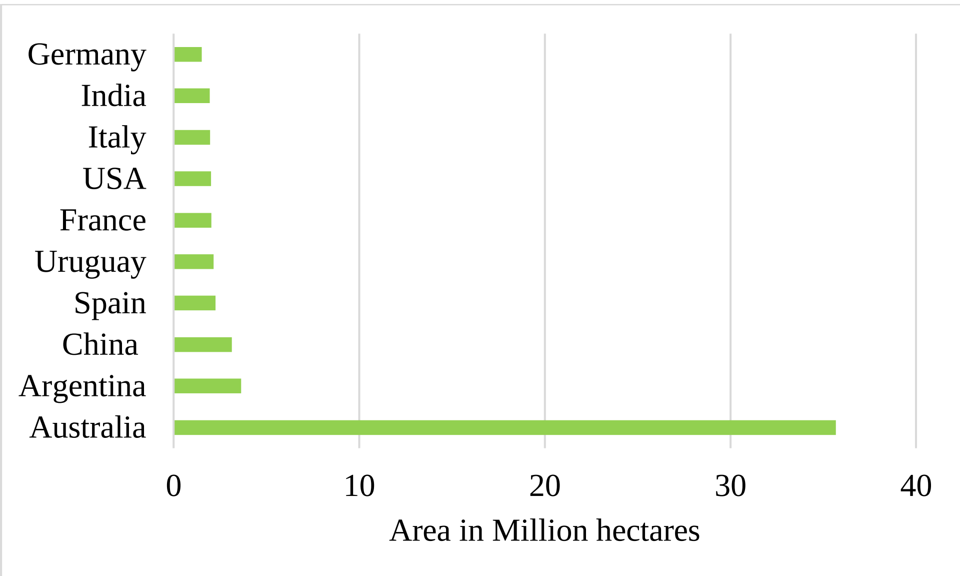
Source: (BoM 2020c)

Figure A.4 Annual rainfall in Australia (1900-2019)



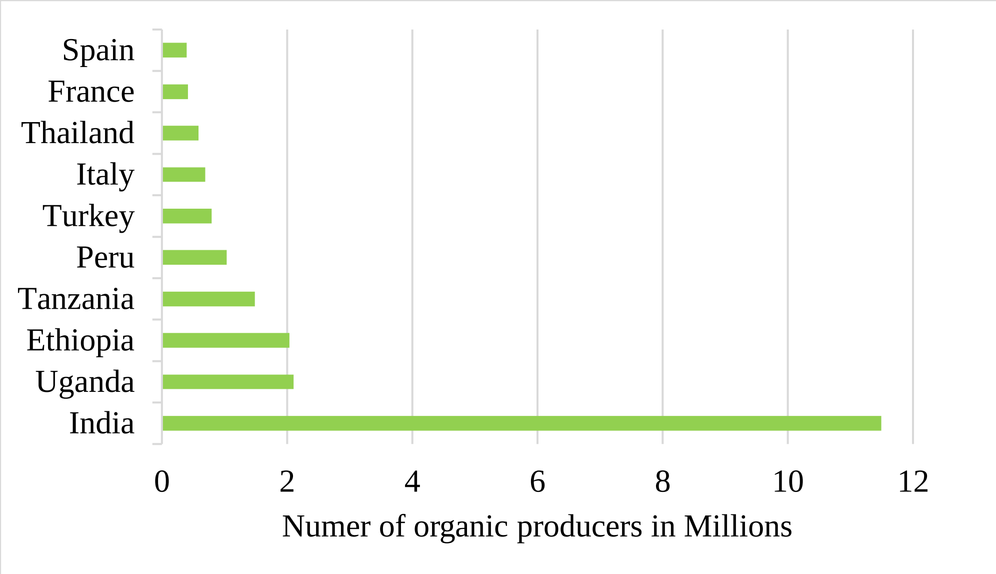
Source: (BoM 2020c)

Figure A.5 Top ten countries with largest certified organic agricultural land in 2018



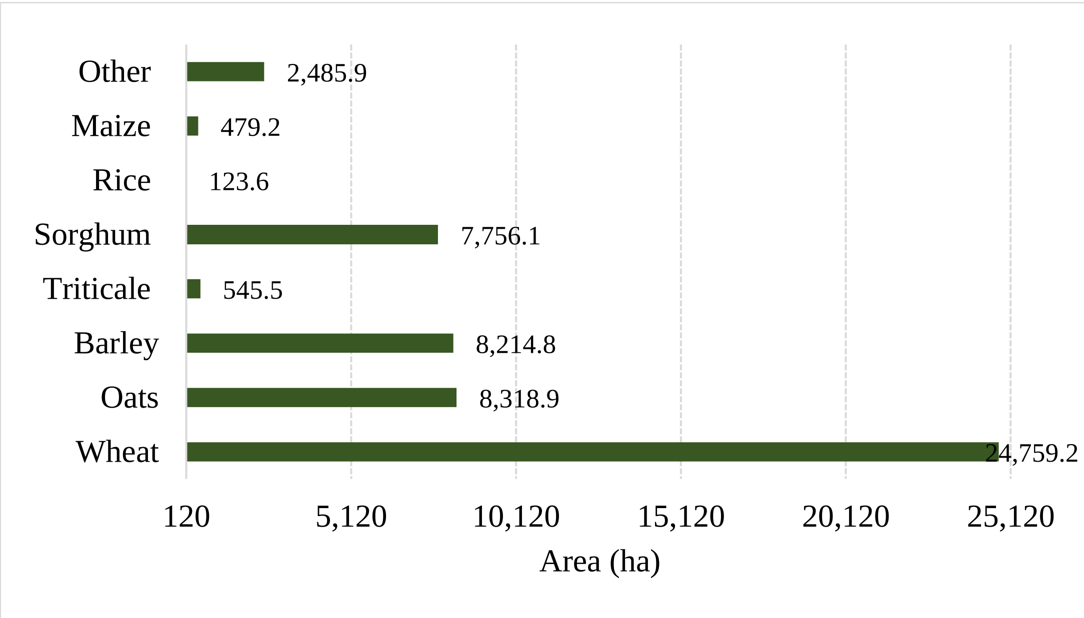
Own figure (data source: Willer et al. (2020))

Figure A.6 Top ten countries with the highest number of certified organic farms (producers) in 2018



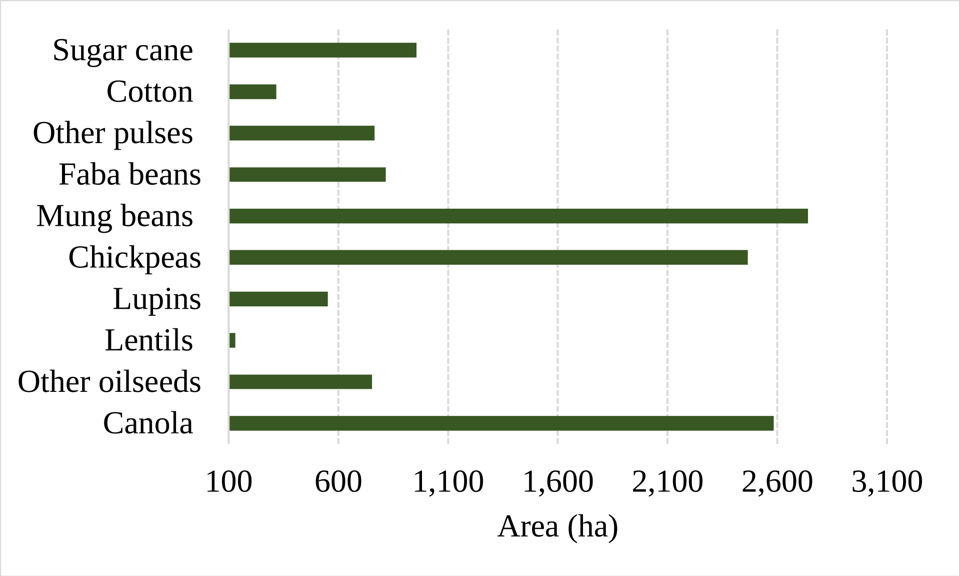
Own figure (data source: Willer et al. (2020))

Figure A.7 Total area of agricultural land holding under organic cereal crop farming in Australia, 2015/16



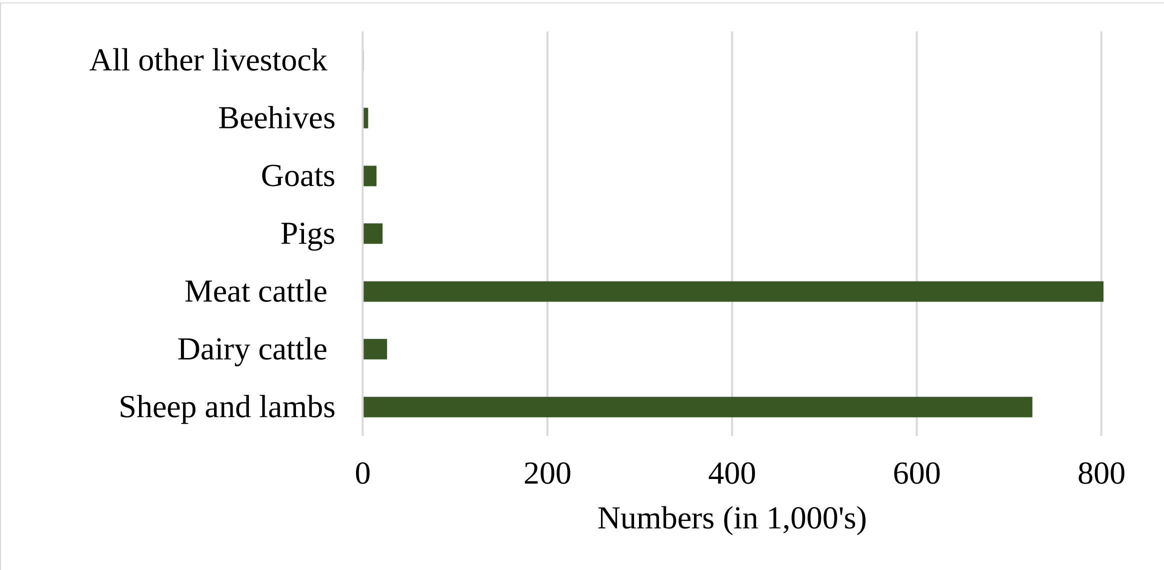
Own figure (data source: customised data request from ABS)

Figure A.8 Total area of agricultural land holding under organic non-cereal crop farming in Australia, 2015/16



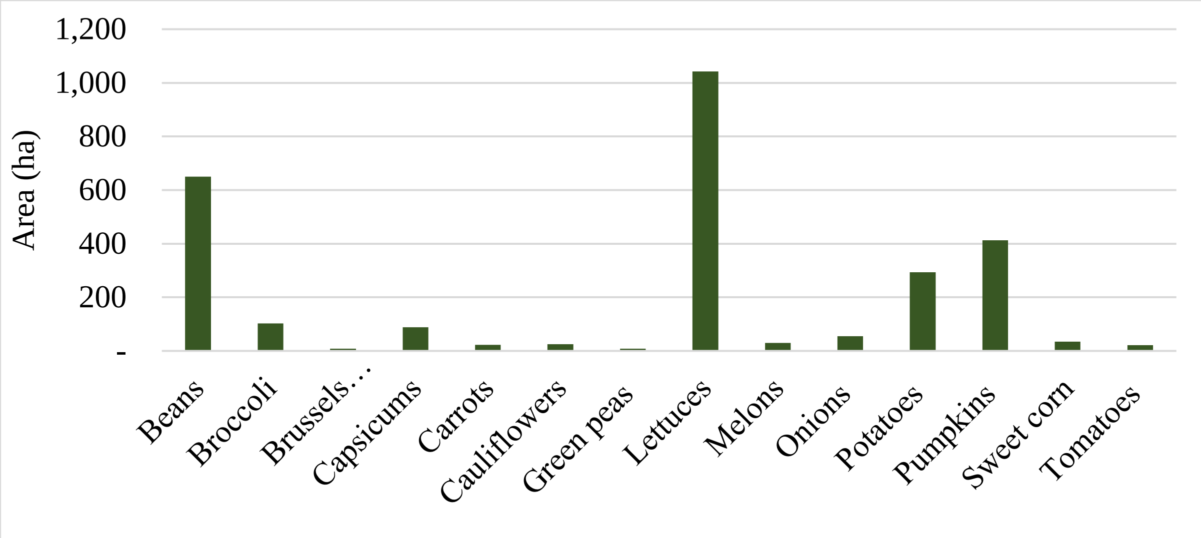
Own figure (data source: customised data request from ABS)

Figure A.9 Total numbers of livestock under organic farm management in Australia, 2015/16



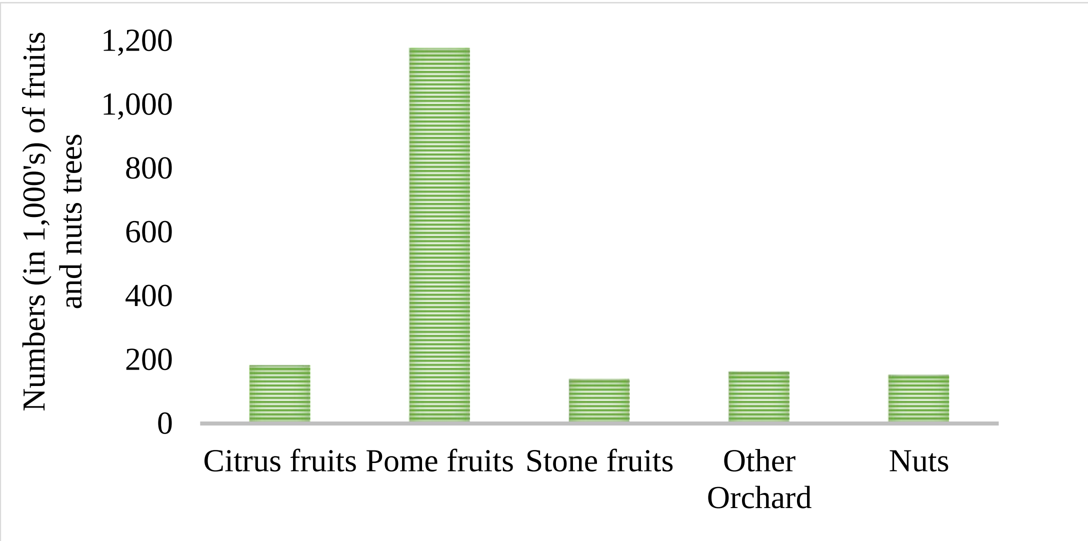
Own figure (data source: customised data request from ABS)

Figure A.10 Total area of agricultural land holding under organic market gardening (vegetables) farming in Australia, 2015/16



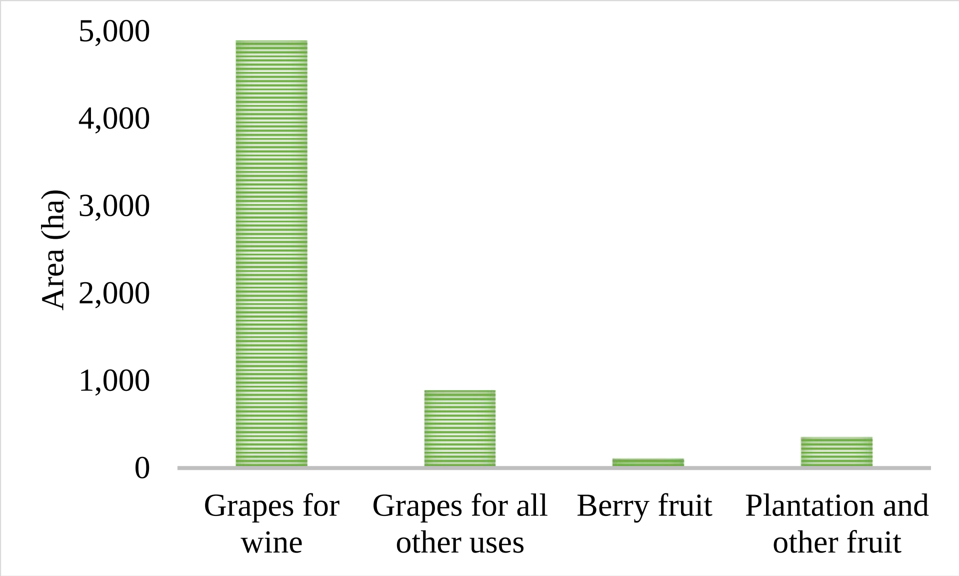
Own figure (data source: customised data request from ABS)

Figure A.11 Total number of trees under organic horticultural farming (fruits and nuts) in Australia, 2015/16



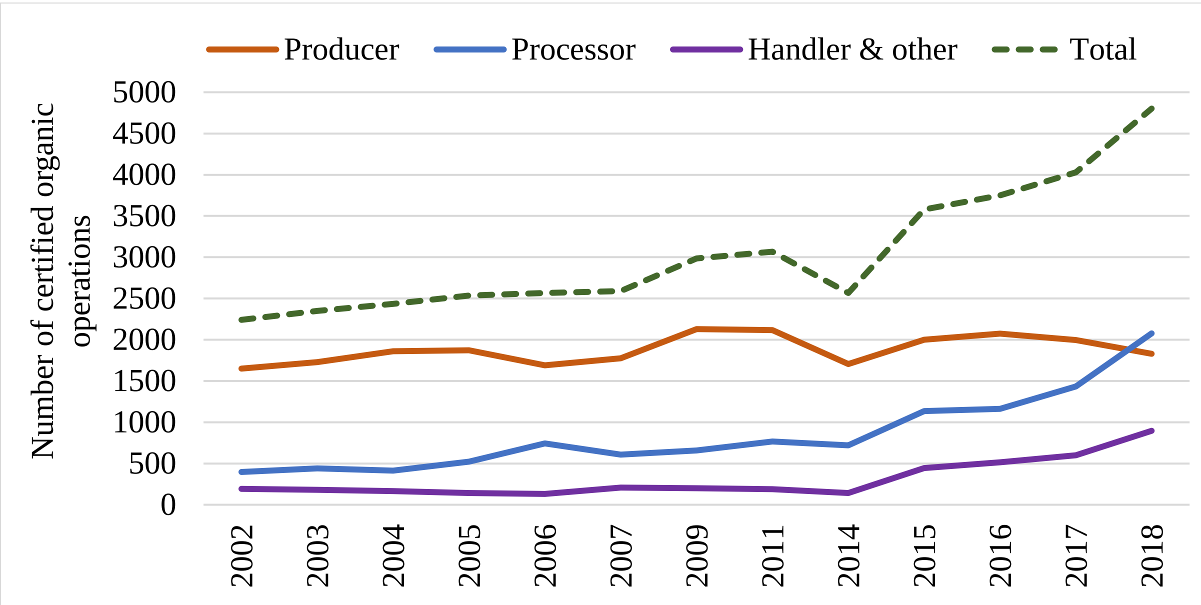
Own figure (data source: customised data request from ABS)

Figure A.12 Total area of agricultural land holding under horticultural farming (fruits and nuts) farming in Australia, 2015/16



Own figure (data source: customised data request from ABS)

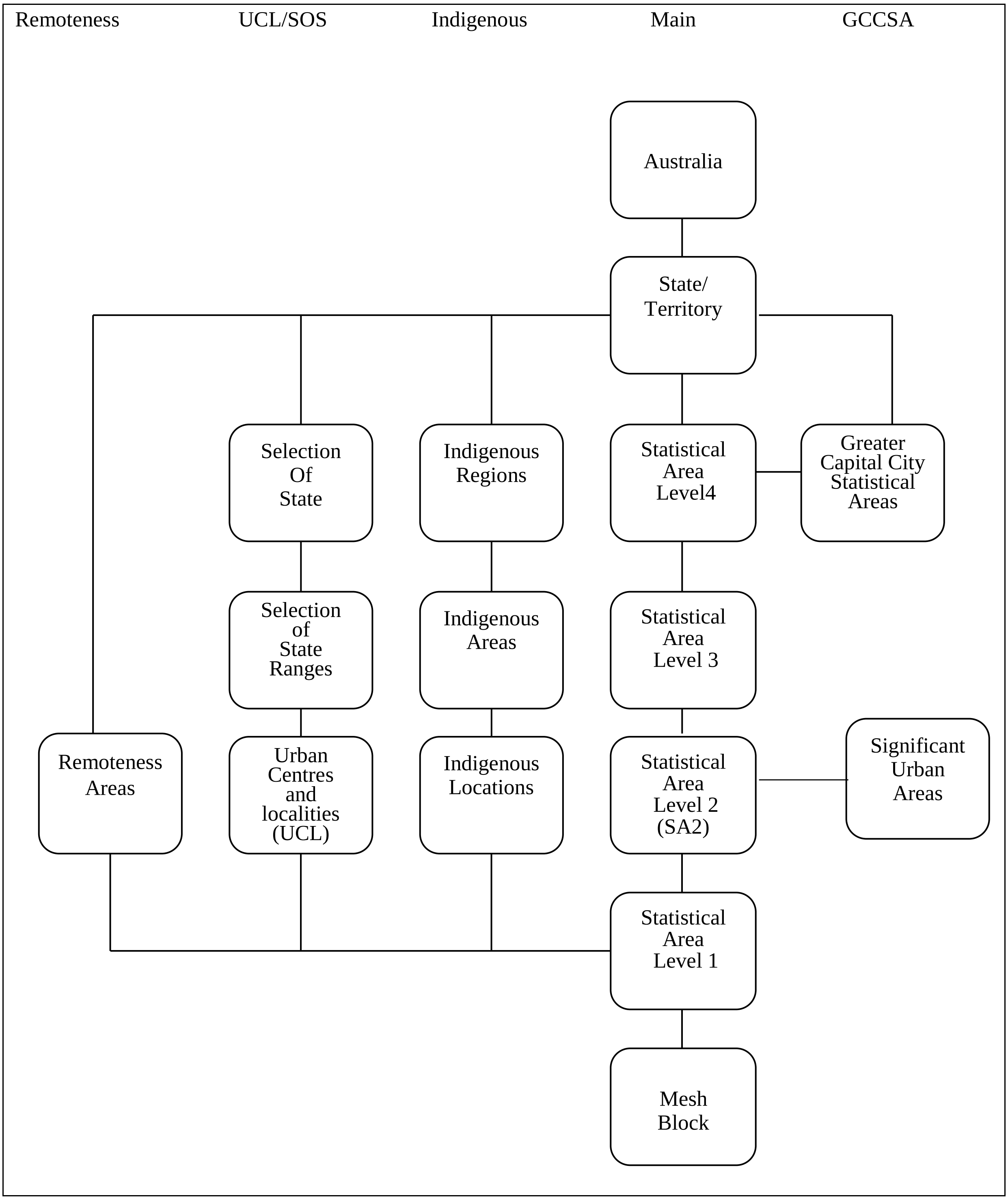
Figure A.13 Organic operations* in Australia, 2002-2018



Own figure (data source: Williams et al. (2019))

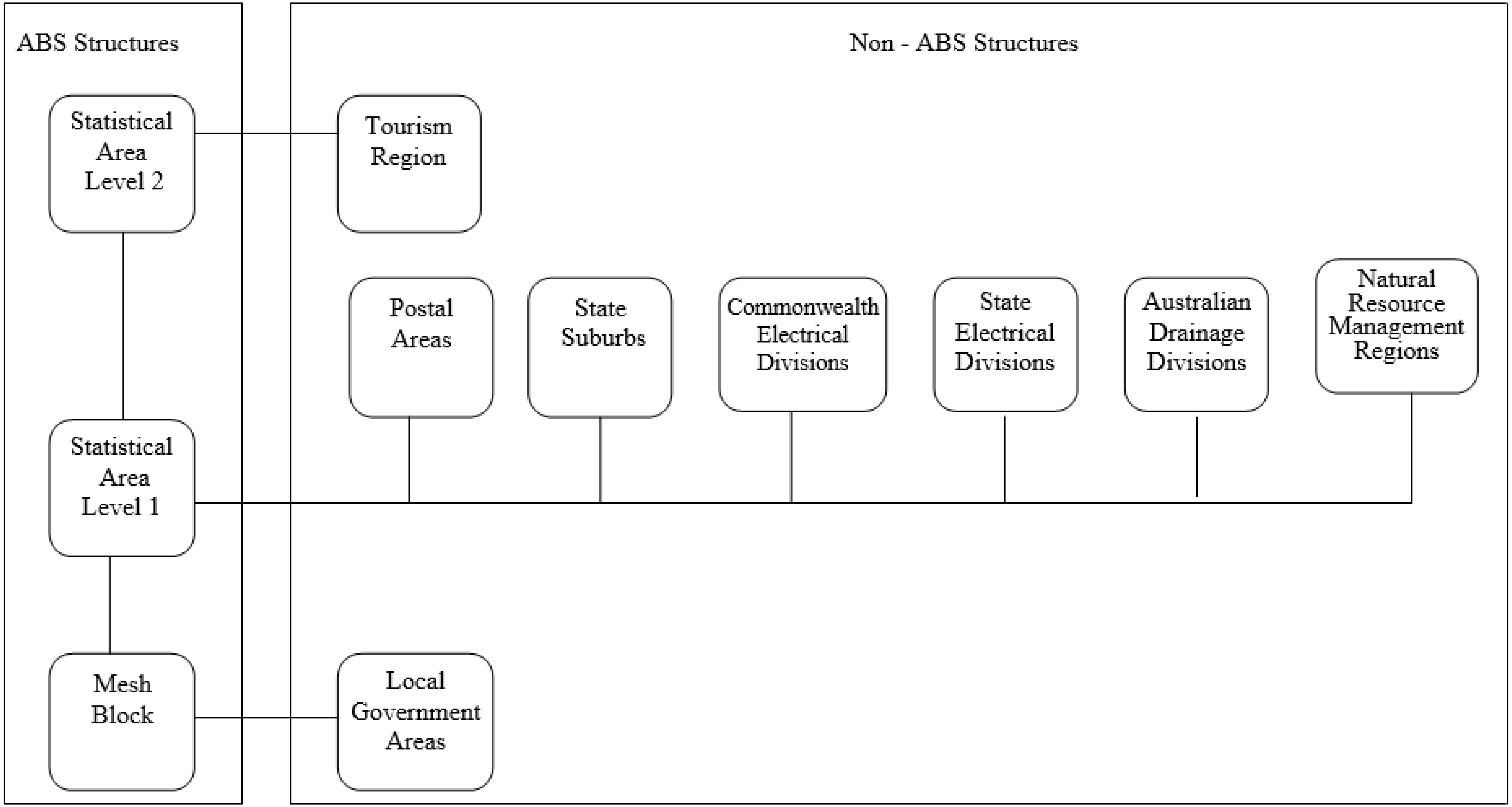
<u>Notes: *</u>Organic operations includes producer, processors (marketer, wholesalers), handlers and others. Data from 2008, 2010, 2012, and 2013 was not available

Figure A.14 ASGS ABS Structure



Source: (ABS 2016b)

Figure A.15 ASGS Non-ABS structure



Source: (ABS 2016h)

Appendix B Supplementary materials for Chapter 2

Table B.1 An overview of the factors contributing to the adoption and diffusion of organic framing: findings from non-spatial and spatial analysis

Variables	*Literature findings*	*How often studied*	*Selected sources*
Farmers characteristics			
Age	Young farmers are more likely to adopt	Often	(Genius et al. 2006; Kallas et al. 2010; Lapple and Kelley 2015; Läpple and Kelley 2013)
	Older farmers are more likely to adopt		(Läpple and Rensburg 2011; Parra-Lopez et al. 2007; Wollni and Andersson 2014)
Education	Educated farmers are more willing to adopt new technology	Often	(Boncinelli et al. 2015; Lohr and Salomonsson 2000; Unay Gailhard et al. 2015)
Gender	Female farmers are more willing to adopt organic farming	Often	(Burton et al. 2003; Kuo and Peters 2017; Läpple 2013; Lohr and Park 2009; Thapa and Rattanasuteerakul 2011)
Agricultural income	Increased income from agriculture discourage adoption	Occasionally	(Marasteanu and Jaenicke 2016)
	Farm households with more revenue/expected return are more willing to adopt		(Lampach et al. 2019; López and Requena 2005; Oelofse et al. 2010)
	Producers' uncertainty about future return will reduce the organic conversion rate		(Kuminoff and Wossink 2010)
Off-farm employment	Off-farm employment increases adoption rate by diversifying and stabilizing household total income	Occasionally	(Boncinelli et al. 2015; López and Requena 2005)
Labour availability	Increased labour supply promotes adoption	Occasionally	(Finley et al. 2018; Jansen 2000)
Environmental attitude	Positive attitudes encourages adoption	Often	(Läpple 2010; Lapple and Kelley 2015; Läpple and Kelley 2013; Läpple and Rensburg 2011; Parra-Lopez et al. 2007)
	Positive externality effects to neighbours discourage adoption		(Wollni and Andersson 2014)
Risk attitude	Risk averse farmers are less willing to adopt	Often	(Kallas et al. 2010; Läpple 2010, 2013; Lapple and Kelley 2015; Parra-Lopez et al. 2007)
Profit orientation	Profit oriented farmers are less likely to adopt	Often	(Läpple 2013; Lapple and Kelley 2015; Mzoughi 2011)
Farm characteristics			

Farm size	Large farms are more likely to adopt	Often	(Boncinelli et al. 2015; Padel 2001; Pietola and Lansink 2001)
	Small farms are more willing to adopt		(Burton et al. 1999; Gabriel et al. 2009; Kallas et al. 2010; Khaledi et al. 2010; Läpple 2010)
Framing type	Mixed dairy farms are more likely to adopt	Occasionally	(Allaire et al. 2015; Gabriel et al. 2009)
	High value crop farms are more willing to adopt skill based technologies		(Allaire et al. 2015; Uematsu and Mishra 2012)
Location	Urban proximity promotes adoption by creating market access	Often	(Boncinelli et al. 2015; Lewis et al. 2011; Malek et al. 2019; Marasteanu and Jaenicke 2016)
	Farms located in rural areas are more likely to adopt		(Gabriel et al. 2009)
Livestock density	Farms with low stocking rate are more willing to adopt	Often	(Läpple 2010; Lohr and Salomonsson 2000; Pietola and Lansink 2001; Schmidtner et al. 2012)
Land value	High farmland value discourage adoption	Rarely	(Lewis et al. 2011)
	High land value encourage adoption		(Kaufmann et al. 2011)
Local market	Direct marketing to local markets promotes adoption	Often	(Kuo and Peters 2017; Petit and Aubry 2014)
	Producers' who relay direct marketing of products are reluctant to be certified organic due to high certification cost		(Veldstra et al. 2014)
	Diversity of sales outlets hinders adoption		(Lohr and Salomonsson 2000)
Downstream operators	Presence of organic processors encourages adoption	Rarely	(Bjørkhaug and Blekesaune 2013)
Climatic and Environmental factors			
Rainfall/aridity index	Favourable climatic condition positively influence adoption	Rarely	(Genius et al. 2006; Schmidtner et al. 2012)
Soil quality	Organic farms are more likely to be located in less favoured areas in terms of soil fertility	Often	(Gabriel et al. 2009; Parra-Lopez et al. 2007; Schmidtner et al. 2012)
Slope/elevation	Positively influence adoption	Occasionally	(Gabriel et al. 2009)
Information access			
Extension service/community/agricultural group/GOs/NGOs membership	Information transmission through extension service and learning from neighbour complements each other	Often	(Lampach et al. 2019; Parra-Lopez et al. 2007; Parra López and Calatrava Requena 2005; Sodjinou et al. 2015; Thapa and Rattanasuteerakul 2011)
Social network (peer effect/social learning)	Farmers are more willing to adopt if neighbours from the social network also adopt through knowledge spill-over from neighbours	Often	(Allaire et al. 2015; Kroma 2006; Läpple 2010; Läpple and Rensburg 2011; Lewis et al. 2011; Lohr and Salomonsson 2000; Nyblom et al. 2003; Schmidtner et al. 2012; Wollni and Andersson 2014)
Socio-economic factors			
Population density	Has positive effect by creating more demand	Often	(Bjørkhaug and Blekesaune 2013; Malek et al. 2019)

	Negative effect on adoption in terms of urbanisation		(Gabriel et al. 2009)
Household income	Consumers increased purchasing power induces adoption	Rarely	(Schmidtner et al. 2012)
Social acceptance	Social conformity has positive effect on adoption	Often	(Marasteanu and Jaenicke 2016; Schmidtner et al. 2012; Wollni and Andersson 2014)
Agricultural policy			
Conservation subsidy	Subsidy for grassland, conserving natural environment promote adoption	Often	(Schmidtner et al. 2012)
Conversion aids	Financial support for conversion encourage adoption	Often	(Boncinelli et al. 2015; Genius et al. 2006; Lohr and Salomonsson 2000; Marasteanu and Jaenicke 2016)

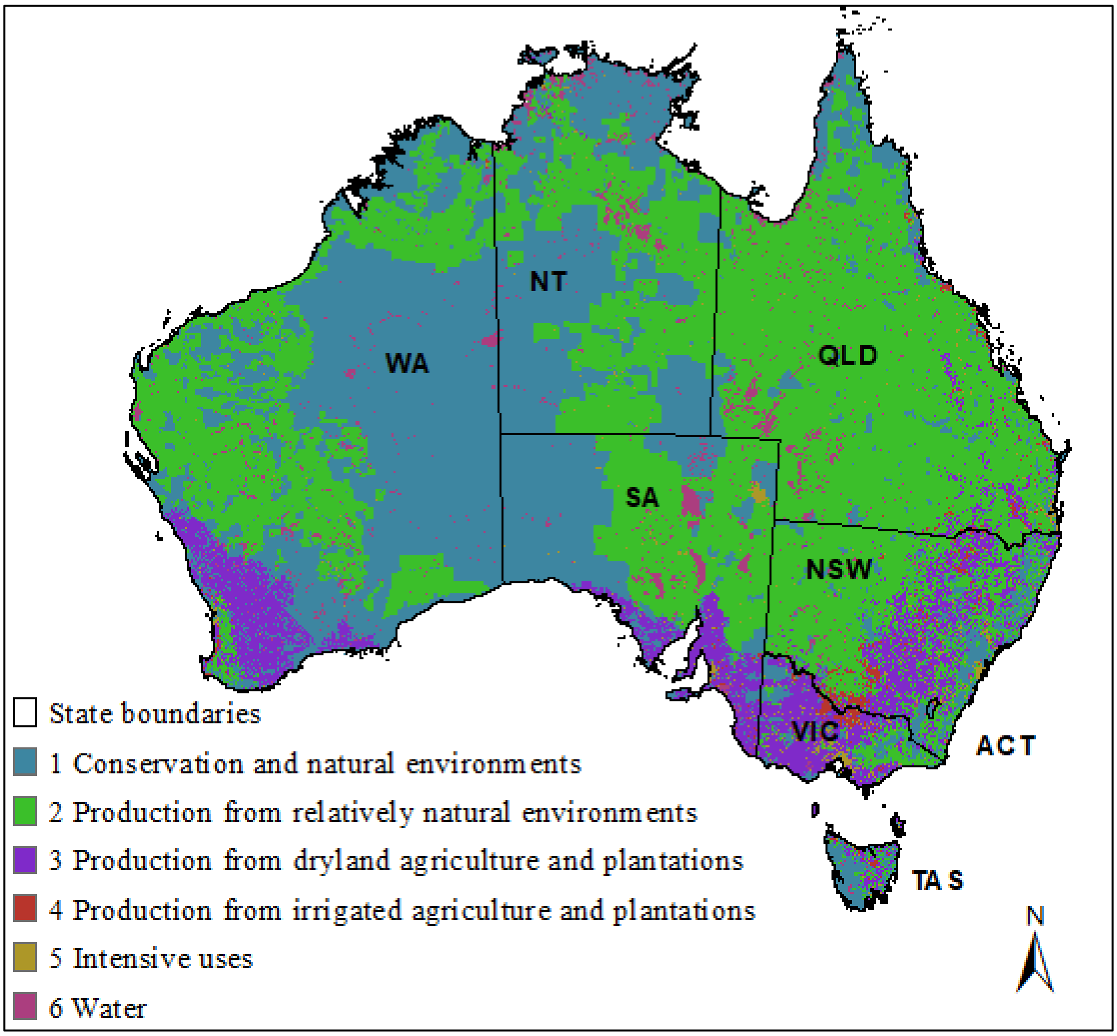
Table B.2 Australian land use and management (ALUM) classification used to determine the regional agricultural specialisation in terms of land use (based on secondary hierarchy level)

Agricultural specialisation	*Primary level*	*Secondary level*	*Tertiary level*	*Chapter*
Conservation land	Conservation and natural environment	Nature conservation	-Strict nature reserve -Wilderness area -National park -Natural feature protection -Habitat/species management area -Protected landscape -Other conserved area	2 & 3
		Managed resource protection	-Biodiversity -Surface water supply -Groundwater -Landscape	
		Other minimal use	-Defence land (natural areas) -Stock route -Residual native cover -Rehabilitation	
Crop	Production from dryland agriculture and plantations	Cropping	-Cereals -Beverages & spice crops -Hay & silage -Oilseeds -Sugar -Cotton -Alkaloid poppies -Pulses	2 & 3
	Production from irrigated agriculture and plantations	Irrigated cropping	-Irrigated cereals -Irrigated rice - Irrigated beverages & spice crops - Irrigated hay & silage - Irrigated oilseeds - Irrigated sugar - Irrigated cotton -Irrigated alkaloid poppies - Irrigated pulses	
Grazing	Production from relatively natural environment	Grazing native vegetation		2 & 3
	Production from dryland agriculture and plantations	Grazing modified pasture	-Native/exotic pasture mosaic -Woody fodder plants -Pasture legumes -Pasture legumes/grass mixtures -Sown grasses	
	Production from irrigated agriculture and plantations	Grazing irrigated modified pasture	-Irrigated native/exotic pasture mosaic - Irrigated woody fodder plants - Irrigated pasture legumes - Irrigated pasture legumes/grass mixtures - Irrigated sown grasses	
	Intensive uses	Intensive animal production	-Dairy sheds & yards -Feedlots -Poultry farms -Piggeries -Aquaculture -Horse studs	

			-Saleyards/stockyards	
Horticulture	Production from dryland agriculture and plantations	Perennial horticulture	-Tree fruits -Olives -Tree nuts -Vine fruits -Shrub berries & fruits -Perennial flowers & bulbs -Perennial vegetables & herbs -Citrus -Grapes	2 & 3
		Seasonal horticulture	-Seasonal fruits -Seasonal flowers & bulbs -Seasonal vegetables & herbs	
	Production from irrigated agriculture and plantations	Perennial horticulture	-Irrigated tree fruits - Irrigated olives - Irrigated tree nuts - Irrigated vine fruits - Irrigated shrub berries & fruits - Irrigated perennial flowers & bulbs - Irrigated perennial vegetables & herbs - Irrigated citrus - Irrigated grapes	
		Seasonal horticulture	- Irrigated seasonal fruits - Irrigated seasonal flowers & bulbs - Irrigated seasonal vegetables & herbs -Irrigated turf farming	
	Intensive uses	Intensive horticulture	-Production nurseries -Shade houses -Glasshouses -Glasshouses-hydroponic	
Water bodies	Water	Lake	-Conservation -Production -Intensive use -Saline	3
		Reservoir/dam	-Reservoir -Water storage -Evaporation basin	
		River	-Conservation -Production -Intensive use	
		Channel/Aqueduct	-Supply channel -Drainage channel -Stormwater	
		Marsh/wetland	-Conservation -Production -Intensive use -Saline	
		Estuary/coastal waters	-Conservation -Production -Intensive use	

Source: Adapted from (ABARES 2016a)

Figure B.1 Land use based on ALUM classification in Australia, 2018



Own map (data sources: state boundaries (ABS 2016m); land use (ABARES 2019b)

Table B.3 List of spatial tools from ArcGIS 10.5.1 software used to prepare the data for Chapter 2, 3 and 4

Name	***Description of the tools***
Project and project raster	Project spatial (vector or raster) data from one coordinate to another.
Spatial join	Based on relative spatial locations join attributes from one feature to another feature and the target features and the joined attributes from the join features are reported to the output feature class.
ASCII to raster	Converts an ASCII-format text file into raster dataset.
Cell statistics	Calculates per cell statistics from a list of input rasters.
Mosaic to new raster	Combine multiple raster datasets into a new raster dataset.
Con	Executes a conditional if/else evaluation on each of the input cells of an input raster.
Extract values to points	Extracts the cell values of raster data by overlaying with input point features and reports the point values in an output feature class.
Tabulate area	Gives an output table by cross tabulating areas between two datasets.
Zonal statistics as table	Summarizes the values of a raster within the zones of another dataset and reports the results to a table.
Calculate distance band from neighbour count	Generates the maximum, minimum, and average distance to the specified n^{th} nearest neighbours for a set of features.
Cluster and outlier analysis	Identifies statistically significant hot-spots, cold-spots and spatial outliers using the Anselin Local Moran's I statistic.
Generate spatial weight matrix	Generates spatial weight matrix file that quantifies the spatial structure of relationships that exist among the features of the input dataset. The spatial structure can be conceptualised as: inverse distance (the impact of one feature on another feature decreases with distance); fixed distance (every feature within a specified distance of each feature is included in the matrix specification); contiguity (polygon features that share a boundary and/or a node are neighbours); K-nearest neighbour (the closest k-features are included, where k is the specified numeric parameter).
Convert spatial weight matrix to table	Converts the spatial weight matrix file created by generate spatial weight matrix tool into a table.

Source: (ESRI 2016)

Table B.4 Pairwise correlation among the explanatory variables (N=2,134) used in the non-spatial tobit model of share of organic area and business

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Farm size	1.00													
(2) Irrigated business	-0.49	1.00												
(3) Livestock density	0.11	-0.24	1.00											
(4) Agricultural labour	0.46	-0.24	0.12	1.00										
(5) Crop	0.07	-0.06	-0.03	0.17	1.00									
(6) Grazing	0.22	-0.19	0.10	-0.02	-0.51	1.00								
(7) Horticulture	-0.25	0.35	-0.12	-0.11	-0.09	-0.30	1.00							
(8) Aridity index	-0.24	0.04	-0.11	-0.20	-0.14	0.00	-0.06	1.00						
(9) Severe drought	0.06	-0.01	0.01	0.03	-0.03	0.01	-0.01	-0.03	1.00					
(10) NDVI	-0.23	0.02	0.16	-0.07	-0.15	0.10	-0.10	0.61	-0.01	1.00				
(11) Elevation	0.30	-0.27	0.20	0.26	-0.10	0.16	-0.17	-0.02	0.02	0.15	1.00			
(12) Soil texture	0.04	-0.04	-0.03	0.04	-0.05	0.15	-0.11	0.27	0.00	0.22	0.13	1.00		
(13) Soil pH	0.35	-0.05	-0.02	0.28	0.21	-0.03	0.04	-0.43	0.05	-0.44	-0.02	0.08	1.00	
(14) Green vote	-0.25	0.11	0.06	-0.24	-0.19	-0.03	0.02	0.17	0.10	0.19	-0.06	-0.08	-0.30	1.00
(15) Conservation land	0.04	0.05	-0.11	-0.03	-0.04	-0.05	0.03	0.21	0.03	0.17	0.13	-0.21	-0.18	0.13
(16) Distance to cities	0.49	-0.18	-0.11	0.27	-0.06	0.13	-0.08	-0.19	0.03	-0.35	0.12	-0.15	0.14	-0.11
(17) SEIFA	-0.39	0.14	0.02	-0.14	-0.02	-0.06	0.07	0.11	-0.09	0.14	-0.05	-0.06	-0.27	0.20
(18) Taxable income	0.29	-0.20	0.09	0.53	0.16	-0.04	-0.10	-0.23	0.01	-0.15	0.17	-0.13	0.14	-0.07
(19) Population	-0.35	0.11	0.00	-0.40	-0.08	0.00	0.06	0.01	-0.06	-0.07	-0.20	-0.05	-0.13	0.09
(20) Year	-0.01	-0.07	0.00	0.00	0.08	-0.05	0.07	-0.32	-0.03	-0.30	0.00	0.00	0.00	-0.07
(21) NSW	-0.05	-0.11	-0.01	-0.02	-0.17	0.22	-0.08	0.17	-0.03	0.23	0.17	0.11	-0.07	0.03
(22) NT	0.20	-0.01	-0.11	-0.04	-0.06	0.06	0.03	-0.01	0.04	-0.14	0.00	-0.17	0.00	-0.14
(23) QLD	0.04	0.06	-0.31	0.01	-0.01	-0.01	-0.03	0.33	-0.03	0.06	-0.05	0.39	-0.06	-0.23
(24) TAS	-0.01	0.13	0.11	-0.03	-0.07	0.00	-0.03	0.05	0.15	0.13	0.00	0.10	0.01	0.37
(25) VIC	-0.10	-0.07	0.29	-0.05	0.04	-0.02	-0.01	-0.13	-0.01	0.00	-0.02	0.07	-0.13	0.02
(26) WA	0.03	0.04	-0.05	0.00	0.18	-0.23	0.10	-0.31	-0.01	-0.27	-0.09	-0.56	-0.01	0.05
(27) SA	0.05	0.04	0.06	0.12	0.12	-0.07	0.08	-0.26	-0.03	-0.20	-0.06	-0.25	0.39	-0.05

Table B.4 continued

	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)
(15) Conservation land	1.00												
(16) Distance to cities	0.20	1.00											
(17) SEIFA	0.00	-0.33	1.00										
(18) Taxable income	0.04	0.23	0.05	1.00									
(19) Population	-0.24	-0.22	0.15	-0.11	1.00								
(20) Year	0.02	0.00	-0.06	0.06	0.07	1.00							
(21) NSW	0.03	-0.11	0.00	-0.13	0.10	0.00	1.00						
(22) NT	0.21	0.21	-0.18	-0.03	-0.13	0.00	-0.08	1.00					
(23) QLD	-0.07	0.04	-0.01	-0.13	-0.07	0.00	-0.32	-0.07	1.00				
(24) TAS	0.14	-0.02	-0.14	-0.05	-0.18	0.00	-0.15	-0.03	-0.14	1.00			
(25) VIC	-0.19	-0.11	0.14	0.11	0.15	0.00	-0.33	-0.08	-0.30	-0.14	1.00		
(26) WA	0.17	0.16	0.06	0.14	-0.02	0.00	-0.20	-0.05	-0.18	-0.09	-0.19	1.00	
(27) SA	-0.05	0.03	-0.05	0.14	-0.05	0.00	-0.19	-0.04	-0.17	-0.08	-0.18	-0.11	1.00

Note: The level of significance for pairwise correlation are not reported in the table due to space limitation. The results are available from the author upon request.

Table B.5 Pairwise correlation among the explanatory variables (N=2,134) used in the spatial models (SLX, SDM and SDEM) of share of organic area and farm business

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Farm size	1.00													
(2) Irrigated business	-0.49	1.00												
(3) Livestock density	0.11	-0.24	1.00											
(4) Agricultural labour	0.46	-0.24	0.12	1.00										
(5) Crop	0.07	-0.06	-0.03	0.17	1.00									
(6) Grazing	0.22	-0.19	0.10	-0.02	-0.51	1.00								
(7) Horticulture	-0.25	0.35	-0.12	-0.11	-0.09	-0.30	1.00							
(8) Aridity index	-0.24	0.04	-0.11	-0.20	-0.14	0.00	-0.06	1.00						
(9) Severe drought	0.06	-0.01	0.01	0.03	-0.03	0.01	-0.01	-0.03	1.00					
(10) NDVI	-0.23	0.02	0.16	-0.07	-0.15	0.10	-0.10	0.61	-0.01	1.00				
(11) Elevation	0.30	-0.27	0.20	0.26	-0.10	0.16	-0.17	-0.02	0.02	0.15	1.00			
(12) Soil texture	0.04	-0.04	-0.03	0.04	-0.05	0.15	-0.11	0.27	0.00	0.22	0.13	1.00		
(13) Soil pH	0.35	-0.05	-0.02	0.28	0.21	-0.03	0.04	-0.43	0.05	-0.44	-0.02	0.08	1.00	
(14) Green vote	-0.25	0.11	0.06	-0.24	-0.19	-0.03	0.02	0.17	0.10	0.19	-0.06	-0.08	-0.30	1.00
(15) Conservation land	0.04	0.05	-0.11	-0.03	-0.04	-0.05	0.03	0.21	0.03	0.17	0.13	-0.21	-0.18	0.13
(16) Distance to cities	0.49	-0.18	-0.11	0.27	-0.06	0.13	-0.08	-0.19	0.03	-0.35	0.12	-0.15	0.14	-0.11
(17) SEIFA	-0.39	0.14	0.02	-0.14	-0.02	-0.06	0.07	0.11	-0.09	0.14	-0.05	-0.06	-0.27	0.20
(18) Taxable income	0.29	-0.20	0.09	0.53	0.16	-0.04	-0.10	-0.23	0.01	-0.15	0.17	-0.13	0.14	-0.07
(19) Population	-0.35	0.11	0.00	-0.40	-0.08	0.00	0.06	0.01	-0.06	-0.07	-0.20	-0.05	-0.13	0.09
(20) Year	-0.01	-0.07	0.00	0.00	0.08	-0.05	0.07	-0.32	-0.03	-0.30	0.00	0.00	0.00	-0.07
(21) NSW	-0.05	-0.11	-0.01	-0.02	-0.17	0.22	-0.08	0.17	-0.03	0.23	0.17	0.11	-0.07	0.03
(22) NT	0.20	-0.01	-0.11	-0.04	-0.06	0.06	0.03	-0.01	0.04	-0.14	0.00	-0.17	0.00	-0.14
(23) QLD	0.04	0.06	-0.31	0.01	-0.01	-0.01	-0.03	0.33	-0.03	0.06	-0.05	0.39	-0.06	-0.23
(24) TAS	-0.01	0.13	0.11	-0.03	-0.07	0.00	-0.03	0.05	0.15	0.13	0.00	0.10	0.01	0.37
(25) VIC	-0.10	-0.07	0.29	-0.05	0.04	-0.02	-0.01	-0.13	-0.01	0.00	-0.02	0.07	-0.13	0.02
(26) WA	0.03	0.04	-0.05	0.00	0.18	-0.23	0.10	-0.31	-0.01	-0.27	-0.09	-0.56	-0.01	0.05
(27) SA	0.05	0.04	0.06	0.12	0.12	-0.07	0.08	-0.26	-0.03	-0.20	-0.06	-0.25	0.39	-0.05
(28) W_Farm size	0.16	-0.02	-0.06	-0.14	-0.02	0.12	-0.01	-0.07	0.00	-0.21	0.05	0.07	0.11	-0.07
(29) W_Irrigated business	-0.63	0.54	-0.19	-0.43	-0.03	-0.24	0.30	0.14	-0.01	0.09	-0.33	-0.11	-0.23	0.28
(30) W_Livestock density	-0.20	-0.03	0.52	-0.07	-0.02	0.02	-0.02	-0.20	0.00	0.12	0.08	-0.04	-0.05	0.19
(31) W_Agricultural labour	0.33	-0.18	0.19	0.43	0.20	0.00	-0.05	-0.29	-0.04	-0.12	0.17	0.10	0.44	-0.30
(32) W_Crop	-0.12	0.09	-0.02	-0.02	0.54	-0.44	0.11	-0.17	-0.05	-0.18	-0.12	-0.21	0.07	-0.14
(33) W_Grazing	-0.26	0.09	0.00	-0.33	-0.39	0.40	-0.05	0.25	-0.02	0.19	0.00	0.27	-0.19	0.16

(34) W_Horticulture	-0.39	0.35	-0.15	-0.22	0.06	-0.32	0.46	-0.19	0.00	-0.25	-0.25	-0.33	-0.02	0.10
(35) W_Severe drought	0.04	0.04	0.03	-0.03	-0.05	0.04	0.02	-0.03	0.23	-0.02	0.04	0.02	0.03	0.28
(36) W_Conservation land	-0.15	0.17	-0.15	-0.26	0.02	-0.09	0.11	0.19	0.03	0.01	-0.06	-0.24	-0.17	0.16
(37) W_Taxable income	-0.09	0.02	0.21	0.03	0.15	-0.14	0.13	-0.52	-0.02	-0.34	-0.04	-0.36	0.18	0.02

Table B. 5 continued

	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)
(15) Conservation land	1.00													
(16) Distance to cities	0.20	1.00												
(17) SEIFA	0.00	-0.33	1.00											
(18) Taxable income	0.04	0.23	0.05	1.00										
(19) Population	-0.24	-0.22	0.15	-0.11	1.00									
(20) Year	0.02	0.00	-0.06	0.06	0.07	1.00								
(21) NSW	0.03	-0.11	0.00	-0.13	0.10	0.00	1.00							
(22) NT	0.21	0.21	-0.18	-0.03	-0.13	0.00	-0.08	1.00						
(23) QLD	-0.07	0.04	-0.01	-0.13	-0.07	0.00	-0.32	-0.07	1.00					
(24) TAS	0.14	-0.02	-0.14	-0.05	-0.18	0.00	-0.15	-0.03	-0.14	1.00				
(25) VIC	-0.19	-0.11	0.14	0.11	0.15	0.00	-0.33	-0.08	-0.30	-0.14	1.00			
(26) WA	0.17	0.16	0.06	0.14	-0.02	0.00	-0.20	-0.05	-0.18	-0.09	-0.19	1.00		
(27) SA	-0.05	0.03	-0.05	0.14	-0.05	0.00	-0.19	-0.04	-0.17	-0.08	-0.18	-0.11	1.00	
(28) W_Farm size	-0.01	0.12	-0.16	-0.17	-0.01	-0.01	-0.23	0.42	0.12	-0.09	0.09	-0.11	0.05	1.00
(29) W_Irrigated business	-0.02	-0.33	0.32	-0.29	0.21	-0.15	-0.18	-0.01	0.07	0.18	-0.08	0.10	0.06	-0.08
(30) W_Livestock density	-0.16	-0.27	0.17	0.03	0.12	-0.01	-0.05	-0.21	-0.61	0.19	0.64	-0.14	0.09	-0.07
(31) W_Agricultural labour	-0.22	-0.07	-0.16	0.22	-0.17	-0.02	-0.16	-0.15	0.03	-0.18	0.10	-0.09	0.38	0.12
(32) W_Crop	0.02	-0.14	0.06	0.02	0.03	0.17	-0.39	-0.11	0.03	-0.14	0.10	0.34	0.20	0.00
(33) W_Grazing	-0.12	-0.15	0.13	-0.29	0.23	-0.07	0.34	0.08	-0.04	0.00	0.14	-0.50	-0.17	0.36
(34) W_Horticulture	0.02	-0.13	0.18	-0.07	0.15	0.24	-0.22	0.10	-0.09	-0.10	-0.05	0.34	0.22	-0.10
(35) W_Severe drought	0.07	0.03	-0.07	0.00	-0.10	-0.09	-0.09	0.09	-0.07	0.41	-0.03	-0.03	-0.06	0.06
(36) W_Conservation land	0.48	0.10	-0.03	-0.18	-0.04	0.04	0.02	0.42	-0.07	0.18	-0.30	0.28	-0.12	0.24
(37) W_Taxable income	-0.15	-0.14	0.20	0.23	0.11	0.20	-0.31	-0.06	-0.48	-0.12	0.41	0.24	0.44	0.04

Table B. 5 continued

	(29)	(30)	(31)	(32)	(33)	(34)	(35)	(36)	(37)
(29) W_Irrigated business	1.00								
(30) W_Livestock density	0.01	1.00							
(31) W_Agricultural labour	-0.37	0.13	1.00						
(32) W_Crop	0.17	0.01	0.16	1.00					
(33) W_Grazing	0.16	0.19	-0.28	-0.62	1.00				
(34) W_Horticulture	0.59	-0.02	-0.13	0.36	-0.23	1.00			
(35) W_Severe drought	0.08	0.07	-0.10	-0.11	0.05	0.05	1.00		
(36) W_Conservation land	0.28	-0.21	-0.40	0.15	0.03	0.23	0.11	1.00	
(37) W_Taxable income	0.09	0.50	0.39	0.32	-0.15	0.38	-0.09	-0.12	1.00

Note: The level of significance for pairwise correlation are not reported in the table due to space limitation. The results are available from the author upon request.

Table B.6 Collinearity check among the explanatory variables for non-spatial tobit and spatial tobit models using variance inflation factor (VIF)

	Unbalanced panel model (N=2,134)		*Balanced panel model (N=1,754)*		*Balanced panel model with randomly generated numbers (N=1,898)*	
	SLX tobit	***tobit***	***SLX tobit***	***tobit***	***SLX tobit***	***tobit***
Farm size	2.74	2.31	3.19	2.64	3.35	2.71
Irrigated business	1.61	1.55	1.75	1.66	1.78	1.68
Livestock density	1.52	1.37	1.67	1.45	1.67	1.45
Agricultural labour	2.33	2.04	2.30	2.08	2.24	1.97
Crop	1.95	1.49	2.19	1.76	2.23	1.78
Grazing	1.93	1.52	2.13	1.87	2.13	1.90
Horticulture	1.42	1.23	1.54	1.37	1.58	1.40
Aridity index	3.15	2.75	3.14	2.74	3.07	2.74
Severe drought	1.09	1.04	1.09	1.05	1.12	1.05
NDVI	2.62	2.37	2.68	2.49	2.73	2.58
Elevation	1.44	1.37	1.44	1.35	1.44	1.35
Soil texture	2.34	2.30	2.34	2.30	2.39	2.36
Soil pH	2.24	2.13	2.27	2.15	2.31	2.21
Green vote	1.75	1.59	1.78	1.59	1.76	1.59
Conservation land	1.66	1.49	1.78	1.54	1.81	1.56
Distance to cities	1.98	1.71	2.15	1.80	2.20	1.87
SEIFA	1.60	1.38	1.63	1.43	1.69	1.46
Taxable income	1.76	1.65	0.56	1.67	1.71	1.60
Population	1.57	1.55	1.52	1.50	1.53	1.51
Year	2.77	1.39	2.27	1.42	2.21	1.41
NSW	3.65	2.12	3.69	2.12	3.61	2.12
NT	2.32	1.44	2.41	1.42	2.59	1.53
SA	4.54	2.53	4.74	2.51	5.04	2.61
TAS	3.24	1.78	3.55	1.86	3.67	1.86
VIC	7.46	2.49	7.74	2.57	7.71	2.51
WA	5.42	3.33	5.74	3.31	6.09	3.33
W_Farm size	3.67		0.28		3.78	
W_Irrigated business	4.55		0.18		5.50	
W_Livestock density	4.85		0.20		5.26	
W_Agricultural labour	2.98		0.30		2.98	
W_Crop	4.21		4.92		4.77	
W_Grazing	6.34		9.05		8.39	
W_Horticulture	3.28		4.06		4.16	
W_Severe drought	1.58		0.68		1.60	
W_Conservation land	2.86		2.86		2.95	
W_Taxable income	4.31		0.19		4.59	
Mean VIF	2.91	1.84	3.16	1.91	3.16	1.93

Note: Variables name started with W indicates explanatory variables with spatial lag

Table B.7 Estimated coefficients of the SDM tobit balanced panel models for spatial diffusion of OA in Australia, 2010/11 – 2015/16 (N = 1,754)

	Model I (share of organic area)				***Model II (share of organic businesses)***			
	X	***Std. Err.***	***WX***	***Std. Err.***	***X***	***Std. Err.***	***WX***	***Std. Err.***
Farm size	0.793**	0.315	0.436	0.980	0.746**	0.294	-0.367	0.650
Irrigated business (%)	0.071***	0.023	-0.109*	0.060	0.062***	0.021	-0.046	0.061
Livestock density	-1.186**	0.600	1.958	2.111	-0.322	0.585	0.468	1.638
Agricultural labour (%)	0.459***	0.127	0.555	0.763	0.400***	0.107	1.203**	0.502
Crop (%)	-0.004	0.023	-0.075	0.075	0.009	0.023	-0.052	0.066
Grazing (%)	0.029	0.024	-0.125*	0.074	0.022	0.021	-0.066	0.054
Horticulture (%)	0.028	0.031	0.120	0.201	0.017	0.028	0.124	0.157
Aridity index	1.253	1.308	-	-	1.094	1.04	-	-
Severe drought dummy	9.092	7.160	-1.831	21.579	2.689	3.698	-8.928	18.282
NDVI index	11.653*	6.796	-	-	12.772**	5.727	-	-
Elevation	0.004***	0.002	-	-	0.004**	0.002	-	-
Soil texture index	-0.145	0.461	-	-	0.035	0.422	-	-
Soil pH	0.234	0.457	-	-	0.461	0.436	-	-
Green vote (%)	0.266	0.189	-	-	0.353**	0.178	-	-
Conservation land (%)	-0.013	0.023	-0.058	0.069	-0.005	0.020	-0.021	0.059
Distance to cities	0.000	0.000	-	-	0.000	0.000	-	-
Taxable income	0.000*	0.006	0.000	0.000	0.000***	0.005	0.000	0.100
SEIFA index	0.000	0.000	-	-	-0.006	0.000	-	-
Population (numbers)	0.000	0.000	-	-	0.000	0.000	-	-
Year	-0.976	1.036	-	-	-1.135	0.979	-	-
NSW	1.035	1.304	-	-	0.793	1.112	-	-
NT	2.153	3.446	-	-	3.919	3.288	-	-
SA	2.262	2.044	-	-	2.443	1.825	-	-
TAS	-5.571*	3.072	-	-	-4.591	3.022	-	-
VIC	1.715	1.746	-	-	1.695	1.572	-	-
WA	-1.892	2.496	-	-	-1.500	2.319	-	-
Spatial lag (*ρ*)	**0.058**				**0.173**			
Left-censored	1,148				1148			
Uncensored	606				606			
LR test SDM vs OLS (ρ=0)	0.195				1.867			
LR test WX's = 0	28.32				22.24			

Notes: X and WX indicates direct and indirect (local spatial spill-over) marginal effects, respectively. Asterisks *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table B.8 Estimated coefficients of the SDEM tobit balanced panel models to explain the spatial diffusion of certified organic farming in Australia, 2010/11 – 2015/16 (N = 1,754)

	Model I (share of organic area)				***Model II (share of organic businesses)***			
	X	***Std. Err.***	***WX***	***Std. Err.***	***X***	***Std. Err.***	***WX***	***Std. Err.***
Farm size	0.788**	0.320	0.382	0.903	0.742**	0.295	-0.320	0.647
Irrigated business (%)	0.071***	0.023	-0.111**	0.056	0.062***	0.021	-0.045	0.060
Livestock density	-1.256**	0.624	2.160	2.098	-0.347	0.597	0.607	1.692
Agricultural labour (%)	0.454***	0.126	0.481	0.738	0.400***	0.107	1.195**	0.506
Crop (%)	-0.006	0.023	-0.076	0.073	0.009	0.023	-0.053	0.066
Grazing (%)	0.029	0.024	-0.129*	0.073	0.022	0.021	-0.068	0.055
Horticulture (%)	0.028	0.032	0.096	0.189	0.018	0.028	0.126	19.243
Aridity index	1.305	1.277			1.132	1.052		
Severe drought dummy	8.808	7.073	6.798	22.704	2.733	3.774	-7.205	19.243
NDVI index	10.852*	6.517			12.797**	5.820		
Elevation	0.004***	0.002			0.004**	0.002		
Soil texture index	-0.131	0.454			0.054	0.423		
Soil pH	0.209	0.448			0.447	0.442		
Green vote (%)	0.256	0.186			0.356**	0.177		
Conservation land (%)	-0.012	0.023	-0.053	0.064	-0.005	0.020	-0.024	0.058
Distance to cities	0.000	0.000			0.000	0.000		
Taxable income	0.001	0.000			-0.007	0.000		
SEIFA index	0.000*	0.006	0.000	0.000	0.000***	0.005	0.000	0.000
Population (numbers)	0.000	0.000			0.000	0.000		
Year	-0.719	1.028			-1.193	0.971		
NSW	0.925	1.267			0.769	1.125		
NT	2.209	3.219			3.958	3.286		
SA	2.458	2.001			2.648	1.819		
TAS	-5.787*	3.016			-4.765	3.030		
VIC	1.609	1.711			1.601	1.603		
WA	-1.570	2.417			-1.612	2.294		
Spatial error (λ)	**-0.163**				**-0.017**			
Left-censored	1,148				1,148			
Uncensored	606				606			
LR test SDEM vs OLS (λ=0)	0.857				0.015			

Notes: The outcome variable is the share of organic area in total area of agricultural holding in *Model I* and share of organic farm business in total agricultural business in *Model II*. X and WX indicates direct and indirect (local spatial spill-over) marginal effects, respectively. Asterisks *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table B.9 Marginal effects of the tobit random-effects unbalanced panel models to explain the spatial diffusion of certified organic farming in Australia, 2010/11–2015/16 (N=2,134)

	Share of organic area		***Share of organic farm***	
	tobit	***SLX tobit***	***tobit***	***SLX tobit***
Farm size	0.032***	0.026***	0.026***	0.019**
	(0.006)	(0.006)	(0.006)	(0.006)
Irrigated business (%)	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Livestock density	-0.018	-0.022*	-0.017	-0.021*
	(0.009)	(0.010)	(0.009)	(0.009)
Agricultural labour (%)	0.010***	0.008***	0.010***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)
Crop (%)	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Grazing (%)	0.001	0.001*	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Horticulture (%)	0.001*	0.002*	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Aridity index	0.033	0.037	0.037	0.036
	(0.026)	(0.027)	(0.024)	(0.025)
Severe drought dummy	0.191***	0.186***	0.046	0.048
	(0.057)	(0.056)	(0.055)	(0.052)
NDVI index	0.495***	0.426***	0.485***	0.412***
	(0.100)	(0.103)	(0.101)	(0.102)
Elevation	0.000**	0.000*	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Soil texture index	-0.000	-0.001	0.009	0.009
	(0.013)	(0.013)	(0.013)	(0.013)
Soil pH	0.034**	0.030*	0.033*	0.025
	(0.012)	(0.013)	(0.013)	(0.013)
Green vote (%)	0.003	0.004*	0.004*	0.004*
	(0.002)	(0.002)	(0.002)	(0.002)
Conservation land (%)	-0.001*	-0.001*	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)
Distance to cities	-0.000	-0.000	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
SEIFA index	-0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Taxable income	0.000*	0.000	0.000**	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Population (numbers)	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Year dummy	0.021	0.053**	0.009	0.036*

	(0.013)	(0.018)	(0.012)	(0.017)
NSW	0.031	0.023	0.032	0.014
	(0.025)	(0.030)	(0.026)	(0.031)
NT	0.118	0.168	0.114	0.154
	(0.083)	(0.109)	(0.084)	(0.106)
SA	0.080	0.104	0.107*	0.118
	(0.044)	(0.060)	(0.047)	(0.062)
TAS	-0.081**	-0.100**	-0.084**	-0.114**
	(0.029)	(0.035)	(0.030)	(0.036)
VIC	0.107***	0.110*	0.114***	0.100
	(0.031)	(0.052)	(0.032)	(0.052)
WA	0.039	0.041	0.049	0.042
	(0.047)	(0.058)	(0.050)	(0.060)
W_Farm size		-0.017		-0.022
		(0.014)		(0.014)
W_Irrigated business		-0.000		-0.000
		(0.001)		(0.001)
W_Livestock density		0.019		0.017
		(0.039)		(0.039)
W_Agricultural labour		0.025*		0.031**
		(0.012)		(0.012)
W_Crop		-0.002		-0.003*
		(0.002)		(0.001)
W_Grazing		-0.002		-0.001
		(0.001)		(0.001)
W_Horticulture		-0.008*		-0.009**
		(0.003)		(0.003)
W_Severe drought		0.534		0.571*
		(0.282)		(0.263)
W_Conservation land		0.002		0.003*
		(0.001)		(0.001)
W_Taxable income		-0.000		0.000
		(0.000)		(0.000)
Left-censored	1,525		1,525	
Right-censored	3		4	
Uncensored	606		605	
Log likelihood	-2,662.23	-2,649.51	-2,685.79	-2,670.23
Wald Chi2	213.060***	218.590***	217.310***	227.340***
AIC	5,382.47	5,377.01	5,429.58	5,418.47
BIC	5,546.78	5,597.98	5,593.88	5,693.43

Notes: The outcome variable is the share of organic area in total area of agricultural holding in *Model I* and share of organic farm business in total agricultural business in *Model II*. Variables name started with W indicates explanatory variables with spatial lag. Asterisks *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively. Figures in the parenthesis indicates standard errors. dy/dx for factor levels is the discrete change from the base level.

Table B.10 Marginal effects of the tobit random-effects balanced panel models to explain the spatial diffusion of certified organic farming in Australia, 2010/11–2015/16 (N = 1,754)

	Share of organic area (Model I)		***Share of organic farm (Model II)***	
	tobit	***SLX tobit***	***tobit***	***SLX tobit***
Farm size	0.030***	0.015	0.027***	0.015
	(0.008)	(0.008)	(0.008)	(0.009)
Irrigated business (%)	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Livestock density	-0.025*	-0.035**	-0.016	-0.024*
	(0.011)	(0.012)	(0.012)	(0.012)
Agricultural labour (%)	0.013***	0.010***	0.013***	0.010***
	(0.002)	(0.002)	(0.002)	(0.003)
Crop (%)	-0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Grazing (%)	0.000	0.001	0.000	0.001
	(0.000)	(0.000)	(0.000)	(0.000)
Horticulture (%)	0.001	0.001	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Aridity index	0.049	0.059	0.044	0.050
	(0.033)	(0.035)	(0.034)	(0.036)
Severe drought dummy	0.282***	0.262***	0.076	0.064
	(0.074)	(0.073)	(0.079)	(0.078)
NDVI index	0.378**	0.350**	0.423**	0.373**
	(0.126)	(0.128)	(0.131)	(0.133)
Elevation	0.000*	0.000*	0.000*	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Soil texture index	-0.002	-0.003	0.004	0.002
	(0.015)	(0.015)	(0.016)	(0.016)
Soil pH	0.013	0.002	0.019	0.007
	(0.015)	(0.015)	(0.016)	(0.016)
Green vote (%)	0.002	0.003	0.006*	0.007**
	(0.002)	(0.002)	(0.002)	(0.002)
Conservation land (%)	-0.001*	-0.002*	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Distance to cities	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
SEIFA index	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Taxable income	0.000*	0.000	0.000**	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Population numbers)	-0.000**	-0.000**	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Year (base=2011)	0.009	0.008	-0.014	-0.013
	(0.016)	(0.021)	(0.017)	(0.022)
NSW (base=QLD)	0.064*	0.054	0.051	0.036
	(0.029)	(0.040)	(0.032)	(0.042)

NT	-0.007	0.023	0.008	0.044
	(0.076)	(0.117)	(0.088)	(0.127)
SA	0.157**	0.098	0.175**	0.121
	(0.056)	(0.075)	(0.059)	(0.080)
TAS	-0.080*	-0.136**	-0.106**	-0.151**
	(0.036)	(0.049)	(0.039)	(0.052)
VIC	0.137***	0.058	0.109**	0.056
	(0.036)	(0.062)	(0.038)	(0.066)
WA	0.053	-0.039	0.028	-0.055
	(0.056)	(0.066)	(0.059)	(0.070)
W_Farm size		0.023		0.003
		(0.020)		(0.021)
W_Irrigated business		-0.002		-0.002
		(0.001)		(0.001)
W_Livestock density		0.077		0.065
		(0.043)		(0.045)
W_Agricultural labour		0.013		0.029
		(0.016)		(0.016)
W_Crop		-0.004		-0.004*
		(0.002)		(0.002)
W_Grazing		-0.005**		-0.004*
		(0.002)		(0.002)
W_Horticulture		-0.004		-0.002
		(0.004)		(0.004)
W_Severe drought		0.536		0.315
		(0.363)		(0.376)
W_Conservation land		0.001		0.002
		(0.002)		(0.002)
W_Taxable income		0.000		0.000
		(0.000)		(0.000)
Left-censored	1,148		1,148	
Right-censored	1		1	
Uncensored	605		605	
Log likelihood	-2,511.907	-2,494.967	-2,491.857	-2,477.427
Wald Chi2	184.51***	200.18***	182.01***	192.853***
AIC	5,081.815	5,067.933	5,041.713	5,032.853
BIC	5,240.435	5,281.250	5,200.333	5,246.170

Notes: The outcome variable is the share of organic area in total area of agricultural holding in *Model I* and share of organic farm business in total agricultural business in *Model II*. Variables name started with W indicates explanatory variables with spatial lag. Asterisks *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively. Figures in the parenthesis indicates standard errors. dy/dx for factor levels is the discrete change from the base level.

Table B.11 Marginal effects of the tobit random-effects balanced panel models to explain the spatial diffusion of certified organic farming in Australia with randomly generated organic business, 2010/11–2015/16 (N=1,898)

	Model I		***Model II***		***Model III***	
	tobit	***SLX tobit***	***tobit***	***SLX tobit***	***tobit***	***SLX tobit***
Farm size	0.030***	0.022**	0.038***	0.033***	0.038***	0.033***
	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)
Irrigated business (%)	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Livestock density	-0.019	-0.028*	-0.019	-0.029*	-0.018	-0.028*
	(0.012)	(0.013)	(0.012)	(0.013)	(0.012)	(0.013)
Agricultural labour (%)	0.014***	0.011***	0.015***	0.013***	0.016***	0.013***
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
Crop (%)	-0.000	0.000	-0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Grazing (%)	0.000	0.001	0.001	0.001	0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Horticulture (%)	0.000	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Aridity index	0.040	0.054	0.049	0.061	0.051	0.063
	(0.035)	(0.037)	(0.036)	(0.038)	(0.036)	(0.038)
Severe drought dummy	0.028	0.001	0.008	-0.025	0.007	-0.021
	(0.087)	(0.087)	(0.091)	(0.091)	(0.091)	(0.092)
NDVI index	0.470***	0.432**	0.491***	0.458***	0.492***	0.466***
	(0.131)	(0.134)	(0.131)	(0.134)	(0.131)	(0.134)
Elevation	0.000*	0.000	0.000*	0.000	0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Soil texture index	0.009	0.006	0.009	0.008	0.008	0.007
	(0.016)	(0.016)	(0.015)	(0.015)	(0.015)	(0.015)
Soil pH	0.023	0.013	0.025	0.015	0.024	0.014
	(0.016)	(0.016)	(0.015)	(0.016)	(0.015)	(0.016)
Green vote (%)	0.006**	0.006**	0.007**	0.007**	0.007**	0.007**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Conservation land (%)	-0.000	-0.001	-0.000	-0.000	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Distance to cities	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SEIFA index	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Taxable income	0.000**	0.000*	0.000*	0.000*	0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Population (numbers)	-0.000	-0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year (base=2011)	0.033	0.031	0.056**	0.049*	0.059**	0.050*
	(0.017)	(0.022)	(0.018)	(0.023)	(0.018)	(0.023)
NSW (QLD)	0.044	0.020	0.036	-0.006	0.039	-0.000

	(0.031)	(0.040)	(0.031)	(0.040)	(0.031)	(0.040)
NT	0.058	0.050	0.078	0.092	0.073	0.090
	(0.089)	(0.120)	(0.091)	(0.126)	(0.090)	(0.125)
SA	0.171**	0.122	0.162**	0.105	0.165**	0.100
	(0.058)	(0.080)	(0.057)	(0.079)	(0.057)	(0.079)
TAS	-0.101*	-0.147**	-0.103*	-0.157**	-0.100*	-0.148**
	(0.040)	(0.054)	(0.040)	(0.056)	(0.041)	(0.057)
VIC	0.100**	0.045	0.097**	0.025	0.102**	0.031
	(0.036)	(0.064)	(0.036)	(0.064)	(0.036)	(0.064)
WA	0.039	-0.009	0.041	0.002	0.040	-0.000
	(0.059)	(0.077)	(0.058)	(0.080)	(0.058)	(0.079)
W_Farm size		0.005		-0.010		-0.008
		(0.018)		(0.019)		(0.019)
W_Irrigated business		-0.002		-0.003		-0.002
		(0.001)		(0.001)		(0.001)
W_Livestock density		0.072		0.081		0.075
		(0.047)		(0.047)		(0.047)
W_Agricultural labour		0.024		0.023		0.023
		(0.015)		(0.015)		(0.015)
W_Crop		-0.004		-0.003		-0.003
		(0.002)		(0.002)		(0.002)
W_Grazing		-0.003		-0.001		-0.001
		(0.002)		(0.002)		(0.002)
W_Horticulture		0.004		0.006		0.006
		(0.004)		(0.004)		(0.004)
W_Severe drought		0.465		0.553		0.450
		(0.364)		(0.372)		(0.375)
W_Conservation land		0.001		0.001		0.000
		(0.002)		(0.002)		(0.002)
W_Taxable income		-0.000		-0.000		-0.000
		(0.000)		(0.000)		(0.000)
Left-censored	1,220					
Right-censored	1					
Uncensored	677					
Log likelihood	-2,721.487	-2,822.204	-2,768.012	-2,929.472	-2,798.405	-2,939.663
Wald Chi2	167.05***	180.22***	165.98***	183.05***	162.12***	182.69***
AIC	5,724.527	5,722.408	5,939.098	5,936.943	5,958.107	5,957.326
BIC	5,885.435	5,938.802	6,100.006	6,153.337	6,119.015	6,173.720

Notes: The outcome variable is the share of organic farm business in total agricultural business. Model I generates random numbers within the default range (0 to 1), in Model II the range is (1 to 2) and in model III the range is within (1.12 to 2.42) based on the observations from 2010/11 and 2015/16. Variables name started with W indicates explanatory variables with spatial lag. Asterisks *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively. Figures in the parenthesis indicates standard errors. dy/dx for factor levels is the discrete change from the base level.

Table B.12 Robustness check of the marginal effects of the tobit random-effects unbalanced panel models to explain the spatial diffusion of certified organic farming in Australia, 2010/11 – 2015/16 (N = 2,098[43])

	Share of organic area (Model I)		***Share of organic farm (model II)***	
	tobit	***SLX tobit***	***tobit***	***SLX tobit***
Farm size	0.031***	0.028***	0.028***	0.024***
	(0.006)	(0.006)	(0.006)	(0.006)
Irrigated business (%)	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Livestock density	-0.017	-0.021*	-0.018*	-0.021*
	(0.009)	(0.009)	(0.009)	(0.009)
Agricultural labour (%)	0.009***	0.007***	0.009***	0.007**
	(0.002)	(0.002)	(0.002)	(0.002)
Crop (%)	0.000	0.000	0.000	0.001
	(0.000)	(0.000)	(0.000)	(0.000)
Grazing (%)	0.001*	0.001	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Horticulture (%)	0.001	0.002**	0.001	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
Aridity index	0.023	0.019	0.040	0.036
	(0.026)	(0.027)	(0.024)	(0.024)
Severe drought dummy	0.039	0.028	0.058	0.048
	(0.064)	(0.066)	(0.060)	(0.060)
NDVI index	0.481***	0.362***	0.492***	0.380***
	(0.101)	(0.103)	(0.102)	(0.101)
Elevation	0.000**	0.000**	0.000**	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Soil texture index	0.004	0.005	0.014	0.014
	(0.013)	(0.013)	(0.013)	(0.013)
Soil pH	0.037**	0.032*	0.035**	0.029*
	(0.013)	(0.013)	(0.013)	(0.013)
Green vote (%)	0.004**	0.005**	0.004*	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
Conservation land (%)	-0.000	-0.001*	-0.000	-0.001*
	(0.000)	(0.000)	(0.000)	(0.000)
Distance to cities	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
SEIFA index	-0.000	0.000	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Taxable income	0.000**	0.000*	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Population (numbers)	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Year (base=2011)	0.013	0.040*	0.009	0.043**

[43] Inverse distance matrix with a cut-off of 335km and 273km in 2010/11 and 2015/16 drops 36 SA2s that have no neighbours within the specified threshold distance.

	(0.013)	(0.017)	(0.012)	(0.016)
NSW (base=QLD)	0.030	0.026	0.038	0.036
	(0.025)	(0.026)	(0.025)	(0.025)
NT	0.121	0.155	0.117	0.125
	(0.087)	(0.102)	(0.087)	(0.094)
SA	0.084	0.160**	0.127**	0.211***
	(0.046)	(0.058)	(0.048)	(0.059)
TAS	-0.085**	-0.073*	-0.081**	-0.068*
	(0.029)	(0.033)	(0.029)	(0.032)
VIC	0.110***	0.164***	0.124***	0.188***
	(0.031)	(0.045)	(0.031)	(0.043)
WA	0.038	0.088	0.076	0.131*
	(0.049)	(0.059)	(0.053)	(0.061)
W_Farm size		-0.032**		-0.029**
		(0.011)		(0.011)
W_Irrigated business		-0.000		0.000
		(0.001)		(0.001)
W_Livestock density		-0.012		-0.027
		(0.030)		(0.029)
W_Agricultural labour		0.025**		0.025***
		(0.008)		(0.007)
W_Crop		-0.001		-0.002
		(0.001)		(0.001)
W_Grazing		0.001		0.000
		(0.001)		(0.001)
W_Horticulture		-0.008**		-0.010***
		(0.002)		(0.002)
W_Severe drought		-0.040		0.023
		(0.310)		(0.281)
W_Conservation land		0.002*		0.002*
		(0.001)		(0.001)
W_Taxable income		-0.000*		-0.000
		(0.000)		(0.000)
Left-censored	1,499		1,499	
Right-censored	3		4	
Uncensored	596		595	
Log likelihood	-2,596.905	-2,581.184	-2,642.668	-2,623.562
Wald Chi2	205.64***	215.57***	217.77***	233.18***
AIC	5,251.809	5,240.369	5,343.336	5,325.125
BIC	5,415.623	5,460.670	5,507.150	5,545.426

Notes: The outcome variable is the share of organic area in total area of agricultural holding in *Model I* and share of organic farm business in total agricultural business in *Model II*. Variables name started with W indicates explanatory variables with spatial lag. Asterisks *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively. Figures in the parenthesis indicates standard errors. dy/dx for factor levels is the discrete change from the base level.

Table B.13 Robustness check of the marginal effects of the tobit random-effects balanced panel models to explain the spatial diffusion of certified organic farming in Australia, 2010/11 – 2015/16 (N = 1,734[44])

	Share of organic area (Model I)		***Share of organic farm (Model II)***	
	tobit	***SLX tobit***	***tobit***	***SLX tobit***
Farm size	0.026***	0.016	0.026***	0.018*
	(0.008)	(0.008)	(0.008)	(0.009)
Irrigated business (%)	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Livestock density	-0.023*	-0.030*	-0.016	-0.020
	(0.011)	(0.012)	(0.012)	(0.012)
Agricultural labour (%)	0.012***	0.009***	0.013***	0.010***
	(0.002)	(0.003)	(0.003)	(0.003)
Crop (%)	-0.000	0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Grazing (%)	0.000	0.001	0.000	0.001
	(0.000)	(0.000)	(0.000)	(0.000)
Horticulture (%)	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Aridity index	0.035	0.013	0.045	0.031
	(0.034)	(0.036)	(0.034)	(0.037)
Severe drought dummy	0.069	0.053	0.082	0.085
	(0.083)	(0.086)	(0.086)	(0.089)
NDVI index	0.377**	0.343**	0.461***	0.421**
	(0.129)	(0.131)	(0.133)	(0.136)
Elevation	0.000**	0.000*	0.000*	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Soil texture index	0.003	-0.001	0.008	0.005
	(0.016)	(0.016)	(0.016)	(0.016)
Soil pH	0.015	0.003	0.021	0.010
	(0.015)	(0.016)	(0.016)	(0.016)
Green vote (%)	0.004	0.006*	0.006**	0.007**
	(0.002)	(0.002)	(0.002)	(0.002)
Conservation land (%)	-0.001	-0.001*	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Distance to cities	0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
SEIFA index	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Taxable income	0.000*	0.000*	0.000**	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Population (numbers)	-0.000**	-0.000**	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Year (base=2011)	0.001	-0.030	-0.012	-0.030

[44] Inverse distance matrix with a cut-off of 304 km in 2010/11 and 2015/16 drops 20 SA2s that have no neighbours within the specified threshold distance.

	(0.016)	(0.020)	(0.017)	(0.021)
NSW (base=QLD)	0.061*	0.027	0.055	0.032
	(0.030)	(0.036)	(0.032)	(0.037)
NT	-0.011	-0.005	0.013	0.012
	(0.077)	(0.099)	(0.090)	(0.107)
SA	0.152**	0.096	0.183**	0.134
	(0.057)	(0.072)	(0.060)	(0.076)
TAS	-0.085*	-0.085	-0.101**	-0.105*
	(0.036)	(0.054)	(0.039)	(0.053)
VIC	0.138***	0.079	0.116**	0.084
	(0.037)	(0.055)	(0.038)	(0.057)
WA	0.051	-0.049	0.058	-0.032
	(0.059)	(0.064)	(0.063)	(0.069)
W_Farm size		-0.000		-0.003
		(0.017)		(0.017)
W_Irrigated business		-0.004**		-0.002
		(0.001)		(0.001)
W_Livestock density		0.039		0.024
		(0.032)		(0.034)
W_Agricultural labour		0.013		0.017
		(0.010)		(0.011)
W_Crop		-0.002		-0.003
		(0.002)		(0.002)
W_Grazing		-0.002		-0.002
		(0.001)		(0.001)
W_Horticulture		0.006*		0.003
		(0.003)		(0.003)
W_Severe drought		-0.357		-0.434
		(0.414)		(0.423)
W_Conservation land		0.002		0.002
		(0.002)		(0.002)
W_Taxable income		-0.000		0.000
		(0.000)		(0.000)
Left-censored	1,136		1,136	
Right-censored	1		1	
Uncensored	597		597	
Log likelihood	-2,456.069	-2,439.113	2,460.846	-2,449.142
Wald Chi2	169.78***	190.57***	178.87***	190.69***
AIC	4,970.138	4,956.227	4,979.693	4,976.284
BIC	5,128.426	5,169.096	5,137.980	5,189.153

Notes: The outcome variable is the share of organic area in total area of agricultural holding in *Model I* and share of organic farm business in total agricultural business in *Model II*. Variables name started with W indicates explanatory variables with spatial lag. Asterisks *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively. Figures in the parenthesis indicates standard errors. dy/dx for factor levels is the discrete change from the base level.

Table B.14 Robustness check (SA2s without rangeland) of the marginal effects of the tobit random-effects unbalanced panel models to explain the spatial diffusion of certified organic farming in Australia, 2010/11 – 2015/16 (N = 1,962[45])

	Share of organic area (Model I)		*Share of organic farm (model II)*	
	tobit	***SLX tobit***	***tobit***	***SLX tobit***
Farm size	0.022***	0.013	0.020**	0.010
	(0.007)	(0.007)	(0.007)	(0.007)
Irrigated business	0.001***	0.001***	0.001**	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Livestock density	-0.016	-0.019*	-0.017	-0.019*
	(0.009)	(0.009)	(0.009)	(0.009)
Agricultural labour	0.011***	0.009***	0.010***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)
Crop	0.001	0.001	0.000	0.001
	(0.000)	(0.000)	(0.000)	(0.000)
Grazing	0.001**	0.001**	0.001	0.001*
	(0.000)	(0.000)	(0.000)	(0.000)
Horticulture	0.001	0.002**	0.001	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
Aridity index	0.030	0.026	0.043	0.050
	(0.026)	(0.029)	(0.025)	(0.027)
Severe drought	-0.040	-0.017	-0.046	-0.022
	(0.089)	(0.091)	(0.085)	(0.083)
NDVI	0.581***	0.519***	0.602***	0.537***
	(0.109)	(0.113)	(0.110)	(0.112)
Elevation	0.000*	0.000*	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Soil texture	-0.004	-0.008	0.012	0.007
	(0.014)	(0.014)	(0.014)	(0.015)
Soil pH	0.029*	0.017	0.026	0.015
	(0.013)	(0.014)	(0.014)	(0.014)
Green vote	0.004*	0.005*	0.004*	0.004*
	(0.002)	(0.002)	(0.002)	(0.002)
Conservation land	-0.001	-0.001*	-0.001	-0.001*
	(0.000)	(0.001)	(0.000)	(0.000)
Distance to cities	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
SEIFA	-0.000	-0.000	-0.000**	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Taxable income	0.000**	0.000*	0.000**	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Population	-0.000***	-0.000**	-0.000***	-0.000***

[45] 172 SA2s that were located in the rangeland were dropped from the sample.

	(0.000)	(0.000)	(0.000)	(0.000)
Year (base=2011)	0.017	0.034	0.011	0.041
	(0.013)	(0.024)	(0.013)	(0.022)
NSW (base=QLD)	0.015	0.014	0.030	0.034
	(0.026)	(0.034)	(0.027)	(0.033)
SA	0.070	0.097	0.134*	0.148
	(0.049)	(0.075)	(0.053)	(0.077)
TAS	-0.077**	-0.072	-0.068*	-0.061
	(0.030)	(0.042)	(0.030)	(0.040)
VIC	0.104**	0.102	0.122***	0.125*
	(0.032)	(0.059)	(0.032)	(0.057)
WA	0.052	0.062	0.103	0.111
	(0.054)	(0.074)	(0.059)	(0.077)
W_Farm size		0.017		0.013
		(0.022)		(0.021)
W_Irrigated business		-0.001		0.000
		(0.001)		(0.001)
W_Livestock density		-0.019		-0.052
		(0.044)		(0.044)
W_Agricultural labour		0.024		0.018
		(0.015)		(0.015)
W_Crop		-0.003		-0.003*
		(0.002)		(0.002)
W_Grazing		-0.001		-0.002
		(0.001)		(0.001)
W_Horticulture		-0.011**		-0.017***
		(0.004)		(0.004)
W_Severe drought		0.201		0.391
		(0.403)		(0.366)
W_Conservation land		0.001		0.000
		(0.002)		(0.002)
W_Taxable income		0.000		0.000
		(0.000)		(0.000)
Left-censored	1,432		1,432	
Right-censored	2		3	
Uncensored	528		527	
Log likelihood	-2,280.926	-2,269.192	-2,341.673	-2,324.945
Wald Chi2	175.68***	178.55***	192.70***	203.35***
AIC	4,617.851	4,614.384	4,739.346	4,725.89
BIC	4,774.139	4,826.489	4,895.634	4,937.995

Notes: The outcome variable is the share of organic area in total area of agricultural holding in *Model I* and share of organic farm business in total agricultural business in *Model II*. Variables name started with W indicates explanatory variables with spatial lag. Asterisks *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively. Figures in the parenthesis indicates standard errors. dy/dx for factor levels is the discrete change from the base level.

Table B.15 **Robustness check (SA2s without rangeland) of the marginal effects of the tobit random-effects balanced panel models to explain the spatial diffusion of certified organic farming in Australia, 2010/11 – 2015/16 (N = 1,600[46])**

	Share of organic area (Model I)		*Share of organic farm (model II)*	
	tobit	***SLX tobit***	***tobit***	***SLX tobit***
Farm size	0.019*	0.007	0.021*	0.011
	(0.009)	(0.009)	(0.009)	(0.010)
Irrigated business	0.001***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Livestock density	-0.021	-0.031*	-0.015	-0.021
	(0.011)	(0.012)	(0.012)	(0.012)
Agricultural labour	0.013***	0.011***	0.013***	0.011***
	(0.003)	(0.003)	(0.003)	(0.003)
Crop	0.000	0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Grazing	0.000	0.001	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Horticulture	0.000	0.001	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Aridity index	0.030	0.032	0.039	0.059
	(0.033)	(0.038)	(0.034)	(0.039)
Severe drought	-0.048	-0.002	-0.077	-0.022
	(0.113)	(0.116)	(0.118)	(0.120)
NDVI	0.486***	0.377**	0.543***	0.432**
	(0.137)	(0.142)	(0.142)	(0.148)
Elevation	0.000*	0.000*	0.000*	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Soil texture	-0.001	-0.006	0.012	0.007
	(0.017)	(0.017)	(0.018)	(0.018)
Soil pH	0.018	0.004	0.021	0.011
	(0.016)	(0.017)	(0.017)	(0.018)
Green vote	0.005*	0.006**	0.006**	0.007**
	(0.002)	(0.002)	(0.002)	(0.003)
Conservation land	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Distance to cities	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
SEIFA	-0.000	-0.000	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Taxable income	0.000*	0.000*	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Population	-0.000**	-0.000**	-0.000**	-0.000*

[46] 154 SA2s that were located in the rangeland were dropped from the sample.

	(0.000)	(0.000)	(0.000)	(0.000)
Year (base=2011)	-0.001	0.011	-0.016	0.011
	(0.017)	(0.026)	(0.018)	(0.027)
NSW (base=QLD)	0.037	0.035	0.044	0.064
	(0.032)	(0.045)	(0.034)	(0.046)
SA	0.133*	0.135	0.193**	0.189
	(0.063)	(0.102)	(0.066)	(0.104)
TAS	-0.089*	-0.111*	-0.094*	-0.103
	(0.036)	(0.053)	(0.039)	(0.053)
VIC	0.127***	0.090	0.113**	0.111
	(0.038)	(0.074)	(0.039)	(0.074)
WA	0.053	0.005	0.079	0.042
	(0.064)	(0.088)	(0.069)	(0.093)
W_Farm size		0.037		0.029
		(0.036)		(0.037)
W_Irrigated business		-0.001		0.001
		(0.002)		(0.002)
W_Livestock density		0.067		0.034
		(0.050)		(0.052)
W_Agricultural labour		0.026		0.031
		(0.020)		(0.020)
W_Crop		-0.004		-0.005*
		(0.002)		(0.002)
W_Grazing		-0.004*		-0.004*
		(0.002)		(0.002)
W_Horticulture		-0.005		-0.007
		(0.005)		(0.005)
W_Severe drought		-0.065		-0.134
		(0.540)		(0.547)
W_Conservation land		0.001		0.001
		(0.002)		(0.002)
W_Taxable income		-0.000		-0.000
		(0.000)		(0.000)
Left-censored	1,072		1,072	
Right-censored	1		1	
Uncensored	527		527	
Log likelihood	-2,177.281	-2,166.749	-2,199.615	-2,191.621
Wald Chi2	150.06***	158.34***	163.50***	167.00***
AIC	4,410.562	4,409.497	4,455.231	4,459.242
BIC	4,561.139	4,613.852	4,605.808	4,663.597

Notes: The outcome variable is the share of organic area in total area of agricultural holding in *Model I* and share of organic farm business in total agricultural business in *Model II*. Variables name started with W indicates explanatory variables with spatial lag. Asterisks *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively. Figures in the parenthesis indicates standard errors. dy/dx for factor levels is the discrete change from the base level.

Table B.16 Robustness check (quadratic term for soil pH level) of the marginal effects of the tobit random-effects unbalanced panel models to explain the spatial diffusion of certified organic farming in Australia, 2010/11 – 2015/16 (N = 2,134)

	Share of organic area (Model I)		*Share of organic farm (model II)*	
	tobit	***SLX tobit***	***tobit***	***SLX tobit***
Farm size	0.032***	0.026***	0.026***	0.019**
	(0.006)	(0.006)	(0.006)	(0.006)
Irrigated business	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Livestock density	-0.016	-0.021*	-0.015	-0.020*
	(0.009)	(0.010)	(0.009)	(0.009)
Agricultural labour	0.010***	0.008***	0.010***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)
Crop	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Grazing	0.001*	0.001*	0.000	0.001
	(0.000)	(0.000)	(0.000)	(0.000)
Horticulture	0.001*	0.002**	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Aridity index	0.032	0.035	0.036	0.034
	(0.026)	(0.027)	(0.024)	(0.025)
Severe drought	0.189***	0.183**	0.044	0.045
	(0.057)	(0.056)	(0.055)	(0.052)
NDVI	0.489***	0.423***	0.479***	0.409***
	(0.100)	(0.103)	(0.101)	(0.102)
Elevation	0.000**	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Soil texture	-0.001	-0.002	0.008	0.008
	(0.013)	(0.013)	(0.013)	(0.013)
Soil pH	**-0.093**	**-0.085**	**-0.106**	**-0.098**
	(0.089)	**(0.090)**	**(0.093)**	**(0.095)**
Soil pH square	**0.011**	**0.010**	**0.012**	**0.011**
	(0.008)	**(0.008)**	**(0.008)**	**(0.008)**
Green vote	0.003	0.003	0.004*	0.004*
	(0.002)	(0.002)	(0.002)	(0.002)
Conservation land	-0.001*	-0.001**	-0.001	-0.001*
	(0.000)	(0.000)	(0.000)	(0.000)
Distance to cities	-0.000	-0.000	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
SEIFA	-0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Taxable income	0.000*	0.000	0.000**	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Population	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Year (base=2011)	0.020	0.052**	0.008	0.035*
	(0.013)	(0.018)	(0.012)	(0.017)

NSW (base=QLD)	0.032	0.022	0.033	0.013
	(0.025)	(0.030)	(0.026)	(0.032)
NT	0.110	0.156	0.106	0.142
	(0.082)	(0.108)	(0.084)	(0.106)
SA	0.071	0.091	0.096*	0.104
	(0.044)	(0.060)	(0.047)	(0.063)
TAS	-0.078**	-0.103**	-0.081**	-0.116**
	(0.030)	(0.036)	(0.031)	(0.037)
VIC	0.103***	0.101	0.111***	0.091
	(0.031)	(0.052)	(0.032)	(0.052)
WA	0.044	0.042	0.054	0.043
	(0.048)	(0.058)	(0.050)	(0.061)
W_Farm size		-0.017		-0.022
		(0.014)		(0.014)
W_Irrigated business		-0.000		-0.000
		(0.001)		(0.001)
W_Livestock density		0.026		0.023
		(0.039)		(0.039)
W_Agricultural labour		0.023		0.029*
		(0.012)		(0.012)
W_Crop		-0.002		-0.003*
		(0.002)		(0.001)
W_Grazing		-0.002		-0.001
		(0.001)		(0.001)
W_Horticulture		-0.008**		-0.009**
		(0.003)		(0.003)
W_Severe drought		0.550		0.583*
		(0.282)		(0.263)
W_Conservation land		0.002		0.003*
		(0.001)		(0.001)
W_Taxable income		-0.000		0.000
		(0.000)		(0.000)
Left-censored	1,525		1,525	
Right-censored	3		4	
Uncensored	606		605	
Log likelihood	-2,661.196	-2,648.692	-2,684.661	-2,669.380
Wald Chi2	214.13***	219.50***	218.59***	228.40***
AIC	5,382.392	5,377.384	5,429.321	5,418.761
BIC	5,552.364	5,604.015	5,599.294	5,645.391

Notes: The outcome variable is the share of organic area in total area of agricultural holding in *Model I* and share of organic farm business in total agricultural business in *Model II*. Variables name started with W indicates explanatory variables with spatial lag. Asterisks *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively. Figures in the parenthesis indicates standard errors. dy/dx for factor levels is the discrete change from the base level.

Appendix C Supplementary materials for Chapter 3

Table C.1 Overview of literature: Effects of organic agriculture (OA), environmental heterogeneity (habitat, climate, productivity, and topography), and urbanisation on plant (PSR) and bird species richness (BSR)

Variables	*Literature findings*	*Selected sources*
Organic (OA)and conventional agriculture (CA)	Higher PSR and BSR on organic fields or farms than their conventional counterparts, irrespective of land use types (cropland or grassland)	(Batáry et al. 2010)
	Higher PSR (>20%) on organic farms and the effects are immediate after transition from conventional farming and the speed of response doesn't vary with landscape complexity	(Jonason et al. 2011)
	Higher BSR on perennial organic apple farming and organic vineyards	(Katayama 2016; Rollan et al. 2019)
	Higher PSR on organic rice fields and organic vineyards	(Katayama et al. 2019; Puig-Montserrat et al. 2017)
	Higher PSR on organic fields (local scale) and at landscape scale. Higher proportion of organic land at landscape level also has positive spill-overs effects on adjoining conventional field margins	(Rundlöf et al. 2010)
	30% higher overall species richness	(Bengtsson et al. 2005; Tuck et al. 2014)
	10.5% higher overall species richness	(Schneider et al. 2014)
	Species richness are (median value) 95% higher for plants, and 35% higher for birds on OA compared to CA	(Stein-Bachinger et al. 2020)
	Higher species richness in intensive agricultural landscapes with higher percentages of arable fields	(Schneider et al. 2014; Tuck et al. 2014)
	Effects of OA vary among taxa and organism groups	(Bengtsson et al. 2005; Fuller et al. 2005; Hole et al. 2005)
	Effects of OA vary among spatial scale (plot; field; farm; landscape)	(Gabriel et al. 2006; Gabriel et al. 2010)
	Effects are more prominent at plot/field level and start to decrease at farm and landscape/regional scales	. (Schneider et al. 2014)
	Biodiversity impact (increased PSR and BSR) of OA influenced by farm size: 50% more species were found in small rather than large organic farms	(Belfrage et al. 2005)
	Biodiversity benefits of AEM schemes are higher in simple landscape (low proportion of semi-natural habitats) compared to complex landscapes (higher proportion of semi natural habitats; >20%)	(Batáry et al. 2011; Hiron et al. 2013)
	Effects of hedge length is more pronounced than organic field management in increasing BSR, but the effect of hedge length is only significant in simple landscapes	(Batáry et al. 2010)
	Species richness is higher in complex/heterogeneous landscapes, even without organic farming or hedge management	(Batáry et al. 2010; Benton et al. 2003; Fahrig et al. 2011; Fischer et al. 2011; Tscharntke et al. 2005; Weibull et al. 2003)
	OA has significant biodiversity benefits in simple/homogeneous landscapes	(Batáry et al. 2010; Dänhardt et al. 2010)
	OA has positive effects on PSR and BSR in all types of landscape, but the effects start to decrease with	(Winqvist et al. 2011)

	more extensive simplification of landscape in terms of increased arable land: increase in arable land from 20% to 100% reduces PSR and BSR by 16 and 34%, respectively	
	OA is beneficial for farmland BSR in a heterogeneous landscape	(Goded et al. 2018)
	Mixed effect of OA on BSR (increased species only in summer, not in winter)	(Fischer et al. 2011)
	No significant effects of OA on BSR	(Hiron et al. 2013; Puig-Montserrat et al. 2017)
	More birds were found on conventional farms, despite higher availability of food resources on organic farms	(Gabriel et al. 2010)
	Landscape features, such as proportion of semi-natural habitats, arable land, grassland, hedge length, and field margin, appear to be more beneficial for BSR compared to farm management	(Chamberlain et al. 2010; Piha et al. 2007)
	Effects of OA are higher and consistent for PSR than any other taxa	(Bengtsson et al. 2005; Fuller et al. 2005; Tuck et al. 2014)
	No significant difference, in terms of PSR, was found between organic and conventional farms in semi-natural areas, despite OA having more semi-natural habitats, whereas OA increases plant richness in arable fields in complex landscapes	(Gibson et al. 2007)
	PSR doesn't differ significantly between organic and conventional farming systems	(Goded et al. 2019; Weibull et al. 2003)
	Positive effects of OA on bird abundance depends on agricultural land use intensification at a regional scale and the effect deceases with decreasing agricultural intensification	(Kirk et al. 2020)
Habitat diversity	Human* land cover (%) has positive effects on BSR	(Koh et al. 2006; Zhang et al. 2013)
	Woody plant species richness is positively correlated with BSR	(Kissling et al. 2008; Liang et al. 2018; Zhang et al. 2013)
	Land cover (numbers) has negative effects on PSR	(Xu et al. 2016)
	Landscape heterogeneity** positively influence BSR	(Hawkins et al. 2005; Heikkinen et al. 2004; Luck et al. 2010; McKinney and Kark 2017; Redlich et al. 2018)
	Vegetation cover (numbers) positively correlates with PSR and BSR	BSR (Jetz and Rahbek 2002; Kreft and Jetz 2007)
	Diminishing marginal effects of native vegetation cover (%) on BSR	(Cunningham et al. 2014)
Elevation	PSR and BSR positively associated with increased average elevation and elevation range	(Lee et al. 2004; Xu et al. 2015; Xu et al. 2016)
Temperature	Mean annual temperature has positive effects on BSR	(Diniz-Filho and Bini 2005; Katayama et al. 2019; Zhang et al. 2013)
	Mean annual temperature has negative effects on PSR	(Sommer et al. 2010)
	Maximum temperature of the warmest month is positively correlated with PSR	(Xu et al. 2016)
	Minimum temperature of the coldest month has positive effects on PSR	(Tripathi et al. 2019)
	Annual minimum temperature has negative effects on BSR	(Diniz-Filho and Bini 2005; McKinney and Kark 2017)
Rainfall	Mean precipitation of the driest month is positively correlated with PSR	(Tripathi et al. 2019)
	Mean precipitation of the driest quarter has positive effects on tree species richness	(Kwon et al. 2018)

	Precipitation seasonality is negatively correlated with tree species richness	(Kwon et al. 2018)
	Number of wet days/mean annual precipitation is positively correlated with PSR	(Katayama et al. 2019; Kreft and Jetz 2007)
Actual/potential evapotranspiration (AET/PET)	AET positively is correlated with BSR	(Coops et al. 2018; Diniz-Filho and Bini 2005; Hawkins et al. 2005; Symonds and Johnson 2008)
	PET has positive effects on PSR	(Kreft and Jetz 2007)
Net/gross primary productivity (NPP/GPP)	NPP/GPP has positive effects on PSR and BSR	(Coops et al. 2018; Jetz and Rahbek 2002; Luck et al. 2010; Xu et al. 2016)
Normalised difference vegetation index (NDVI)	Positively correlated with PSR and BSR	(Hawkins et al. 2005; Koh et al. 2006; Lee et al. 2004; McKinney and Kark 2017; Parviainen et al. 2010)
Urbanisation	Human footprint*** has positive effects on BSR	(Luck et al. 2010; McKinney and Kark 2017)
	Urbanisation**** has negative effects on BSR and diversity of forest trees	(Lee et al. 2004; Polyakov et al. 2008)
	population density is inversely correlated with BSR	(Koh et al. 2006)
Conservation land	Positive correlation exists between proportion of conservation land and BSR (Luck et al. 2010)	(Luck et al. 2010)
Area (size of the geographic unit)	Forest area is positively correlated with tree species richness	(Kwon et al. 2018)
	Area is a positive predictor of PSR	(Kreft and Jetz 2007; Sommer et al. 2010)

*Land cover types includes percentage of agricultural, forest harvesting, urban, roads and industrial areas
**Measured by the Shannon diversity index of proportional cover of perennial non-crop habitat
***The index includes population density, land use, infrastructure, and access to roads
****Road density and built area (%) was used as proxies to indicate urbanisation

Table C.2 Dynamic land cover classes

Common Name	***ISO Class Descriptor***
No Data	No Data
Mines and Quarries	Extraction Sites
Urban areas	Urban Areas
Lakes and dams	Inland Waterbodies
Salt lakes	Salt Lakes
Irrigated cropping	Irrigated Cropping
Rain fed cropping	Rain fed Cropping
Irrigated pasture	Irrigated Pasture
Rain fed pasture	Rain fed Pasture
Irrigated sugar	Irrigated Sugar
Rain fed sugar	Rain fed Sugar
Wetlands	Wetlands
Alpine meadows	Alpine Grasses - Open
Open Hummock Grassland	Hummock Grasses - Open
Closed Tussock Grassland	Tussock Grasses - Closed
Open Tussock Grassland	Tussock Grasses - Open
Scattered shrubs and grasses	Shrub sand Grasses- Sparse Scattered
Dense Shrub land	Shrubs - Closed
Open Shrub land	Shrubs - Open
Closed Forest	Trees - Closed
Open Forest	Trees - Open
Woodland	Trees - Sparse
Open Woodland	Trees - Scattered

Source: (Lymburner et al. 2015)

Table C.3 Collinearity check among the explanatory variables for empirical models of vascular plant and bird species richness using variance inflation factor (VIF)

Variables	***Label***	***Vascular plant species richness***		***Bird species richness***	
		N=5,440	***N=4,768***	***N=5,440***	***N=4,768***
Average vascular plant species richness in natural logarithm (numbers)	VPSR	-	-	1.94	1.88
Organic farming business (numbers)	OFB	1.37	1.34	1.38	1.35
Agricultural land parcels (numbers)	ALP	1.69	1.58	1.86	1.75
Annual average actual evapotranspiration (mm)	AET	2.39	2.53	2.39	2.54
Land cover diversity index	LCDI	2.03	1.81	2.05	1.82
Normalised difference vegetation index	NDVI	3.1	3.11	3.12	3.12
Conservation land (%)	ConL	1.83	1.82	1.86	1.85
Water bodies (%)	WB	1.26	1.24	1.28	1.26
Crop land (%)	CL	3.37	3.25	3.37	3.26
Grazing land (%)	GL	3.68	3.2	3.68	3.21
Horticultural land (%)	HL	1.36	1.37	1.36	1.38
Elevation range (m)	ER	2.43	2.26	2.58	2.43
Soil diversity index	SDI	1.79	1.88	1.81	1.93
Urban accessibility index in natural logarithm	UAI	3.21	2.95	3.21	2.95
Distance to road (km)	DR	2.47	1.33	2.47	1.35
Distance to coast (km)	DC	4.07	2.95	4.15	3.02
Trend (1=2001 to 16=2016)	Tre	1.18	1.18	1.18	1.18
Alinytjara Wilurara	AW	1.25	1.2	1.25	1.21
Eyre Peninsula	EP	2	2.11	2.01	2.13
Kangaroo Island	KI	1.19	1.21	1.2	1.22
Northern and Yorke	NY	3.2	3.1	3.24	3.14
SA Arid Land	SAAL	4.08	4.19	4.08	4.19
SA Murray Darling Basin	SAMDB	3.13	2.98	3.13	2.98
South East	SE	1.93	1.92	1.94	1.94
Mean VIF		2.35	2.20	2.36	2.21

Table C.4 Pairwise correlation among the explanatory variables (N=5,440) used in the empirical models of bird species richness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)
VPSR (1)	1.00																								
OFB (2)	0.33	1.00																							
ALP (3)	0.42	0.36	1.00																						
AET (4)	-0.05	-0.02	0.03	1.00																					
LCDI (5)	0.36	0.20	0.29	-0.12	1.00																				
NDVI (6)	0.11	0.11	0.27	0.65	0.12	1.00																			
ConL (7)	0.29	0.14	0.03	0.04	0.26	0.15	1.00																		
WB (8)	0.20	0.12	0.06	-0.17	0.22	-0.14	0.00	1.00																	
CL (9)	-0.14	-0.07	0.17	-0.15	-0.07	-0.01	-0.21	-0.06	1.00																
GL (10)	0.39	0.19	0.33	-0.09	0.42	0.13	-0.04	0.11	-0.09	1.00															
HL (11)	0.04	0.14	0.03	0.20	0.14	0.32	0.10	0.01	-0.17	-0.08	1.00														
ER (12)	0.41	0.14	0.20	-0.06	0.17	0.02	0.14	0.09	0.04	0.48	-0.06	1.00													
SDI (13)	0.00	0.01	-0.01	0.24	-0.16	0.29	0.01	-0.08	0.11	0.09	0.13	0.42	1.00												
UAI (14)	-0.28	-0.11	-0.23	0.25	-0.32	0.02	-0.20	-0.17	-0.40	-0.53	0.10	-0.42	-0.04	1.00											
DR (15)	0.28	0.17	-0.03	-0.12	-0.07	-0.16	0.25	0.14	-0.16	0.22	-0.03	0.36	0.06	-0.30	1.00										
DC (16)	0.34	0.19	0.03	-0.39	0.09	-0.34	0.20	0.13	-0.03	0.37	-0.02	0.30	-0.01	-0.45	0.64	1.00									
Tre (17)	0.07	0.19	0.02	-0.21	0.00	-0.03	0.06	0.06	0.03	-0.11	-0.01	0.00	0.00	0.01	0.00	0.00	1.00								
AMLR (18)	-0.23	-0.14	-0.34	0.38	-0.31	0.13	-0.02	-0.17	-0.47	-0.54	0.22	-0.32	0.08	0.69	-0.11	-0.42	0.00	1.00							
AW (19)	0.12	-0.02	0.04	-0.08	0.00	-0.08	0.26	-0.01	-0.04	-0.05	-0.02	0.07	-0.03	-0.10	0.26	0.08	0.00	-0.05	1.00						
EP (20)	-0.05	-0.02	-0.02	-0.16	0.08	-0.12	0.12	-0.02	0.19	0.04	-0.11	0.00	-0.14	-0.27	-0.05	-0.05	0.00	-0.26	-0.02	1.00					
KI (21)	-0.01	0.05	0.03	0.08	0.05	0.15	0.09	-0.02	-0.06	0.12	-0.04	-0.03	-0.08	-0.09	0.00	-0.05	0.00	-0.10	-0.01	-0.03	1.00				
NY (22)	-0.15	-0.08	0.10	-0.08	-0.09	-0.01	-0.21	-0.02	0.65	-0.02	-0.15	0.22	0.28	-0.23	-0.13	-0.10	0.00	-0.42	-0.02	-0.13	-0.05	1.00			
SAAL (23)	0.22	0.01	-0.13	-0.30	-0.10	-0.37	0.06	0.22	-0.18	0.36	-0.09	0.44	0.09	-0.32	0.51	0.64	0.00	-0.23	-0.01	-0.07	-0.03	-0.11	1.00		
SAMDB (24)	0.29	0.25	0.23	-0.22	0.43	-0.03	0.08	0.09	0.01	0.31	0.03	0.02	-0.21	-0.20	-0.02	0.30	0.00	-0.40	-0.02	-0.13	-0.05	-0.20	-0.11	1.00	
SE (25)	0.08	0.03	0.33	0.12	0.12	0.25	-0.05	0.06	-0.06	0.24	-0.05	-0.14	-0.17	-0.08	-0.05	0.00	0.00	-0.23	-0.01	-0.07	-0.03	-0.12	-0.06	-0.11	1.00

Table C.5 Pairwise correlation among the explanatory variables (N=5,440) used in the empirical models of vascular plant species richness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
OFB (1)	1.00																							
ALP (2)	0.36	1.00																						
AET (3)	-0.02	0.03	1.00																					
LCDI (4)	0.20	0.29	-0.12	1.00																				
NDVI (5)	0.11	0.27	0.65	0.12	1.00																			
ConL (6)	0.14	0.03	0.04	0.26	0.15	1.00																		
WB (7)	0.12	0.06	-0.17	0.22	-0.14	0.00	1.00																	
CL (8)	-0.07	0.17	-0.15	-0.07	-0.01	-0.21	-0.06	1.00																
GL (9)	0.19	0.33	-0.09	0.42	0.13	-0.04	0.11	-0.09	1.00															
HL (10)	0.14	0.03	0.20	0.14	0.32	0.10	0.01	-0.17	-0.08	1.00														
ER (11)	0.14	0.20	-0.06	0.17	0.02	0.14	0.09	0.04	0.48	-0.06	1.00													
SDI (12)	0.01	-0.01	0.24	-0.16	0.29	0.01	-0.08	0.11	0.09	0.13	0.42	1.00												
UAI (13)	-0.11	-0.23	0.25	-0.32	0.02	-0.20	-0.17	-0.40	-0.53	0.10	-0.42	-0.04	1.00											
DR (14)	0.17	-0.03	-0.12	-0.07	-0.16	0.25	0.14	-0.16	0.22	-0.03	0.36	0.06	-0.30	1.00										
DC (15)	0.19	0.03	-0.39	0.09	-0.34	0.20	0.13	-0.03	0.37	-0.02	0.30	-0.01	-0.45	0.64	1.00									
Tre (16)	0.19	0.02	-0.21	0.00	-0.03	0.06	0.06	0.03	-0.11	-0.01	0.00	0.00	0.01	0.00	0.00	1.00								
AMLR (17)	-0.14	-0.34	0.38	-0.31	0.13	-0.02	-0.17	-0.47	-0.54	0.22	-0.32	0.08	0.69	-0.11	-0.42	0.00	1.00							
AW (18)	-0.02	0.04	-0.08	0.00	-0.08	0.26	-0.01	-0.04	-0.05	-0.02	0.07	-0.03	-0.10	0.26	0.08	0.00	-0.05	1.00						
EP (19)	-0.02	-0.02	-0.16	0.08	-0.12	0.12	-0.02	0.19	0.04	-0.11	0.00	-0.14	-0.27	-0.05	-0.05	0.00	-0.26	-0.02	1.00					
KI (20)	0.05	0.03	0.08	0.05	0.15	0.09	-0.02	-0.06	0.12	-0.04	-0.03	-0.08	-0.09	0.00	-0.05	0.00	-0.10	-0.01	-0.03	1.00				
NY (21)	-0.08	0.10	-0.08	-0.09	-0.01	-0.21	-0.02	0.65	-0.02	-0.15	0.22	0.28	-0.23	-0.13	-0.10	0.00	-0.42	-0.02	-0.13	-0.05	1.00			
SAAL (22)	0.01	-0.13	-0.30	-0.10	-0.37	0.06	0.22	-0.18	0.36	-0.09	0.44	0.09	-0.32	0.51	0.64	0.00	-0.23	-0.01	-0.07	-0.03	-0.11	1.00		
SA MDB (23)	0.25	0.23	-0.22	0.43	-0.03	0.08	0.09	0.01	0.31	0.03	0.02	-0.21	-0.20	-0.02	0.30	0.00	-0.40	-0.02	-0.13	-0.05	-0.20	-0.11	1.00	
SE (24)	0.03	0.33	0.12	0.12	0.25	-0.05	0.06	-0.06	0.24	-0.05	-0.14	-0.17	-0.08	-0.05	0.00	0.00	-0.23	-0.01	-0.07	-0.03	-0.12	-0.06	-0.11	1.00

Table C.6 Pairwise correlation among the explanatory variables (N=4,768) used in the empirical models of vascular plant species richness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
OFB (1)	1.00																							
ALP (2)	0.33	1.00																						
AET (3)	-0.02	0.04	1.00																					
LCDI (4)	0.16	0.22	-0.14	1.00																				
NDVI (5)	0.08	0.23	0.69	0.03	1.00																			
ConL (6)	0.11	-0.04	0.05	0.17	0.10	1.00																		
WB (7)	0.11	0.04	-0.17	0.20	-0.17	-0.03	1.00																	
CL (8)	-0.11	0.10	-0.16	-0.23	-0.08	-0.29	-0.09	1.00																
GL (9)	0.15	0.27	-0.09	0.30	0.05	-0.15	0.07	-0.22	1.00															
HL (10)	0.12	0.00	0.22	0.09	0.31	0.08	0.00	-0.21	-0.14	1.00														
ER (11)	0.10	0.13	-0.07	0.03	-0.07	0.07	0.06	-0.05	0.41	-0.10	1.00													
SDI (12)	-0.01	-0.06	0.26	-0.25	0.26	-0.04	-0.11	0.08	0.04	0.13	0.41	1.00												
UAI (13)	-0.08	-0.13	0.34	-0.13	0.21	-0.14	-0.15	-0.25	-0.45	0.19	-0.39	0.06	1.00											
DR (14)	-0.01	-0.11	-0.03	-0.16	-0.09	0.07	-0.01	-0.13	0.18	0.01	0.23	0.11	-0.18	1.00										
DC (15)	0.17	-0.02	-0.41	0.01	-0.40	0.17	0.11	-0.08	0.32	-0.04	0.27	-0.04	-0.49	0.36	1.00									
Tre (16)	0.20	0.02	-0.19	0.00	-0.02	0.07	0.07	0.04	-0.12	-0.01	0.00	0.00	-0.01	0.00	0.00	1.00								
AMLR (17)	-0.09	-0.27	0.42	-0.17	0.25	0.09	-0.14	-0.41	-0.45	0.30	-0.23	0.16	0.65	-0.04	-0.38	0.00	1.00							
AW (18)	-0.02	0.03	-0.09	-0.01	-0.08	0.26	-0.01	-0.04	-0.06	-0.02	0.07	-0.04	-0.12	-0.02	0.08	0.00	-0.05	1.00						
EP (19)	-0.04	-0.05	-0.17	0.04	-0.15	0.10	-0.03	0.16	0.00	-0.12	-0.03	-0.17	-0.28	-0.08	-0.07	0.00	-0.24	-0.02	1.00					
KI (20)	0.04	0.02	0.08	0.03	0.14	0.09	-0.03	-0.08	0.11	-0.05	-0.04	-0.09	-0.08	0.05	-0.06	0.00	-0.09	-0.01	-0.04	1.00				
NY (21)	-0.11	0.06	-0.08	-0.20	-0.05	-0.26	-0.03	0.64	-0.10	-0.17	0.18	0.29	-0.12	-0.09	-0.14	0.00	-0.39	-0.03	-0.15	-0.06	1.00			
SAAL (22)	0.01	-0.16	-0.31	-0.17	-0.40	0.04	0.22	-0.21	0.35	-0.10	0.46	0.09	-0.39	0.43	0.63	0.00	-0.21	-0.02	-0.08	-0.03	-0.13	1.00		
SA MDB (23)	0.23	0.20	-0.23	0.42	-0.08	0.04	0.07	-0.04	0.27	0.01	-0.03	-0.27	-0.19	-0.04	0.29	0.00	-0.37	-0.03	-0.15	-0.05	-0.23	-0.12	1.00	
SE (24)	0.02	0.31	0.13	0.09	0.24	-0.07	0.05	-0.09	0.22	-0.06	-0.19	-0.21	-0.02	-0.06	-0.02	0.00	-0.22	-0.02	-0.09	-0.03	-0.14	-0.07	-0.13	1.00

Table C.7 Pairwise correlation among the explanatory variables (N=4,768) used in the empirical models of bird species richness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)
VPSR (1)	1.00																								
OFB (2)	0.32	1.00																							
ALP (3)	0.39	0.33	1.00																						
AET (4)	-0.04	-0.02	0.04	1.00																					
LCDI (5)	0.29	0.16	0.22	-0.14	1.00																				
NDVI (6)	0.04	0.08	0.23	0.69	0.03	1.00																			
ConL (7)	0.25	0.11	-0.04	0.05	0.17	0.10	1.00																		
WB (8)	0.18	0.11	0.04	-0.17	0.20	-0.17	-0.03	1.00																	
CL (9)	-0.24	-0.11	0.10	-0.16	-0.23	-0.08	-0.29	-0.09	1.00																
GL (10)	0.31	0.15	0.27	-0.09	0.30	0.05	-0.15	0.07	-0.22	1.00															
HL (11)	0.00	0.12	0.00	0.22	0.09	0.31	0.08	0.00	-0.21	-0.14	1.00														
ER (12)	0.36	0.10	0.13	-0.07	0.03	-0.07	0.07	0.06	-0.05	0.41	-0.10	1.00													
SDI (13)	-0.08	-0.01	-0.06	0.26	-0.25	0.26	-0.04	-0.11	0.08	0.04	0.13	0.41	1.00												
UAI (14)	-0.25	-0.08	-0.13	0.34	-0.13	0.21	-0.14	-0.15	-0.25	-0.45	0.19	-0.39	0.06	1.00											
DR (15)	0.03	-0.01	-0.11	-0.03	-0.16	-0.09	0.07	-0.01	-0.13	0.18	0.01	0.23	0.11	-0.18	1.00										
DC (16)	0.30	0.17	-0.02	-0.41	0.01	-0.40	0.17	0.11	-0.08	0.32	-0.04	0.27	-0.04	-0.49	0.36	1.00									
Tre (17)	0.07	0.20	0.02	-0.19	0.00	-0.02	0.07	0.07	0.04	-0.12	-0.01	0.00	0.00	-0.01	0.00	0.00	1.00								
AMLR (18)	-0.13	-0.09	-0.27	0.42	-0.17	0.25	0.09	-0.14	-0.41	-0.45	0.30	-0.23	0.16	0.65	-0.04	-0.38	0.00	1.00							
AW (19)	0.13	-0.02	0.03	-0.09	-0.01	-0.08	0.26	-0.01	-0.04	-0.06	-0.02	0.07	-0.04	-0.12	-0.02	0.08	0.00	-0.05	1.00						
EP (20)	-0.09	-0.04	-0.05	-0.17	0.04	-0.15	0.10	-0.03	0.16	0.00	-0.12	-0.03	-0.17	-0.28	-0.08	-0.07	0.00	-0.24	-0.02	1.00					
KI (21)	-0.03	0.04	0.02	0.08	0.03	0.14	0.09	-0.03	-0.08	0.11	-0.05	-0.04	-0.09	-0.08	0.05	-0.06	0.00	-0.09	-0.01	-0.04	1.00				
NY (22)	-0.21	-0.11	0.06	-0.08	-0.20	-0.05	-0.26	-0.03	0.64	-0.10	-0.17	0.18	0.29	-0.12	-0.09	-0.14	0.00	-0.39	-0.03	-0.15	-0.06	1.00			
SAAL (23)	0.21	0.01	-0.16	-0.31	-0.17	-0.40	0.04	0.22	-0.21	0.35	-0.10	0.46	0.09	-0.39	0.43	0.63	0.00	-0.21	-0.02	-0.08	-0.03	-0.13	1.00		
SAMDB (24)	0.27	0.23	0.20	-0.23	0.42	-0.08	0.04	0.07	-0.04	0.27	0.01	-0.03	-0.27	-0.19	-0.04	0.29	0.00	-0.37	-0.03	-0.15	-0.05	-0.23	-0.12	1.00	
SE (25)	0.05	0.02	0.31	0.13	0.09	0.24	-0.07	0.05	-0.09	0.22	-0.06	-0.19	-0.21	-0.02	-0.06	-0.02	0.00	-0.22	-0.02	-0.09	-0.03	-0.14	-0.07	-0.13	1

Table C.8 Results of OLS regression (panel random effects) models of bird and vascular plant species richness for full and reduced samples in South Australia, 2001–2016

	N=5,440 (all postcodes)				*N=4,768 (excluding postcodes without any agriculture production in all 16 years)*			
	Bird Species Richness (Model I)		*Vascular plant species richness (Model II)*		*Bird Species Richness (Model III)*		*Vascular plant species richness (Model IV)*	
	Coefficient	***Std. Err.***	***Coefficient***	***Std. Err.***	***Coefficient***	***Std. Err.***	***Coefficient***	***Std. Err.***
Organic farming business	0.004	0.027	0.086***	0.025	0.010	0.024	0.092***	0.026
Land cover diversity index	0.342***	0.078	0.531***	0.124	0.331***	0.085	0.397***	0.134
Elevation range	0.001***	0.000	0.003***	0.000	0.001***	0.000	0.003***	0.000
Conservation land	0.003*	0.002	0.000	0.003	0.004*	0.002	-0.001	0.003
Water bodies	0.023***	0.007	0.026***	0.010	0.021***	0.008	0.025**	0.010
Soil diversity index	-1.775***	0.399	-1.298*	0.776	-2.558***	0.435	-2.644***	0.843
Evapotranspiration	-0.001***	0.000	0.001***	0.000	-0.001***	0.000	0.001***	0.000
Plant richness	0.352***	0.021	-	-	0.347***	0.022	-	-
NDVI	1.227***	0.340	0.831**	0.403	1.405***	0.355	0.853**	0.417
Agricultural land parcels	0.002***	0.000	0.002***	0.000	0.002***	0.000	0.002***	0.000
Crop land	-0.003	0.002	-0.006**	0.003	-0.003	0.002	-0.007**	0.003
Grazing land	-0.002	0.002	0.003	0.003	-0.001	0.002	0.002	0.003
Horticultural land	-0.005	0.003	-0.005	0.003	-0.004	0.003	-0.005*	0.003
Urban accessibility index	-0.001	0.012	-0.015	0.020	-0.015	0.015	-0.044**	0.021
Distance to road	0.002	0.002	0.000	0.003	-0.009	0.006	-0.017**	0.007
Distance to coast	0.001	0.001	0.005***	0.001	0.003***	0.001	0.005***	0.001
Trend	0.038***	0.005	0.033***	0.005	0.045***	0.006	0.030***	0.006
AW (base=AMLR)	0.664**	0.287	2.695***	0.377	0.749***	0.225	2.139***	0.345
EP	-0.183	0.184	-0.465*	0.268	-0.376*	0.195	-0.771***	0.256
KI	-0.381	0.302	-0.901	1.025	-0.520**	0.258	-1.111	0.889
NY	0.175	0.150	-0.708***	0.215	0.113	0.150	-0.810***	0.200
SAAL	0.633*	0.352	-0.214	0.569	0.557	0.339	-0.333	0.548
SAMDB	0.317**	0.144	0.113	0.238	0.061	0.148	-0.089	0.223
SE	-0.112	0.175	-0.469*	0.262	-0.293	0.180	-0.694***	0.258
Constant	1.477***	0.302	1.097*	0.591	1.844***	0.330	2.148***	0.669
sigma_u	0.402		0.862		0.416		0.843	
sigma_e	0.920		1.101		0.921		1.156	
Within R^2	0.166		0.024		0.190		0.021	

Notes: The outcome variable is the average bird species richness in *Model I* and *Model III* and vascular plant species richness in *Model II* and *Model IV*, respectively. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table C.9 Sensitivity analysis using postcode areas: Results of SDEM of bird and vascular plant species richness in South Australia, 2001–2016 (N = 5,440)

	Bird Species Richness (Model I)						Vascular plant species richness (Model II)					
	Direct effect	*Std. Err.*	*Indirect effect*	*Std. Err.*	*Total effect*	*Std. Err.*	*Direct effect*	*Std. Err.*	*Indirect effect*	*Std. Err.*	*Total effect*	*Std. Err.*
Organic farm businesses	-0.022	0.021	-0.019	0.068	-0.042	0.077	0.057**	0.025	0.167*	0.100	0.223**	0.112
Land cover diversity index	0.351***	0.070	-0.045	0.206	0.307	0.222	0.564***	0.103	-0.355	0.366	0.209	0.399
Elevation range	0.001***	0.000	0.001***	0.000	0.002***	0.000	0.002***	0.000	0.002***	0.000	0.004***	0.001
Conservation land	0.002	0.002	0.006	0.005	0.008	0.005	0.000	0.002	0.000	0.008	0.000	0.008
Water bodies	0.014***	0.005	0.068***	0.021	0.082***	0.023	0.014*	0.008	0.058	0.036	0.072*	0.039
Soil diversity index	-1.254***	0.331	-1.134***	0.305	-2.387***	0.633	-1.399***	0.530	-1.871***	0.718	-3.270***	1.245
Evapotranspiration	-0.001**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001**	0.001	0.001**	0.000
Vascular plant richness	0.360***	0.012	-0.111***	0.031	0.249***	0.031	-	-	-	-	-	-
NDVI	0.598	0.444	1.222*	0.669	1.820***	0.617	1.203**	0.562	-0.077	0.946	1.126	0.903
Agricultural land parcels	0.001***	0.000	0.001	0.000	0.002***	0.000	0.001***	0.000	-0.001	0.001	0.001	0.001
Crop land	-0.005***	0.002	0.003	0.004	-0.002	0.004	-0.007***	0.002	0.008	0.007	0.001	0.008
Grazing land	-0.002	0.002	0.001	0.004	-0.002	0.004	-0.001	0.002	0.015**	0.006	0.013*	0.007
Horticultural land	-0.003	0.003	0.001	0.008	-0.002	0.008	-0.006*	0.003	0.007	0.013	0.001	0.014
Postcode area	0.019**	0.008	0.017	0.010	0.035**	0.014	0.039***	0.013	0.010	0.020	0.049*	0.027
Urban accessibility index	-0.001	0.011	-0.001	0.010	-0.001	0.021	-0.020	0.016	-0.027	0.022	-0.048	0.038
Distance to road	-0.001	0.002	-0.001	0.002	-0.002	0.004	-0.006*	0.003	-0.008*	0.004	-0.013*	0.008
Distance to coast	0.000	0.001	0.000	0.001	-0.001	0.002	0.001	0.002	0.002	0.002	0.003	0.004
Trend	0.021***	0.004	0.019***	0.003	0.041***	0.007	0.013***	0.004	0.018***	0.005	0.031***	0.009
AW (base=AMLR)	-2.458	1.503	-2.223	1.369	-4.680	2.870	-4.587*	2.417	-6.133*	3.254	-10.720*	5.664
EP	-0.229	0.157	-0.207	0.142	-0.436	0.299	-0.620**	0.245	-0.829**	0.331	-1.448**	0.574
KI	-0.411	0.300	-0.371	0.272	-0.782	0.571	-1.000**	0.478	-1.337**	0.643	-2.337**	1.120
NY	0.022	0.145	0.019	0.131	0.041	0.276	-0.598***	0.225	-0.800***	0.304	-1.398***	0.528
SAAL	0.078	0.252	0.071	0.228	0.149	0.481	-0.531	0.395	-0.710	0.529	-1.242	0.924
SAMDB	0.212	0.154	0.191	0.139	0.403	0.293	-0.065	0.242	-0.087	0.324	-0.153	0.566
SE	-0.185	0.201	-0.167	0.182	-0.352	0.383	-0.280	0.308	-0.374	0.413	-0.654	0.721
Spatial error (λ)	0.518***						0.625***					
Pseudo R2	0.645						0.481					
AIC	14328.670						15824.480					

Notes: The outcome variable is the average bird and vascular plant species richness in *Model I* and *Model II*, respectively. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table C.10 Results of SDEM (nearest neighbour matrix) of bird and vascular plant species richness in South Australia, 2001–2016 (N = 5,440)

	Bird Species Richness (Model I)						*Vascular plant species richness (Model II)*					
	Direct effect	***Std. Err.***	***Indirect effect***	***Std. Err.***	***Total effect***	***Std. Err.***	***Direct effect***	***Std. Err.***	***Indirect effect***	***Std. Err.***	***Total effect***	***Std. Err.***
Organic farming business	-0.018	0.020	-0.007	0.051	-0.025	0.059	0.051**	0.024	0.118*	0.062	0.170**	0.073
Land cover diversity index	0.288***	0.076	0.096	0.142	0.384***	0.139	0.512***	0.109	-0.230	0.204	0.282	0.201
Elevation range	0.001***	0.000	-	-	0.001***	0.000	0.003***	0.000	-	-	0.003***	0.000
Conservation land	0.002	0.002	0.001	0.004	0.003	0.004	0.005**	0.002	-0.001	0.005	0.004	0.005
Water bodies	0.020***	0.006	0.042***	0.015	0.062***	0.016	0.024***	0.007	0.033	0.020	0.057**	0.023
Soil diversity index	-1.769***	0.387	-	-	-1.769***	0.387	-1.601***	0.584	-	-	-1.601***	0.584
Evapotranspiration	0.000	0.000	0.000	0.001	-0.001*	0.000	0.001*	0.000	0.000	0.001	0.001	0.000
Vascular Plant richness	0.368***	0.012	-0.071***	0.024	0.298***	0.026	-	-	-	-	-	-
NDVI	0.564	0.538	0.807	0.725	1.371**	0.586	1.798***	0.685	-0.663	0.953	1.135	0.801
Agricultural land parcels	0.001***	0.000	0.001	0.000	0.002***	0.000	0.002***	0.000	-0.001	0.001	0.001**	0.001
Crop land	-0.004*	0.002	0.001	0.003	-0.003	0.003	-0.001	0.003	-0.003	0.004	-0.005	0.004
Grazing land	0.001	0.002	-0.004	0.003	-0.003	0.003	0.003	0.002	0.003	0.004	0.006	0.004
Horticultural land	-0.003	0.003	-0.003	0.005	-0.006	0.005	-0.003	0.003	0.002	0.007	-0.001	0.007
Urban accessibility index	-0.004	0.012	-	-	-0.004	0.012	-0.033**	0.017	-	-	-0.033**	0.017
Distance to road	0.002	0.002	-	-	0.002	0.002	0.000	0.003	-	-	0.000	0.003
Distance to coast	0.001	0.001	-	-	0.001	0.001	0.004***	0.001	-	-	0.004***	0.001
Trend	0.038***	0.006	-	-	0.038***	0.006	0.024***	0.009	-	-	0.024***	0.009
AW (base=AMLR)	0.842	0.635	-	-	0.842	0.635	2.076**	0.968	-	-	2.076**	0.968
EP	-0.277	0.199	-	-	-0.277	0.199	-0.672**	0.296	-	-	-0.672**	0.296
KI	-0.486	0.336	-	-	-0.486	0.336	-1.121**	0.507	-	-	-1.121**	0.507
NY	0.026	0.183	-	-	0.026	0.183	-0.727***	0.272	-	-	-0.727***	0.272
SAAL	0.362	0.291	-	-	0.362	0.291	-0.332	0.431	-	-	-0.332	0.431
SAMDB	0.175	0.175	-	-	0.175	0.175	0.103	0.263	-	-	0.103	0.263
SE	-0.346	0.248	-	-	-0.346	0.248	-0.451	0.369	-	-	-0.451	0.369
Spatial error (λ)	0.541***						0.629***					
Pseudo R^2	0.639						0.477					
AIC	14352.710						15882.290					
BIC	14610.170						16126.550					

Notes: The outcome variable is the average bird and vascular plant species richness in *Model I* and *Model II*, respectively. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table C.11 Results of SDM (contiguity matrix) of bird and vascular plant species richness in South Australia, 2001–2016 (N = 5,440)

	Bird Species Richness (Model I)						***Vascular plant species richness (Model II)***					
	Direct effect	***Std. Err.***	***Indirect effect***	***Std. Err.***	***Total effect***	***Std. Err.***	***Direct effect***	***Std. Err.***	***Indirect effect***	***Std. Err.***	***Total effect***	***Std. Err.***
Organic farming business	-0.020	0.021	-0.033	0.068	-0.053	0.077	0.058**	0.025	0.154	0.100	0.212*	0.112
Land cover diversity index	0.334***	0.070	-0.093	0.203	0.242	0.217	0.556***	0.104	-0.308	0.364	0.247	0.395
Elevation range	0.001***	0.000	0.001***	0.000	0.002***	0.000	0.002***	0.000	0.002***	0.001	0.004***	0.001
Conservation land	0.001	0.002	0.007	0.005	0.009*	0.005	0.000	0.002	-0.001	0.008	-0.001	0.008
Water bodies	0.016***	0.005	0.074***	0.021	0.090***	0.023	0.016**	0.008	0.058	0.036	0.074*	0.039
Soil diversity index	-1.308***	0.332	-1.183***	0.307	-2.492***	0.635	-1.428***	0.534	-1.906***	0.723	-3.334***	1.254
Evapotranspiration	-0.001**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001**	0.001	0.001**	0.000
Vascular Plant richness	0.361***	0.012	-0.109**	0.031	0.252***	0.031	-	-	-	-	-	-
NDVI	0.556	0.445	1.261*	0.670	1.816***	0.617	1.149**	0.564	-0.028	0.947	1.121	0.903
Agricultural land parcels	0.001***	0.000	0.001*	0.000	0.002***	0.001	0.001***	0.000	-0.001	0.001	0.001	0.001
Crop land	-0.005***	0.002	0.003	0.004	-0.002	0.004	-0.007***	0.002	0.008	0.007	0.001	0.008
Grazing land	-0.002	0.002	0.001	0.004	-0.001	0.004	-0.002	0.002	0.013**	0.006	0.012*	0.007
Horticultural land	-0.004	0.003	0.000	0.008	-0.004	0.008	-0.006*	0.003	0.006	0.013	0.000	0.014
Urban accessibility index	-0.001	0.011	-0.001	0.010	-0.002	0.022	-0.019	0.016	-0.025	0.022	-0.044	0.038
Distance to road	0.000	0.002	0.000	0.001	0.001	0.003	0.000	0.003	0.000	0.004	-0.001	0.006
Distance to coast	0.001	0.001	0.001	0.001	0.002	0.001	0.002**	0.001	0.003**	0.002	0.006**	0.003
Trend	0.021***	0.004	0.019***	0.003	0.041**	0.007	0.013***	0.004	0.018***	0.005	0.031**	0.009
AW (base=AMLR)	0.717	0.598	0.649	0.541	1.366	1.139	1.872*	0.965	2.500*	1.293	4.372*	2.255
EP	-0.225	0.158	-0.204	0.143	-0.429	0.301	-0.619**	0.247	-0.826**	0.334	-1.445**	0.580
KI	-0.409	0.301	-0.370	0.273	-0.779	0.574	-0.966**	0.484	-1.291**	0.650	-2.257**	1.132
NY	0.028	0.146	0.025	0.132	0.054	0.278	-0.572**	0.228	-0.763**	0.306	-1.335**	0.532
SAAL	0.114	0.253	0.103	0.228	0.217	0.481	-0.564	0.395	-0.754	0.529	-1.318	0.923
SAMDB	0.110	0.146	0.099	0.132	0.209	0.278	-0.125	0.232	-0.166	0.310	-0.291	0.542
SE	-0.224	0.199	-0.203	0.180	-0.427	0.379	-0.250	0.308	-0.334	0.412	-0.584	0.720
Spatial lag (ρ)	0.518***						0.624***					
Pseudo R^2	0.646						0.476					
AIC	14331.740						15828.940					
BIC	14589.200						16073.200					

Notes: The outcome variable is the average bird and vascular plant species richness in *Model I* and *Model II*, respectively. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table C.12 Results of SDM (nearest neighbour matrix) of bird and vascular plant species richness in South Australia, 2001–2016 (N = 5,440)

	Bird Species Richness (Model I)						*Vascular plant species richness (Model II)*					
	Direct effect	***Std. Err.***	***Indirect effect***	***Std. Err.***	***Total effect***	***Std. Err.***	***Direct effect***	***Std. Err.***	***Indirect effect***	***Std. Err.***	***Total effect***	***Std. Err.***
Organic farming business	-0.021	0.021	0.005	0.076	-0.017	0.085	0.052**	0.025	0.154	0.107	0.206*	0.118
Land cover diversity index	0.304***	0.075	0.186	0.228	0.490**	0.242	0.590***	0.111	-0.158	0.394	0.433	0.420
Elevation range	0.001***	0.000	0.001***	0.000	0.003***	0.000	0.003***	0.000	0.003***	0.001	0.006***	0.001
Conservation land	0.002	0.002	-0.001	0.005	0.001	0.005	0.003	0.002	-0.015**	0.008	-0.013	0.008
Water bodies	0.021***	0.006	0.061**	0.027	0.082***	0.029	0.021**	0.008	0.012	0.044	0.033	0.048
Soil diversity index	-1.392***	0.357	-1.377***	0.360	-2.769***	0.713	-1.316**	0.572	-1.774**	0.778	-3.091**	1.347
Evapotranspiration	0.000	0.000	0.000	0.001	0.000	0.000	0.000*	0.000	0.000	0.001	0.001*	0.000
Vascular plant richness	0.372***	0.012	-0.155***	0.031	0.217***	0.032	-	-	-	-	-	-
NDVI	0.700	0.523	1.425*	0.778	2.126***	0.649	1.803***	0.681	-0.959	1.057	0.844	0.901
Agricultural land parcels	0.001***	0.000	0.000	0.001	0.001**	0.001	0.002***	0.000	-0.002**	0.001	0.000	0.001
Crop land	-0.003	0.002	0.005	0.005	0.002	0.005	-0.003	0.003	-0.005	0.008	-0.008	0.008
Grazing land	0.001	0.002	-0.009*	0.004	-0.008*	0.005	0.001	0.002	-0.001	0.007	0.000	0.008
Horticultural land	-0.003	0.003	0.003	0.007	0.000	0.008	-0.004	0.004	-0.004	0.011	-0.009	0.013
Urban accessibility index	0.000	0.012	0.000	0.012	0.000	0.024	-0.039**	0.017	-0.053**	0.023	-0.092**	0.040
Distance to road	0.001	0.002	0.001	0.002	0.002	0.004	-0.001	0.003	-0.001	0.004	-0.003	0.007
Distance to coast	0.001	0.001	0.001	0.001	0.001	0.002	0.002	0.001	0.002	0.002	0.004	0.003
Trend	0.019***	0.003	0.019***	0.003	0.038***	0.007	0.012***	0.004	0.016***	0.005	0.028	0.009
AW (base=AMLR)	0.820	0.644	0.811	0.638	1.631	1.281	1.823*	1.034	2.457*	1.398	4.280*	2.430
EP	-0.218	0.177	-0.216	0.175	-0.434	0.352	-0.587**	0.276	-0.792**	0.374	-1.379**	0.649
KI	-0.393	0.324	-0.389	0.322	-0.781	0.645	-0.847	0.518	-1.142	0.701	-1.989	1.219
NY	-0.116	0.165	-0.114	0.164	-0.230	0.329	-0.503**	0.254	-0.678**	0.343	-1.182**	0.597
SAAL	0.373	0.271	0.369	0.269	0.742	0.540	-0.118	0.421	-0.159	0.567	-0.277	0.988
SAMDB	0.174	0.168	0.173	0.167	0.347	0.335	0.188	0.265	0.253	0.358	0.441	0.623
SE	-0.059	0.225	-0.059	0.222	-0.118	0.447	0.011	0.346	0.015	0.467	0.025	0.813
Spatial lag (ρ)	0.526***						0.609***					
Pseudo R^2	0.630						0.436					
AIC	14323.000						15889.440					
BIC	14580.460						16133.690					

Notes: The outcome variable is the average bird and vascular plant species richness in *Model I* and *Model II*, respectively. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table C.13 Results of SLX (nearest neighbour matrix) of bird and vascular plant species richness in South Australia, 2001–2016 (N = 5,440)

	Bird Species Richness (Model I)						***Vascular plant species richness (Model II)***					
	Direct effect	***Std. Err.***	***Indirect effect***	***Std. Err.***	***Total effect***	***Std. Err.***	***Direct effect***	***Std. Err.***	***Indirect effect***	***Std. Err.***	***Total effect***	***Std. Err.***
Organic farming business	-0.022	0.022	0.028	0.044	0.006	0.045	0.075***	0.028	0.146***	0.053	0.221***	0.055
Land cover diversity index	0.298***	0.085	0.189	0.141	0.486***	0.128	0.554***	0.122	-0.029	0.203	0.525***	0.183
Elevation range	0.001***	0.000	-	-	0.001***	0.000	0.003***	0.000	-	-	0.003***	0.000
Conservation land	0.002	0.002	0.002	0.003	0.003	0.003	0.003	0.003	-0.011***	0.004	-0.008**	0.004
Water bodies	0.021***	0.006	0.063***	0.015	0.083***	0.016	0.026***	0.008	0.028	0.020	0.054**	0.021
Soil diversity index	-1.759***	0.375	-	-	-1.759***	0.375	-1.039*	0.564	-	-	-1.039*	0.564
Evapotranspiration	-0.001	0.000	0.000	0.001	0.000***	0.000	0.001	0.001	0.000	0.001	0.001***	0.000
Vascular plant richness	0.369***	0.014	-0.117***	0.020	0.251***	0.017	-	-	-	-	-	-
NDVI	0.543	0.612	1.448**	0.682	1.991***	0.345	1.472*	0.819	-0.524	0.898	0.948**	0.419
Agricultural land parcels	0.001***	0.000	0.000	0.000	0.002***	0.000	0.002***	0.000	-0.002***	0.000	0.000	0.001
Crop land	-0.004	0.002	0.003	0.003	-0.001	0.003	-0.004	0.003	0.001	0.005	-0.003	0.004
Grazing land	0.000	0.002	-0.007**	0.003	-0.007***	0.002	0.002	0.003	0.005	0.004	0.007**	0.003
Horticultural land	-0.004	0.003	0.002	0.005	-0.002	0.004	-0.005	0.004	0.002	0.006	-0.003	0.006
Urban accessibility index	0.009	0.013	-	-	0.009	0.013	-0.019	0.018	-	-	-0.019	0.018
Distance to road	0.004*	0.002	-	-	0.004*	0.002	0.000	0.003	-	-	0.000	0.003
Distance to coast	0.001	0.001	-	-	0.001	0.001	0.004***	0.001	-	-	0.004***	0.001
Trend	0.036***	0.004	-	-	0.036***	0.004	0.032***	0.004	-	-	0.032***	0.004
AW (base=AMLR)	1.162*	0.677	-	-	1.162*	0.677	2.385**	1.016	-	-	2.385**	1.016
EP	-0.115	0.186	-	-	-0.115	0.186	-0.447	0.274	-	-	-0.447	0.274
KI	-0.219	0.341	-	-	-0.219	0.341	-0.823	0.511	-	-	-0.823	0.511
NY	0.099	0.173	-	-	0.099	0.173	-0.746***	0.254	-	-	-0.746***	0.254
SAAL	0.711**	0.286	-	-	0.711**	0.286	-0.429	0.419	-	-	-0.429	0.419
SAMDB	0.392**	0.177	-	-	0.392**	0.177	0.208	0.263	-	-	0.208	0.263
SE	-0.103	0.237	-	-	-0.103	0.237	-0.056	0.347	-	-	-0.056	0.347
Pseudo R^2	0.634						0.470					
AIC	15259.070						17377.840					
BIC	15509.930						17615.490					

Notes: The outcome variable is the average bird and vascular plant species richness in *Model I* and *Model II*, respectively. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table C.14 Results of SLX (contiguity matrix) of bird and vascular plant species richness in South Australia, 2001–2016 (N = 5,440)

	Bird Species Richness (Model I)						*Vascular plant species richness (Model II)*					
	Direct effect	*Std. Err.*	*Indirect effect*	*Std. Err.*	*Total effect*	*Std. Err.*	*Direct effect*	*Std. Err.*	*Indirect effect*	*Std. Err.*	*Total effect*	*Std. Err.*
Organic farming business	-0.015	0.022	0.017	0.040	0.002	0.042	0.076***	0.028	0.146***	0.049	0.222***	0.051
Land cover diversity index	0.295***	0.081	0.117	0.132	0.412***	0.120	0.496***	0.116	-0.043	0.187	0.452***	0.170
Elevation range	0.001***	0.000	-	-	0.001***	0.000	0.002***	0.000	-	-	0.002***	0.000
Conservation land	0.001	0.002	0.006**	0.003	0.007**	0.003	0.000	0.003	-0.001	0.004	-0.001	0.004
Water bodies	0.014**	0.006	0.065***	0.013	0.079***	0.013	0.017**	0.008	0.046***	0.018	0.063***	0.017
Soil diversity index	-1.602***	0.360	-	-	-1.602***	0.360	-1.025*	0.535	-	-	-1.025*	0.535
Evapotranspiration	-0.001**	0.000	0.000	0.000	-0.001***	0.000	0.000	0.000	0.001***	0.000	0.001***	0.000
Vascular plant richness	0.357***	0.014	-0.094***	0.021	0.263***	0.017	-	-	-	-	-	-
NDVI	0.421	0.531	1.414**	0.574	1.835***	0.336	0.880	0.697	0.115	0.744	0.995**	0.409
Agricultural land parcels	0.001***	0.000	0.000	0.000	0.001***	0.000	0.001***	0.000	-0.001**	0.000	0.001	0.000
Crop land	-0.005**	0.002	0.004	0.003	-0.001	0.002	-0.007**	0.003	0.006	0.004	-0.001	0.003
Grazing land	-0.002	0.002	-0.001	0.003	-0.003	0.002	-0.001	0.002	0.013**	0.003	0.012***	0.003
Horticultural land	-0.005	0.003	0.002	0.005	-0.003	0.005	-0.006	0.004	0.003	0.007	-0.003	0.006
Urban accessibility index	0.008	0.012	-	-	0.008	0.012	-0.009	0.017	-	-	-0.009	0.017
Distance to road	0.002	0.002	-	-	0.002	0.002	-0.001	0.003	-	-	-0.001	0.003
Distance to coast	0.002**	0.001	-	-	0.002**	0.001	0.005***	0.001	-	-	0.005***	0.001
Trend	0.037***	0.004	-	-	0.037***	0.004	0.032***	0.004	-	-	0.032***	0.004
AW (base=AMLR)	1.318**	0.648	-	-	1.318**	0.648	2.650***	0.964	-	-	2.650***	0.964
EP	-0.144	0.170	-	-	-0.144	0.170	-0.471*	0.249	-	-	-0.471*	0.249
KI	-0.384	0.327	-	-	-0.384	0.327	-1.002**	0.484	-	-	-1.002**	0.484
NY	0.112	0.158	-	-	0.112	0.158	-0.779***	0.230	-	-	-0.779***	0.230
SAAL	0.474*	0.273	-	-	0.474*	0.273	-0.566	0.398	-	-	-0.566	0.398
SAMDB	0.319**	0.159	-	-	0.319**	0.159	0.007	0.233	-	-	0.007	0.233
SE	-0.119	0.216	-	-	-0.119	0.216	-0.294	0.312	-	-	-0.294	0.312
Pseudo R^2	0.643						0.495					
AIC	15243.810						17344.230					
BIC	15494.670						17581.880					

Notes: The outcome variable is the average bird and vascular plant species richness in *Model I* and *Model II*, respectively. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table C.15 Results of SDEM (contiguity matrix) of bird and vascular plant species richness in South Australia, 2001–2016 (N = 4,768)

	Bird Species Richness (Model I)						*Vascular plant species richness (Model II)*					
	Direct effect	***Std. Err.***	***Indirect effect***	***Std. Err.***	***Total effect***	***Std. Err.***	***Direct effect***	***Std. Err.***	***Indirect effect***	***Std. Err.***	***Total effect***	***Std. Err.***
Organic farming business	0.004	0.021	-0.023	0.046	-0.018	0.055	0.066**	0.026	0.118**	0.059	0.184**	0.072
Land cover diversity index	0.277***	0.086	-0.002	0.123	0.275**	0.123	0.375***	0.116	-0.177	0.168	0.198	0.173
Elevation range	0.001***	0.000	-	-	0.001***	0.000	0.003***	0.000	-	-	0.003***	0.000
Conservation land	0.002	0.002	0.004	0.003	0.006*	0.003	0.002	0.002	0.013***	0.004	0.015***	0.005
Water bodies	0.016***	0.006	0.035***	0.011	0.051***	0.013	0.020***	0.007	0.040***	0.015	0.061***	0.017
Soil diversity index	-2.398	0.427	-	-	-2.398***	0.427	-2.882***	0.608	-	-	-2.882***	0.608
Evapotranspiration	-0.001***	0.000	0.000	0.000	-0.001*	0.000	0.000	0.000	0.001**	0.001	0.001***	0.000
Vascular plant richness	0.351***	0.013	-0.030	0.023	0.321***	0.025	-	-	-	-	-	-
NDVI	0.225	0.490	1.018*	0.602	1.243**	0.535	1.361**	0.608	-0.235	0.792	1.125	0.763
Agricultural land parcels	0.001***	0.000	0.001***	0.000	0.002***	0.000	0.001***	0.000	0.000	0.000	0.002***	0.000
Crop land	-0.005**	0.002	0.001	0.003	-0.004*	0.003	-0.006**	0.003	0.006	0.004	-0.001	0.004
Grazing land	-0.001	0.002	0.003	0.003	0.001	0.003	-0.001	0.002	0.011***	0.003	0.010***	0.004
Horticultural land	-0.004	0.003	-0.001	0.005	-0.005	0.005	-0.008**	0.004	0.002	0.007	-0.006	0.007
Urban accessibility index	-0.026**	0.013	-	-	-0.026**	0.013	-0.030*	0.017	-	-	-0.030*	0.017
Distance to road	-0.007*	0.004	-	-	-0.007*	0.004	-0.014***	0.005	-	-	-0.014***	0.005
Distance to coast	0.003***	0.001	-	-	0.003***	0.001	0.005***	0.001	-	-	0.005***	0.001
Trend	0.047***	0.006	-	-	0.047***	0.006	0.018**	0.008	-	-	0.018**	0.008
AW (base=AMLR)	0.833	0.620	-	-	0.833	0.620	1.722**	0.874	-	-	1.722**	0.874
EP	-0.492***	0.179	-	-	-0.492***	0.179	-1.020***	0.253	-	-	-1.020***	0.253
KI	-0.783**	0.367	-	-	-0.783**	0.367	-1.769***	0.533	-	-	-1.769***	0.533
NY	0.046	0.163	-	-	0.046	0.163	-0.877***	0.231	-	-	-0.877***	0.231
SAAL	0.096	0.282	-	-	0.096	0.282	-0.550	0.397	-	-	-0.550	0.397
SAMDB	-0.149	0.159	-	-	-0.149	0.159	-0.264	0.225	-	-	-0.264	0.225
SE	-0.612***	0.224	-	-	-0.612***	0.224	-0.863***	0.317	-	-	-0.863***	0.317
Spatial error (λ)	0.506***						0.614***					
Pseudo R^2	0.657						0.492					
AIC	12671.090						14405.950					
BIC	12923.410						14645.320					

Notes: The outcome variable is the average bird and vascular plant species richness in *Model I* and *Model II*, respectively. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table C.16 Results of SDEM (nearest neighbour matrix) of bird and vascular plant species richness in South Australia, 2001–2016 (N=4,768)

	Bird Species Richness (Model I)						*Vascular plant species richness (Model II)*					
	Direct effect	***Std. Err.***	***Indirect effect***	***Std. Err.***	***Total effect***	***Std. Err.***	***Direct effect***	***Std. Err.***	***Indirect effect***	***Std. Err.***	***Total effect***	***Std. Err.***
Organic farming business	-0.004	0.021	0.005	0.050	0.001	0.058	0.056**	0.025	0.128**	0.064	0.184**	0.075
Land cover diversity index	0.309***	0.088	-0.071	0.150	0.238*	0.144	0.504***	0.122	-0.505**	0.213	-0.001	0.207
Elevation range	0.001***	0.000	-	-	0.001***	0.000	0.003***	0.000	-	-	0.003***	0.000
Conservation land	0.002	0.002	0.003	0.004	0.005	0.004	0.004*	0.002	-0.001	0.005	0.004	0.005
Water bodies	0.017***	0.006	0.050***	0.014	0.067***	0.016	0.023***	0.008	0.041**	0.019	0.064***	0.022
Soil diversity index	-2.427***	0.446	-	-	-2.427***	0.446	-2.631***	0.650	-	-	-2.631***	0.650
Evapotranspiration	-0.001	0.000	0.000	0.001	-0.001*	0.000	0.001*	0.001	0.000	0.001	0.001*	0.001
Vascular plant richness	0.364***	0.013	-0.079***	0.024	0.285***	0.026	-	-	-	-	-	-
NDVI	0.478	0.566	1.032	0.749	1.510**	0.592	1.748**	0.723	-0.532	1.006	1.217	0.847
Agricultural land parcels	0.001***	0.000	0.001*	0.000	0.002***	0.000	0.002***	0.000	-0.001	0.001	0.001**	0.001
Crop land	-0.005**	0.002	0.001	0.003	-0.004	0.003	-0.002	0.003	-0.005	0.004	-0.007*	0.004
Grazing land	0.000	0.002	-0.001	0.003	0.000	0.003	0.002	0.002	0.003	0.004	0.005	0.004
Horticultural land	-0.004	0.003	0.001	0.005	-0.003	0.005	-0.004	0.004	-0.001	0.007	-0.004	0.008
Urban accessibility index	-0.029**	0.014	-	-	-0.029**	0.014	-0.058***	0.017	-	-	-0.058***	0.017
Distance to road	-0.011***	0.004	-	-	-0.011***	0.004	-0.022***	0.006	-	-	-0.022***	0.006
Distance to coast	0.003***	0.001	-	-	0.003***	0.001	0.004***	0.001	-	-	0.004***	0.001
Trend	0.045***	0.007	-	-	0.045***	0.007	0.019*	0.010	-	-	0.019*	0.010
AW (base=AMLR)	0.815	0.637	-	-	0.815	0.637	1.491	0.926	-	-	1.491	0.926
EP	-0.481**	0.202	-	-	-0.481**	0.202	-0.878***	0.295	-	-	-0.878***	0.295
KI	-0.678**	0.344	-	-	-0.678**	0.344	-1.278**	0.499	-	-	-1.278**	0.499
NY	-0.034	0.184	-	-	-0.034	0.184	-0.764***	0.268	-	-	-0.764***	0.268
SAAL	0.202	0.297	-	-	0.202	0.297	-0.369	0.428	-	-	-0.369	0.428
SAMDB	-0.091	0.174	-	-	-0.091	0.174	-0.001	0.253	-	-	-0.001	0.253
SE	-0.611**	0.247	-	-	-0.611**	0.247	-0.667*	0.360	-	-	-0.667*	0.360
Spatial error (λ)	0.521***						0.619***					
Pseudo R^2	0.651						0.467					
AIC	12638.860						14386.770					
BIC	12891.180						14626.150					

Notes: The outcome variable is the average bird and vascular plant species richness in *Model I* and *Model II*, respectively. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table C.17 Results of SDM (contiguity matrix) of bird and vascular plant species richness in South Australia, 2001–2016 (N = 4,768)

	Bird Species Richness (Model I)						***Vascular plant species richness (Model II)***					
	Direct effect	***Std. Err.***	***Indirect effect***	***Std. Err.***	***Total effect***	***Std. Err.***	***Direct effect***	***Std. Err.***	***Indirect effect***	***Std. Err.***	***Total effect***	***Std. Err.***
Organic farming business	-0.008	0.021	-0.064	0.066	-0.072	0.075	0.064**	0.026	0.171*	0.097	0.235**	0.110
Land cover diversity index	0.335***	0.081	-0.061	0.182	0.275	0.200	0.501***	0.116	-0.504	0.315	-0.003	0.351
Elevation range	0.001***	0.000	0.001***	0.000	0.002***	0.000	0.002***	0.000	0.002***	0.000	0.004***	0.001
Agricultural land parcels	0.001***	0.000	0.001**	0.000	0.002***	0.000	0.001***	0.000	-0.001	0.001	0.001	0.001
Water bodies	0.014**	0.006	0.048**	0.019	0.061***	0.021	0.013*	0.008	0.052*	0.030	0.065*	0.034
Soil diversity index	-1.840***	0.390	-1.495***	0.325	-3.334***	0.709	-2.180***	0.597	-2.528***	0.706	-4.708***	1.298
Evapotranspiration	-0.001**	0.000	0.000	0.000	-0.001	0.000	0.000	0.000	0.001**	0.001	0.001**	0.001
Vascular plant richness	0.355***	0.013	-0.100***	0.030	0.255***	0.031	-	-	-	-	-	-
NDVI	0.507	0.468	1.389**	0.664	1.896***	0.601	1.191**	0.600	-0.108	0.942	1.083	0.893
Conservation land	0.002	0.002	0.004	0.004	0.006	0.005	-0.001	0.002	0.002	0.007	0.002	0.008
Crop land	-0.005***	0.002	0.001	0.004	-0.004	0.004	-0.008***	0.003	0.008	0.006	0.000	0.007
Grazing land	-0.002	0.002	0.002	0.004	-0.001	0.004	-0.003	0.002	0.017***	0.006	0.014**	0.007
Horticultural land	-0.004	0.003	0.003	0.008	0.000	0.008	-0.008**	0.004	0.006	0.012	-0.002	0.013
Urban accessibility index	-0.022*	0.013	-0.018*	0.011	-0.040*	0.024	-0.037**	0.018	-0.042**	0.020	-0.079**	0.038
Distance to road	-0.008**	0.004	-0.007**	0.003	-0.015**	0.007	-0.018***	0.006	-0.021***	0.007	-0.040***	0.012
Distance to coast	0.002***	0.001	0.002***	0.001	0.004***	0.001	0.003***	0.001	0.003***	0.001	0.006***	0.002
Trend	0.028***	0.004	0.023***	0.003	0.051***	0.007	0.013***	0.005	0.015***	0.005	0.027***	0.010
AW (base=AMLR)	0.666	0.610	0.541	0.495	1.208	1.104	1.310	0.936	1.520	1.087	2.830	2.022
EP	-0.369**	0.164	-0.300**	0.135	-0.669**	0.298	-0.838***	0.246	-0.972***	0.291	-1.811***	0.536
KI	-0.502	0.313	-0.408	0.255	-0.909	0.567	-1.105**	0.479	-1.282**	0.560	-2.386**	1.037
NY	-0.003	0.148	-0.002	0.120	-0.005	0.269	-0.670***	0.222	-0.777***	0.260	-1.447***	0.481
SAAL	0.084	0.264	0.068	0.214	0.153	0.478	-0.629	0.398	-0.729	0.463	-1.358	0.860
SAMDB	-0.069	0.148	-0.056	0.120	-0.126	0.268	-0.264	0.225	-0.306	0.261	-0.570	0.486
SE	-0.374*	0.203	-0.304*	0.166	-0.679*	0.368	-0.443	0.304	-0.514	0.354	-0.958	0.657
Spatial lag (ρ)	0.495***						0.594***					
Pseudo R^2	0.654						0.468					
AIC	12633.230						14397.840					
AIC	12885.550						14637.220					

Notes: The outcome variable is the average bird and vascular plant species richness in *Model I* and *Model II*, respectively. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table C.18 Results of SDM (nearest neighbour matrix) of bird and vascular plant species richness in South Australia, 2001–2016 (N = 4,768)

	Bird Species Richness (Model I)						***Vascular plant species richness (Model II)***					
	Direct effect	***Std. Err.***	***Indirect effect***	***Std. Err.***	***Total effect***	***Std. Err.***	***Direct effect***	***Std. Err.***	***Indirect effect***	***Std. Err.***	***Total effect***	***Std. Err.***
Organic farming business	-0.010	0.021	-0.005	0.073	-0.015	0.081	0.054**	0.026	0.174	0.107	0.228*	0.119
Land cover diversity index	0.320***	0.086	-0.082	0.227	0.238	0.239	0.569***	0.124	-0.722*	0.394	-0.154	0.420
Elevation range	0.001***	0.000	0.001***	0.000	0.003***	0.000	0.003***	0.000	0.004***	0.001	0.006***	0.001
Conservation land	0.002	0.002	0.004	0.005	0.006	0.005	0.003	0.002	-0.014*	0.008	-0.012	0.008
Water bodies	0.018***	0.006	0.070***	0.023	0.088***	0.026	0.020**	0.008	0.049	0.037	0.070*	0.041
Soil diversity index	-1.958***	0.413	-1.822***	0.395	-3.781***	0.801	-1.977***	0.642	-2.567***	0.846	-4.543***	1.483
Evapotranspiration	-0.001	0.000	0.000	0.001	0.000	0.000	0.001	0.001	0.000	0.001	0.001*	0.001
Vascular plant richness	0.369***	0.013	-0.152***	0.031	0.217***	0.032	-	-	-	-	-	-
NDVI	0.616	0.548	1.487*	0.794	2.102***	0.650	1.830**	0.721	-0.671	1.115	1.159	0.953
Agricultural land parcels	0.001***	0.000	0.000	0.001	0.002**	0.001	0.002***	0.000	-0.002*	0.001	0.000	0.001
Crop land	-0.004*	0.002	0.005	0.005	0.001	0.005	-0.003	0.003	-0.006	0.008	-0.009	0.008
Grazing land	0.000	0.002	-0.003	0.005	-0.003	0.005	0.000	0.002	0.000	0.007	0.000	0.008
Horticultural land	-0.003	0.003	0.009	0.007	0.006	0.008	-0.005	0.004	-0.005	0.012	-0.010	0.013
Urban accessibility index	-0.018	0.013	-0.017	0.013	-0.036	0.026	-0.052***	0.018	-0.067***	0.024	-0.119***	0.042
Distance to road	-0.013***	0.004	-0.012***	0.004	-0.024***	0.008	-0.027***	0.006	-0.035***	0.008	-0.062***	0.014
Distance to coast	0.002***	0.001	0.002***	0.001	0.004***	0.001	0.002*	0.001	0.003*	0.001	0.005*	0.003
Trend	0.024***	0.004	0.022***	0.004	0.046***	0.007	0.008*	0.005	0.011*	0.006	0.019*	0.010
AW (base=AMLR)	0.673	0.641	0.626	0.597	1.299	1.237	1.269	0.999	1.648	1.299	2.916	2.297
EP	-0.420**	0.179	-0.390**	0.169	-0.810**	0.347	-0.748***	0.273	-0.971***	0.360	-1.719***	0.631
KI	-0.532	0.328	-0.496	0.307	-1.028	0.634	-0.847*	0.511	-1.100*	0.667	-1.946*	1.177
NY	-0.180	0.164	-0.168	0.154	-0.348	0.318	-0.589**	0.248	-0.764**	0.324	-1.353**	0.570
SAAL	0.246	0.275	0.229	0.255	0.476	0.530	-0.051	0.420	-0.066	0.545	-0.116	0.965
SAMDB	-0.053	0.165	-0.049	0.154	-0.101	0.319	0.117	0.255	0.152	0.332	0.268	0.587
SE	-0.275	0.223	-0.256	0.208	-0.531	0.430	-0.156	0.338	-0.203	0.440	-0.359	0.778
Spatial lag (ρ)	0.509						0.599					
Pseudo R^2	0.645						0.437					
AIC	12608.580						14402.050					
BIC	12860.900						14641.430					

Notes: The outcome variable is the average bird and vascular plant species richness in *Model I* and *Model II*, respectively. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table C.19 Results of SLX (contiguity matrix) of bird and vascular plant species richness in South Australia, 2001–2016 (N = 4,768)

	Bird Species Richness (Model I)						***Vascular plant species richness (Model II)***					
	Direct effect	***Std. Err.***	***Indirect effect***	***Std. Err.***	***Total effect***	***Std. Err.***	***Direct effect***	***Std. Err.***	***Indirect effect***	***Std. Err.***	***Total effect***	***Std. Err.***
Organic farming business	-0.001	0.022	-0.015	0.041	-0.016	0.042	0.080***	0.029	0.171***	0.051	0.251***	0.053
Land cover diversity index	0.287***	0.093	0.100	0.127	0.387***	0.115	0.414***	0.128	-0.151	0.176	0.264*	0.160
Elevation range	0.001***	0.000	-	-	0.001***	0.000	0.002***	0.000	-	-	0.002***	0.000
Conservation land	0.001	0.002	0.005	0.003	0.006**	0.003	-0.001	0.003	0.000	0.004	-0.001	0.004
Water bodies	0.014**	0.006	0.048***	0.012	0.062***	0.012	0.015*	0.008	0.043***	0.016	0.057***	0.016
Soil diversity index	-2.409***	0.417	-	-	-2.409***	0.417	-2.295***	0.589	-	-	-2.295***	0.589
Evapotranspiration	-0.001*	0.000	0.000	0.000	-0.001***	0.000	0.000	0.001	0.001**	0.001	0.001***	0.000
Vascular plant richness	0.354***	0.014	-0.085***	0.021	0.269***	0.017	-	-	-	-	-	-
NDVI	0.375	0.557	1.503**	0.592	1.878***	0.342	0.927	0.735	0.044	0.777	0.972**	0.432
Agricultural land parcels	0.001***	0.000	0.001**	0.000	0.002***	0.000	0.001***	0.000	-0.001*	0.000	0.001	0.000
Crop land	-0.005**	0.002	0.003	0.003	-0.002	0.002	-0.009***	0.003	0.006	0.004	-0.003	0.003
Grazing land	-0.002	0.002	0.001	0.003	-0.001	0.002	-0.003	0.003	0.015***	0.004	0.011***	0.003
Horticultural land	-0.005	0.003	0.004	0.005	0.000	0.005	-0.008*	0.004	0.005	0.007	-0.003	0.006
Urban accessibility index	-0.017	0.014	-	-	-0.017	0.014	-0.040**	0.018	-	-	-0.040**	0.018
Distance to road	-0.007*	0.004	-	-	-0.007*	0.004	-0.016***	0.006	-	-	-0.016***	0.006
Distance to coast	0.003***	0.001	-	-	0.003***	0.001	0.005***	0.001	-	-	0.005***	0.001
Trend	0.045***	0.004	-	-	0.045***	0.004	0.028***	0.005	-	-	0.028***	0.005
AW (base=AMLR)	1.298**	0.651	-	-	1.298**	0.651	1.850**	0.922	-	-	1.850**	0.922
EP	-0.348**	0.175	-	-	-0.348**	0.175	-0.767***	0.245	-	-	-0.767***	0.245
KI	-0.551*	0.334	-	-	-0.551*	0.334	-1.262***	0.473	-	-	-1.262***	0.473
NY	0.059	0.158	-	-	0.059	0.158	-0.865***	0.221	-	-	-0.865***	0.221
SAAL	0.384	0.282	-	-	0.384	0.282	-0.681*	0.395	-	-	-0.681*	0.395
SAMDB	0.046	0.158	-	-	0.046	0.158	-0.151	0.222	-	-	-0.151	0.222
SE	-0.359*	0.217	-	-	-0.359*	0.217	-0.529*	0.303	-	-	-0.529*	0.303
Pseudo R^2	0.654						0.483					
AIC	13397.490						15619.580					
BIC	13643.340						15852.490					

Notes: The outcome variable is the average bird and vascular plant species richness in *Model I* and *Model II*, respectively. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively

Table C.20 Results of SLX (nearest neighbour matrix) of bird and vascular plant species richness in South Australia, 2001–2016 (N = 4,768)

	Bird Species Richness (Model I)						*Vascular plant species richness (Model II)*					
	Direct effect	*Std. Err.*	*Indirect effect*	*Std. Err.*	*Total effect*	*Std. Err.*	*Direct effect*	*Std. Err.*	*Indirect effect*	*Std. Err.*	*Total effect*	*Std. Err.*
Organic farming business	-0.007	0.022	0.008	0.043	0.002	0.044	0.078***	0.029	0.174***	0.054	0.253***	0.056
Land cover diversity index	0.314***	0.097	0.058	0.149	0.372***	0.131	0.518***	0.135	-0.342	0.208	0.176**	0.183
Elevation range	0.002***	0.000	-	-	0.002***	0.000	0.003***	0.000	-	-	0.003***	0.000
Conservation land	0.002	0.002	0.004	0.003	0.006**	0.003	0.003	0.003	-0.010**	0.004	-0.008*	0.004
Water bodies	0.018***	0.006	0.056***	0.013	0.074***	0.014	0.024***	0.008	0.036**	0.018	0.059***	0.019
Soil diversity index	-2.644***	0.438	-	-	-2.644***	0.438	-2.234***	0.626	-	-	-2.234***	0.626
Evapotranspiration	-0.001**	0.001	0.000	0.001	-0.001***	0.000	0.001	0.001	0.000	0.001	0.001***	0.000
Vascular plant richness	0.364***	0.014	-0.111***	0.020	0.253***	0.017	-	-	-	-	-	-
NDVI	0.479	0.641	1.544**	0.711	2.023***	0.356	1.416*	0.857	-0.353	0.943	1.063	0.451
Agricultural land parcels	0.001***	0.000	0.000	0.000	0.002***	0.000	0.002***	0.000	-0.002***	0.000	0.000	0.001
Crop land	-0.004*	0.002	0.003	0.003	-0.001	0.003	-0.004	0.003	-0.001	0.005	-0.006	0.004
Grazing land	-0.001	0.002	-0.002	0.003	-0.003	0.003	0.001	0.003	0.005	0.004	0.006*	0.004
Horticultural land	-0.005	0.003	0.007	0.005	0.003	0.004	-0.005	0.004	0.000	0.006	-0.005	0.006
Urban accessibility index	-0.016	0.014	-	-	-0.016	0.014	-0.048**	0.019	-	-	-0.048**	0.019
Distance to road	-0.011**	0.004	-	-	-0.011**	0.004	-0.021***	0.006	-	-	-0.021***	0.006
Distance to coast	0.003***	0.001	-	-	0.003***	0.001	0.005***	0.001	-	-	0.005***	0.001
Trend	0.044***	0.004	-	-	0.044***	0.004	0.026***	0.005	-	-	0.026***	0.005
AW (base=AMLR)	1.126*	0.680	-	-	1.126*	0.680	1.762*	0.972	-	-	1.762*	0.972
EP	-0.386**	0.190	-	-	-0.386**	0.190	-0.720***	0.269	-	-	-0.720***	0.269
KI	-0.461	0.347	-	-	-0.461	0.347	-1.019**	0.498	-	-	-1.019**	0.498
NY	0.012	0.174	-	-	0.012	0.174	-0.836***	0.245	-	-	-0.836***	0.245
SAAL	0.539**	0.291	-	-	0.539**	0.291	-0.452	0.412	-	-	-0.452	0.412
SAMDB	0.027	0.175	-	-	0.027	0.175	0.078	0.250	-	-	0.078	0.250
SE	-0.400*	0.237	-	-	-0.400*	0.237	-0.295	0.335	-	-	-0.295	0.335
Pseudo R^2	0.645						0.460					
AIC	13401.030						15646.850					
BIC	13646.880						15879.760					

Notes: The outcome variable is the average bird and vascular plant species richness in *Model I* and *Model II*, respectively. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Appendix D Supplementary materials for Chapter 4

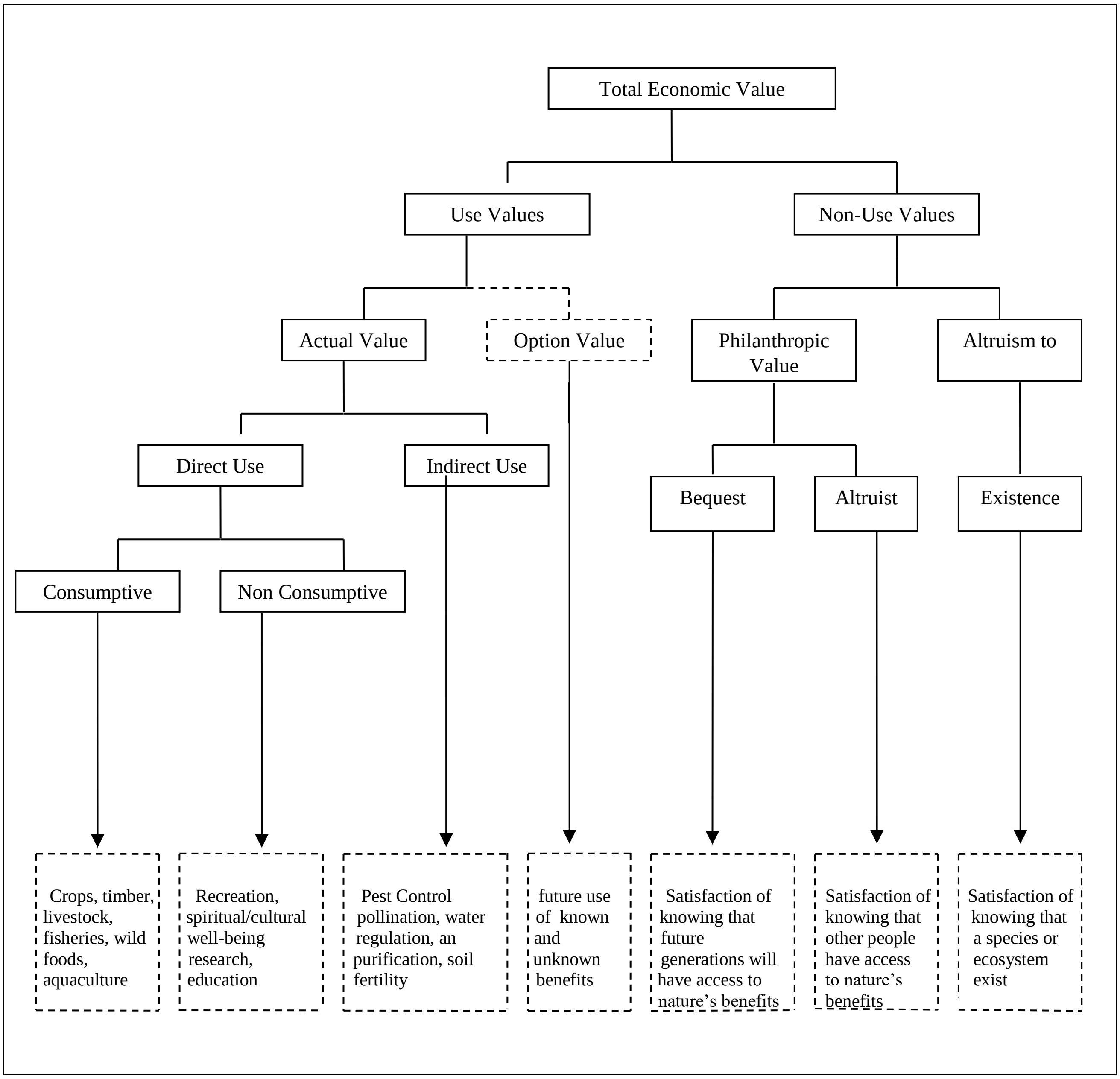
Table D.1 Determinants of agricultural properties price: a synthesis of the literature

Variables	*Influence on land value*	*How often studied*	*Selected sources*
Farm size	Small properties commands significantly higher price	Often	(Eagle et al. 2014; Henneberry and Barrows 1990; Wasson et al. 2013)
	Large properties captures higher price	Often	(Grimes and Aitken 2008; Ifft et al. 2018; Quaye et al. 2018)
	Marginal value of land decreases at a diminishing rate as the farm size increases	Occasionally	(Maddison 2000; Polyakov et al. 2013, 2015)
Structural attributes	Structural improvements on the properties accounts for higher price	Often	(Maddison 2000; Maddison 2009; Walpole and Lockwood 1999)
	Non-linear effects of existence of bedrooms on the lifestyle properties	Rarely	(Polyakov et al. 2013; Tapsuwan and Polyakov 2016)
Land use	Pasture land used for dairy reduces farm land value	Occasionally	(Samarasinghe and Greenhalgh 2013; Uematsu et al. 2013; Wang 2018)
	Farm land used for cropping commands significantly higher price than pasture land	Rarely	(Borchers et al. 2014)
	Land used as orchard/vineyard/greenhouse commands premium price	Often	(Barnard et al. 1997; Deaton and Vyn 2010; Mukherjee and Schwabe 2014; Uematsu et al. 2013)
Water availability	Access to irrigation through surface or groundwater commands premium for agricultural lands	Often	(Buck et al. 2014; Faux and Perry 1999; Sampson et al. 2019; Schlenker et al. 2007)
	More secure water rights are not capitalised into farm land values and the premium for water right is heterogeneous	Rarely	(Brent 2016)
	Groundwater trading restriction reduce farmland value	Rarely	(Bigelow et al. 2019)
Temperature	Increasing average temperature significantly reduces farm land value	Often	(Borchers et al. 2014; Mendelsohn et al. 1994; Wang 2018)
	Increased degree days during growing season has positive effect	Occasionally	(Mukherjee and Schwabe 2014; Schlenker et al. 2006)
Precipitation	Higher land value is significantly correlated with increased average rainfall	Often	(Marano 2001; Mendelsohn et al. 1994; Samarasinghe and Greenhalgh 2013)
	Annual rainfall has negative effects on smaller properties, but positively influence large properties price	Rarely	(Polyakov et al. 2015)
	Increased average rainfall in growing season reduces farm land value	Occasionally	(Mukherjee and Schwabe 2014)
	Higher rainfall in winter and summer increases farmland value but has negative effect in spring and fall	Rarely	(Van Passel et al. 2017)
	Effects of climate change vary between rain-fed and irrigated agriculture (warmer temperature	Rarely	(Mendelsohn and Dinar 2003)

	and less precipitation positively influence irrigated cropland value)		
Natural disaster	Farms located in natural disaster prone (drought, flood and earthquakes) areas receives significantly lower rent/valued compared to other areas	Rarely	(Quaye et al. 2018; Samarasinghe and Greenhalgh 2013)
	Drought significantly reduce crops (corn and soybean) yield, but no significant effect on farm income	Rarely	(Kuwayama et al. 2018)
Soil attributes	Good quality land commands higher price	Often	(Barnard et al. 1997; Schlenker et al. 2006; Uematsu et al. 2013; Xu et al. 1993)
	Basic soil, increased percentage of organic carbon, water holding capacity of soil positively influence irrigated farmland value	Often	(Samarasinghe and Greenhalgh 2013; Sampson et al. 2019)
	Higher clay percentage and soil erodibility reduces agricultural properties price	Often	(Schlenker et al. 2007; Van Passel et al. 2017)
Topography	Properties on steeper slopes reduces farmland value	Occasionally	(Ma and Swinton 2011; Samarasinghe and Greenhalgh 2013; Van Passel et al. 2017)
	Agricultural properties in hilly, plain and grassland topography commands higher price compared to farmlands located in mountain areas	Occasionally	(Zhang et al. 2020)
	Property price increases as elevation increases	Occasionally	(Tapsuwan et al. 2012)
Native woody vegetation	Tree cover increases pastureland values but reduces cropland values	Rarely	(Borchers et al. 2014)
	Non-heritage remnant native vegetation doesn't significantly influence rural property value, whereas native vegetation under heritage agreement negatively influence market value	Rarely	(Marano 2001)
	Decreases property values if it occupies more than 50% of the properties	Rarely	(Walpole and Lockwood 1999)
	Increases rural property values at a diminishing rate	Rarely	(Polyakov et al. 2013, 2015)
	Wooded area reduce market value of the property	Rarely	(Deaton and Vyn 2010; Vyn 2012)
	Greenness (vegetation) increases the sale price of properties	Rarely	(Sengupta and Osgood 2003)
Locational amenities	Proximity to sources of recreational amenities such as river, coast, national conservation reserves/parks significantly increases property price	Occasionally	(Gibbons et al. 2014; Ma and Swinton 2011; Polyakov et al. 2013, 2015; Sengupta and Osgood 2003)
	Properties that are further away from natural park command higher price	Rarely	(Tapsuwan et al. 2012)
	Greater accessibility to transport infrastructure (rail/road) positively capitalised into farmland value	Rarely	(Sengupta and Osgood 2003; Sheng et al. 2018)

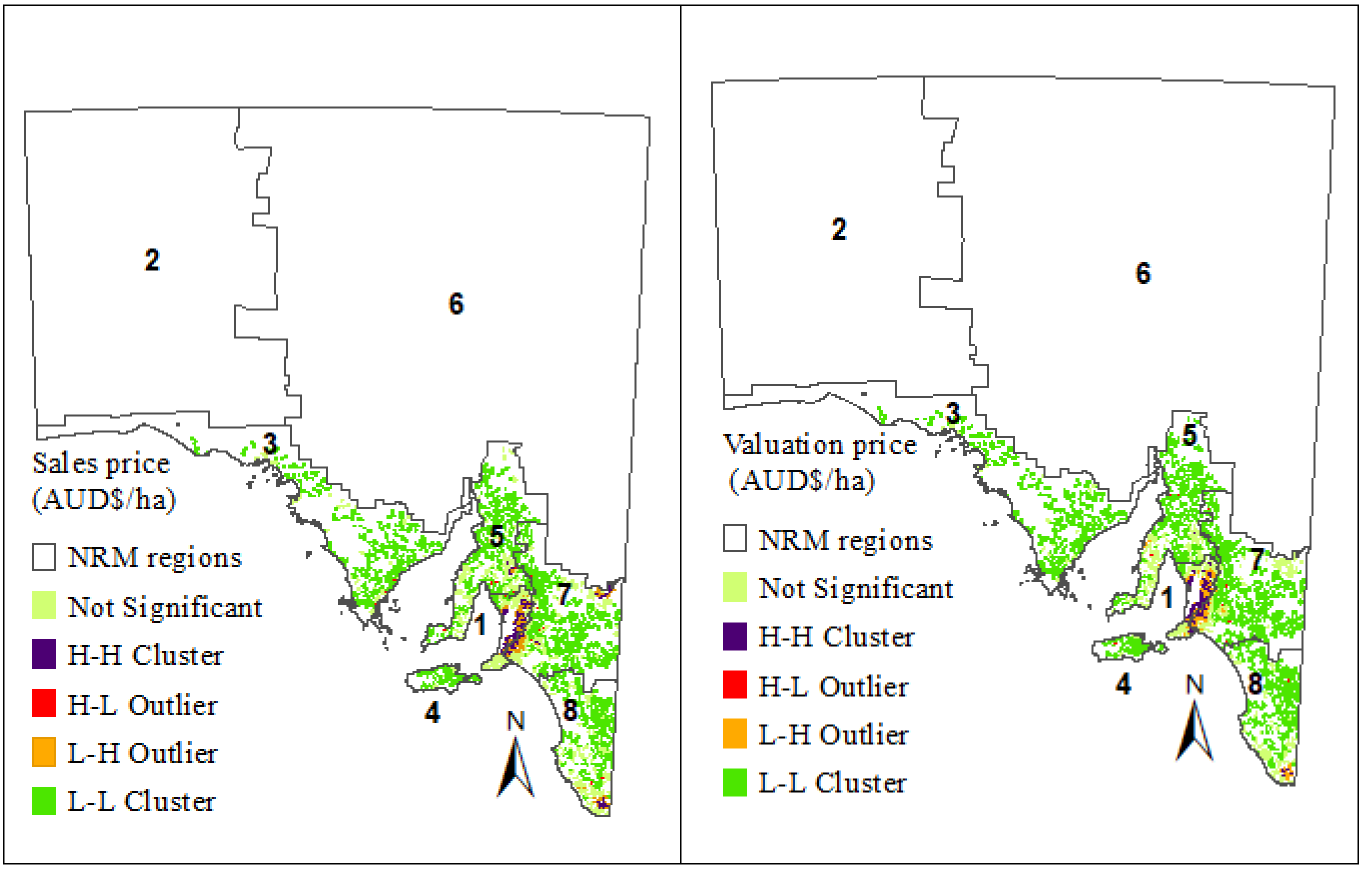
	Proximity to urban centres positively influence property value	Often	(Deaton and Vyn 2010; Delbecq et al. 2014; Huang et al. 2006; Mukherjee and Schwabe 2014; Xu et al. 1993)
Socio-economic conditions	Higher land value is associated with higher median household income/per capital income	Occasionally	(Borchers et al. 2014; Huang et al. 2006; Quaye et al. 2018; Schlenker et al. 2006)
	Population density is positively associated with property price	Often	(Deaton and Vyn 2010; Delbecq et al. 2014; Henderson and Moore 2006; Huang et al. 2006; Schlenker et al. 2007; Sheng et al. 2018; Van Passel et al. 2017)
	Farmland operated by experienced farmers (in terms of operators age) capture higher price	Rarely	(Wang 2018)
Market access	Increased accessibility to different sources of amenities and populated places (measured by gravity index) positively affects property value	Often	(Barnard et al. 1997; Borchers et al. 2014; Maddison 2009; Polyakov et al. 2013, 2015; Sheng et al. 2018)
Return from agriculture	Higher agricultural return (yield, commodity price, etc.) is positively associated with increased agricultural land value	Rarely	(Marano 2001; Wang 2018)
	Dairy density positively influence property price	Rarely	(Kostov 2009)
	Farmland as wildlife recreational source commands higher price	Rarely	(Henderson and Moore 2006)
	Direct government support (grain subsidy, direct payment, energy policy, conservation program, etc.) increases farmland price	Occasionally	(Uematsu et al. 2013; Van Passel et al. 2017; Weersink et al. 1999; Wu and Lin 2010; Zhang et al. 2020)

Table D.2 Total economic value of the ecosystem services derived from the stocks of natural capital



Source: Marais et al. (2019, p. 7)

Figure D.1 Cluster and outliers of agricultural properties per hectare real (base year 2004) sales and valuation price in SA at 11 km threshold inverse distance, 2000-2013



Own maps (data sources: base map – NRM regions (ABS 2011c); customised property transaction datasets (sales and valuation price) - SA Office of the Registrar General)

Notes: H-H (high-high clusters) indicates statistically significant high valued land surrounded by lands with high value; L-L (low-low clusters) means statistically significant low valued land neighboured with farm lands with low value; H-L (high-low outliers) shows statistically significant high valued land bordered by lands with low value; L-H (low-high outliers) indicates statistically significant low valued land encircled by lands with high value.

The numbers in the map indicates NRM regions: 1- Adelaide and Mount Lofty Ranges (AMLR); 2 – Alinytjara Wilurara (AW); 3 – Eyre Peninsula (EP); 4 – Kangaroo Island (KI); 5 – Northern and Yorke (NY); 6 – South Australian Arid Lands (SAAL); 7 – South Australian Murray Darling Basin (SAMDB); 8 – South East (SE).

Table D.3 Agricultural land use categories

Farming industries	*Land use classes*
Broadacre Cropping	Cereals - irrigated - stock watering Small seeds - irrigated - stock watering Fodder crops - irrigated - stock watering Cereals and fodder - irrigated - stock watering Cereals and sheep - irrigated - stock watering Cereals and cattle - irrigated - stock watering Cereals and pigs - irrigated - stock watering Oilseed - irrigated - stock watering Agriculture N.E.C. - irrigated - stock watering
Livestock	Sheep-wool - irrigated pasture - stud - stock paddocks - stock watering Sheep-mutton - irrigated pasture - stud - stock paddocks - stock watering Cattle-dairy - irrigated pasture - stud - stock paddocks - stock watering Cattle-beef - irrigated pasture - stud - stock paddocks - stock watering

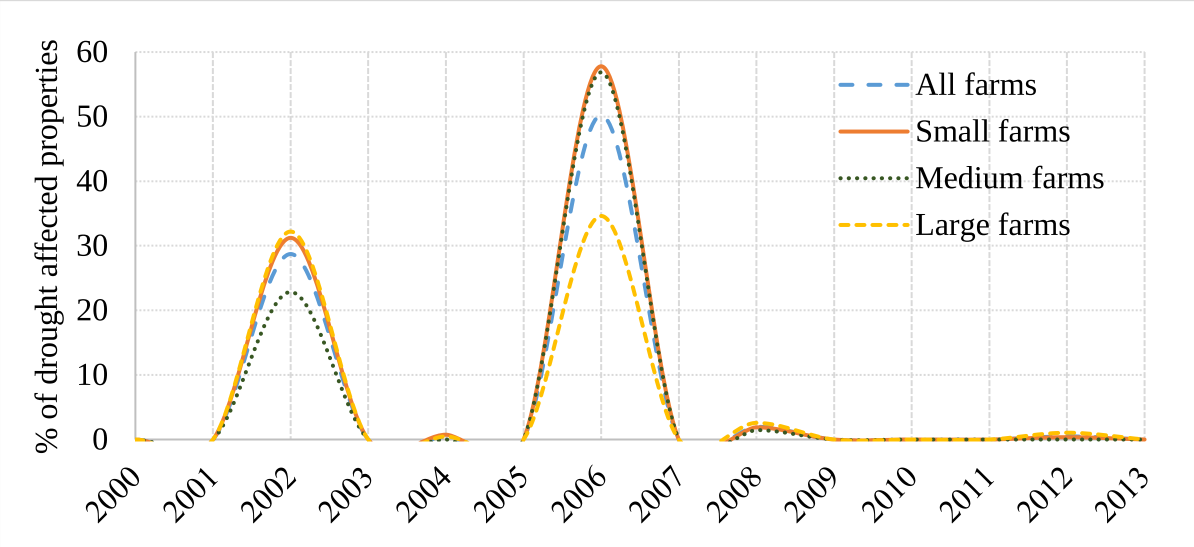
	Sheep and cattle - irrigated pasture - stud - stock paddocks - stock watering Pigs - irrigated pasture - stud - stock paddocks - stock watering Horses - irrigated pasture - stud - stock paddocks - stock watering Goats - irrigated pasture - stud - stock paddocks - stock watering Poultry - broiler - eggs - hatchery - N.E.C. Livestock N.E.C. - irrigated pasture - stud - stock paddocks - stock watering
Horticulture	Citrus - irrigated - nursery - stock watering Stone fruits - irrigated - nursery - stock watering Pome fruits - irrigated - nursery - stock watering Almonds - irrigated - nursery - stock watering Olives - irrigated - nursery

	- stock watering Citrus and others - irrigated - nursery - stock watering Stone fruits and others - irrigated - nursery - stock watering Berry fruits - irrigated - stock watering Horticulture N.E.C. - irrigated - nursery - stock watering
Viticulture	Vines - irrigated - nursery - stock watering Vines and others - irrigated - nursery - stock watering
Mixed farming	Vines and Stock - irrigated - stock watering Dairying and potatoes - irrigated - stock watering Dairying and pigs - irrigated - stock watering Stock and poultry - irrigated - stock watering Cereals, stock, horticulture - irrigated - stock watering Mixed farming N.E.C. - irrigated - stock watering
Market gardening	Vegetables - irrigated - stock watering Flowers - irrigated - stock watering

	Glasshouse - irrigated - stock watering Potatoes - irrigated - stock watering Peas - irrigated - stock watering Tomatoes - irrigated - stock watering Onions - irrigated - stock watering Market gardening and orchard - irrigated - stock watering Market gardening N.E.C. - irrigated - stock watering

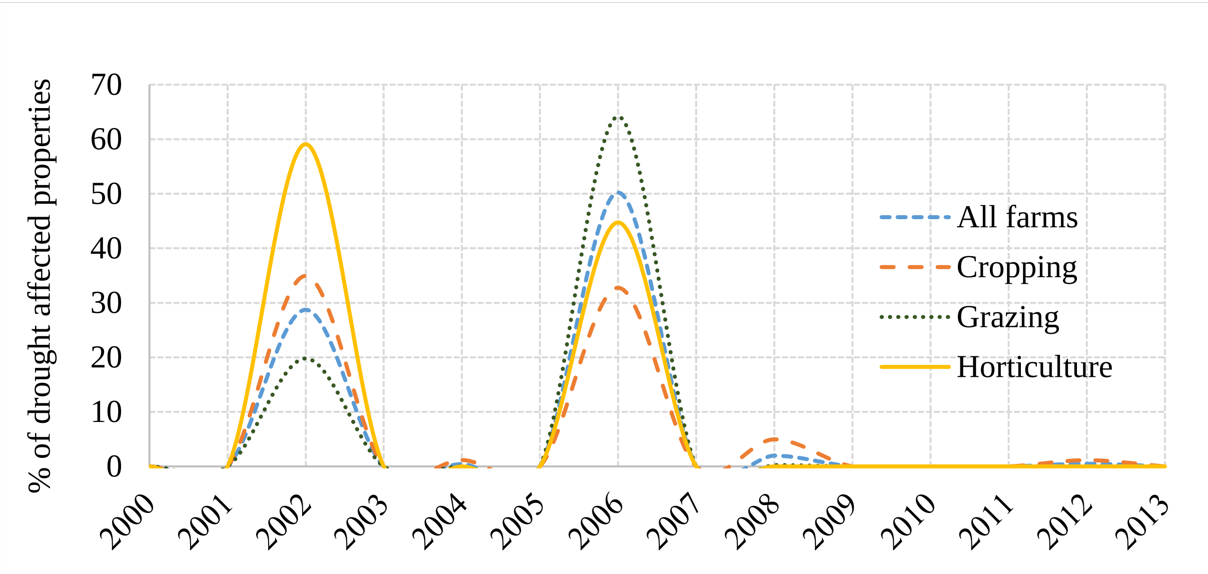
Source: adapted from (OVG 2019)

Figure D.2 Percentage of severe drought (5th percentile rainfall deficiency) across agricultural properties in SA from 2000-2013 by farm size



Own figure (data source: customised property transaction data from the SA Office of the Registrar General and BOM customised data request)

Figure D.3 Percentage of severe drought (5th percentile rainfall deficiency) affected agricultural properties in SA from 2000-2013 by farming industry



Own figure (data source: customised property transaction data from the SA Office of the Registrar General and BOM customised data request)

Table D.4 Collinearity check among the explanatory variables for full sample empirical SP and VP models using variance inflation factor (N=10,513)

Variables	***Label***	***VIF***	***1/VIF***
Native woody vegetation	NWV	11.420	0.088
Vegetation square	NWVS	9.690	0.103
Annual maximum temperature	Temp	7.250	0.138
Remoteness areas index	RAI	6.200	0.161
South East	SE	5.100	0.196
Elevation	Ele	5.090	0.197
Distance to surface-water	DisW	4.750	0.211
Silt	Silt	4.150	0.241
Eyre Peninsula	EP	4.080	0.245
Annual rainfall	Rain	3.830	0.261
Distance to coast	DisC	3.260	0.307
Norther and Yorke	NY	3.110	0.321
Soil organic carbon	SOC	2.790	0.359
Kangaroo Island	KI	2.580	0.387
Lot size	LS	2.350	0.425
Viticulture	Viti	2.170	0.460
Adelaide and Mount lofty Ranges	AMLR	2.150	0.464
Cropping	Crop	2.130	0.469
Clay	Clay	2.110	0.475
Irrigation	Irri	2.060	0.485
Urban accessibility index	UAI	1.890	0.529
SEIFA	SEIFA	1.830	0.546
Sand	Sand	1.830	0.546
Soil water holding capacity	AWC	1.810	0.553
Real commodity price index	CPI	1.690	0.591
Soil erosion index	SEI	1.610	0.620
Trend	Tre	1.610	0.623
Main rooms per hectare	Mroo	1.510	0.661
Distance to conservation reserve	DisCR	1.430	0.700
Horticulture	Hort	1.380	0.726
Basic soil	BS	1.370	0.728
Distance to highway	DisR	1.280	0.781
Structural improvements	Simp	1.220	0.823
Market garden	MG	1.160	0.858
Groundwater bore	Bore	1.150	0.867
Drought	Dro5	1.060	0.947
Mixed farming	Mix	1.020	0.983
Mean	-	-	3.000

Table D.5 Pairwise correlation among the explanatory variables (N=10,513) used in the empirical SP and VP models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Dro5 (1)	1.00															
NWV (2)	0.02	1.00														
Rain (3)	0.08	0.38	1.00													
Temp (4)	-0.03	-0.34	-0.81	1.00												
SOC (5)	0.03	0.35	0.59	-0.61	1.00											
Silt (6)	0.05	0.38	0.45	-0.33	0.60	1.00										
Sand (7)	0.01	0.13	-0.04	-0.03	-0.18	-0.23	1.00									
Clay (8)	0.00	-0.15	-0.07	0.11	0.24	0.26	-0.57	1.00								
SWC (9)	-0.02	0.08	0.25	-0.24	0.33	0.28	-0.35	0.18	1.00							
SEI (10)	0.04	0.35	0.24	-0.20	0.23	0.38	0.19	-0.22	-0.11	1.00						
BS (11)	-0.01	0.16	0.33	-0.38	0.26	0.26	0.00	0.06	0.11	0.20	1.00					
Ele (12)	0.05	0.36	0.34	-0.26	0.44	0.68	-0.10	0.15	0.22	0.38	0.26	1.00				
DisC (13)	0.01	-0.06	-0.22	0.35	-0.25	0.03	0.04	0.01	-0.09	-0.06	0.01	0.21	1.00			
DisCR (14)	-0.02	-0.31	-0.21	0.20	-0.11	-0.06	-0.15	0.24	-0.09	-0.17	-0.01	0.03	0.15	1.00		
DisW (15)	-0.02	-0.29	-0.11	0.12	-0.23	-0.37	0.01	-0.06	0.10	-0.29	-0.09	-0.38	0.23	0.09	1.00	
DisR (16)	0.00	0.05	0.05	-0.13	0.03	-0.01	0.07	-0.11	-0.07	0.10	0.03	0.12	0.03	0.02	-0.12	1.00
LS (17)	-0.03	-0.28	-0.26	0.21	-0.22	-0.25	0.10	-0.06	-0.20	-0.05	-0.10	-0.09	0.06	0.20	0.14	0.24
MRoo (18)	0.04	0.27	0.24	-0.20	0.17	0.16	0.00	-0.04	0.10	0.08	0.08	0.07	-0.08	-0.12	-0.08	-0.11
Simp (19)	0.00	0.19	0.13	-0.12	0.07	0.04	0.16	-0.18	-0.03	0.10	0.07	-0.01	0.00	-0.17	-0.04	-0.06
Irri (20)	0.00	-0.08	-0.16	0.21	-0.15	-0.08	0.04	-0.05	0.06	-0.06	-0.10	-0.16	0.22	-0.17	0.11	-0.11
Bore (21)	0.02	0.03	0.17	-0.18	0.12	0.06	0.01	-0.04	0.04	0.00	0.13	0.04	0.02	-0.07	0.05	0.00
Crop (22)	-0.01	-0.32	-0.39	0.43	-0.25	-0.16	-0.10	0.19	-0.18	-0.14	-0.20	-0.03	0.00	0.35	0.00	0.01
Hort (23)	0.02	0.04	-0.07	0.13	-0.08	0.00	0.05	-0.05	0.01	0.02	-0.04	-0.02	0.15	-0.14	0.01	-0.09
MG (24)	0.01	-0.02	-0.06	0.08	-0.08	-0.02	-0.02	0.00	0.01	-0.05	-0.04	-0.09	-0.03	-0.07	-0.03	-0.07
Mix (25)	0.00	0.00	0.01	0.00	0.01	0.01	-0.01	0.02	0.01	-0.01	0.01	0.02	0.02	0.00	0.00	-0.01
Viti (26)	-0.02	-0.05	-0.08	0.14	-0.08	-0.01	0.03	-0.03	0.11	-0.04	-0.05	-0.06	0.19	-0.14	0.08	-0.10
SEIFA (27)	-0.02	0.30	0.47	-0.44	0.36	0.31	0.06	-0.06	0.09	0.24	0.23	0.28	-0.04	-0.16	-0.16	0.03
CPI (28)	-0.08	-0.01	-0.08	0.08	-0.02	-0.03	0.00	0.01	-0.06	0.01	-0.03	0.00	-0.04	0.04	-0.03	0.02
UAI (29)	0.02	0.17	0.31	-0.27	0.26	0.22	-0.09	0.04	0.19	0.08	0.16	0.06	-0.01	-0.19	-0.08	-0.23
RAI (30)	-0.03	-0.25	-0.29	0.22	-0.18	-0.40	0.12	-0.07	0.05	-0.19	-0.17	-0.33	-0.11	0.08	0.50	-0.09
Tre (31)	-0.12	0.00	-0.01	0.06	-0.02	-0.02	0.00	0.00	0.00	-0.01	-0.03	-0.01	0.00	0.00	0.00	0.01
EP (32)	-0.06	-0.09	-0.19	0.18	-0.03	-0.20	0.06	-0.07	0.13	-0.02	-0.13	-0.12	-0.20	0.02	0.02	-0.07
KI (33)	0.00	0.10	0.04	-0.21	0.13	-0.04	0.11	-0.05	0.02	-0.04	0.00	-0.09	-0.27	-0.11	-0.21	0.11
AMLR (34)	0.01	0.35	0.32	-0.25	0.28	0.39	-0.10	0.06	0.08	0.21	0.18	0.30	-0.19	-0.23	-0.40	0.08
SE (35)	-0.04	-0.13	0.27	-0.38	0.03	-0.27	-0.04	-0.05	0.17	-0.20	0.21	-0.35	0.01	0.00	0.68	-0.01
NY (36)	0.02	-0.17	-0.22	0.32	-0.07	0.13	-0.21	0.35	0.05	-0.07	-0.10	0.20	-0.11	0.32	-0.03	-0.08

Table D.5 continued

	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)	(33)	(34)	(35)	(36)
LS (17)	1.00																			
MRoo (18)	-0.52	1.00																		
Simp (19)	-0.22	0.26	1.00																	
Irri (20)	-0.17	-0.02	0.11	1.00																
Bore (21)	0.02	0.00	0.11	0.05	1.00															
Crop (22)	0.41	-0.25	-0.23	-0.18	-0.17	1.00														
Hort (23)	-0.21	0.09	0.11	0.16	0.05	-0.17	1.00													
MG (24)	-0.11	0.07	0.04	0.14	0.08	-0.09	-0.02	1.00												
Mix (25)	-0.02	-0.01	0.03	0.01	0.02	-0.06	-0.02	-0.01	1.00											
Viti (26)	-0.19	-0.03	0.08	0.64	0.06	-0.19	-0.05	-0.03	-0.02	1.00										
SEIFA (27)	-0.09	0.13	0.15	-0.09	0.14	-0.17	-0.02	-0.08	0.02	-0.01	1.00									
CPI (28)	0.03	0.01	-0.04	-0.17	-0.02	0.10	0.20	0.08	0.01	-0.34	-0.21	1.00								
UAI (29)	-0.56	0.33	0.17	0.17	0.07	-0.39	0.14	0.06	0.04	0.17	0.08	-0.05	1.00							
RAI (30)	0.42	-0.22	-0.11	0.00	-0.07	0.29	-0.05	-0.07	-0.03	-0.01	-0.12	0.03	-0.43	1.00						
Tre (31)	0.00	0.00	-0.03	0.00	-0.01	0.03	0.01	-0.01	0.01	-0.02	-0.33	0.49	0.01	0.04	1.00					
EP (32)	0.28	-0.09	-0.03	-0.07	-0.10	0.32	-0.06	-0.03	-0.02	-0.07	0.04	0.04	-0.29	0.59	0.04	1.00				
KI (33)	0.09	-0.06	-0.05	-0.04	-0.06	-0.10	-0.03	-0.02	-0.01	-0.03	-0.02	0.00	-0.13	0.28	0.01	-0.05	1.00			
AMLR (34)	-0.29	0.23	0.14	-0.04	0.12	-0.22	0.05	0.11	0.04	0.00	0.27	-0.01	0.23	-0.49	-0.02	-0.15	-0.08	1.00		
SE (35)	0.03	0.01	-0.01	-0.04	0.18	-0.26	-0.08	-0.05	0.00	-0.04	0.05	-0.03	0.11	0.23	-0.02	-0.13	-0.08	-0.23	1.00	
NY (36)	0.10	-0.13	-0.19	-0.11	-0.12	0.39	-0.05	-0.05	-0.02	-0.05	-0.18	0.03	-0.15	0.08	0.00	-0.14	-0.08	-0.25	-0.22	1.00

Table D.6 Comparison of full sample OLS regression results between per hectare sales price (SP) and valuation price (VP) model of South Australian agricultural properties, 1998-2013 (N=10,513)

	Sales Price (SP)		***Valuation Price (VP)***	
	Coefficient	***Std. Err.***	***Coefficient***	***Std. Err.***
Drought	0.013	0.027	0.021	0.031
Native woody vegetation	0.607***	0.091	-0.417***	0.092
Vegetation square	-0.751***	0.113	0.293***	0.111
Annual rainfall	0.000	0.000	0.000***	0.000
Annual maximum temperature	-0.081***	0.012	-0.113***	0.016
Soil organic carbon	0.201***	0.034	0.265***	0.039
Silt	0.068***	0.012	0.083***	0.012
Sand	0.000***	0.000	0.000***	0.000
Clay	0.000**	0.000	0.000	0.000
Soil water holding capacity	0.051***	0.012	0.065***	0.017
Soil erosion index	-0.014	0.013	-0.015*	0.014
Basic soil	0.091***	0.018	0.081***	0.011
Elevation	0.000***	0.000	0.000***	0.000
Distance to urban centres	-0.061***	0.024	-0.101***	0.023
Distance to coast	0.012	0.016	-0.013	0.012
Distance to conservation reserve	0.025**	0.018	0.000	0.015
Distance to surface-water	-0.069***	0.013	-0.072***	0.017
Distance to highway	-0.023***	0.014	-0.011	0.013
Lot size	-0.621***	0.011	-0.512***	0.018
Main rooms per hectare	0.293***	0.014	0.217***	0.014
Structural improvements	0.544***	0.023	0.222***	0.022
Irrigation	0.301***	0.055	0.291***	0.041
Groundwater bore	0.125***	0.023	0.094***	0.023
Cropping	0.024	0.024	0.063***	0.027
Horticulture	0.224***	0.045	0.291***	0.031
Market garden	0.259***	0.067	0.403***	0.054
Mixed farming	0.112	0.078	0.133*	0.075
Viticulture	0.132***	0.053	0.226***	0.042
SEIFA	0.000***	0.000	0.000***	0.000
Real commodity price index	0.000***	0.000	0.000***	0.000
Urban accessibility index	0.069***	0.011	0.054***	0.010
Remoteness areas index	-0.082***	0.026	-0.091***	0.028
Trend	0.109***	0.008	0.128***	0.002
EP	-0.118**	0.539	-0.295***	0.052
KI	-0.295***	0.625	-0.383***	0.060
AMLR	0.322***	0.199	0.367***	0.019
SE	0.172***	0.040	0.047	0.039
NY	0.233***	0.309	0.163***	0.029
Intercept	11.45***	0.33	11.22***	0.33
R^2	0.862		0.853	
AIC	21038.95		19814.92	
Root MSE	0.657		0.621	

Notes: The outcome variable is the per hectare real price of agricultural properties. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table D.7 Marginal effects of full sample SDM results of per hectare sales price of South Australian agricultural properties, 1998-2013 (N=10,513)

	Direct effect	*Std. Err.*	*Indirect effect*	*Std. Err.*	*Total effect*	*Std. Err.*
Drought	-0.066*	0.035	0.901**	0.445	0.835*	0.436
Native woody vegetation	0.399***	0.088	14.277***	4.595	14.676***	4.597
Vegetation square	-0.625***	0.104	-2.699***	0.777	-3.324***	0.840
Annual rainfall	0.001***	0.000	-0.003***	0.001	-0.002***	0.001
Annual maximum temperature	0.013	0.015	-0.852***	0.265	-0.839***	0.263
Soil organic carbon	0.037	0.031	2.928	2.473	2.965	2.472
Silt	0.022***	0.007	1.926**	0.928	1.947**	0.927
Sand	0.001	0.001	-0.165*	0.088	-0.164*	0.088
Clay	0.000	0.001	0.341***	0.098	0.340***	0.098
Soil water holding capacity	0.069***	0.007	-2.016***	0.555	-1.947***	0.554
Soil erosion index	-0.012*	0.007	2.650***	0.937	2.637***	0.937
Basic soil	0.076***	0.014	-1.088	1.557	-1.011	1.556
Elevation	0.000	0.000	-0.042***	0.011	-0.042***	0.011
Distance to coast	-0.023**	0.011	-0.097*	0.051	-0.120**	0.061
Distance to conservation reserve	0.033***	0.008	0.142***	0.046	0.174***	0.052
Distance to surface-water	-0.025**	0.010	-0.108**	0.050	-0.133**	0.059
Distance to highway	-0.009*	0.005	-0.041*	0.025	-0.050*	0.030
Lot size	-0.616***	0.006	1.388***	0.518	0.771	0.518
Main rooms per hectare	0.290***	0.012	2.430*	1.426	2.720*	1.427
Structural improvements	0.483***	0.015	-2.816	2.301	-2.333	2.302
Irrigation	0.257***	0.037	25.008***	5.807	25.265***	5.809
Groundwater bore	0.082***	0.020	-1.084	2.602	-1.002	2.603
Cropping	0.025	0.018	0.109	0.083	0.135	0.100
Horticulture	0.220***	0.036	0.949***	0.270	1.169***	0.292
Market garden	0.311***	0.058	1.342***	0.397	1.653***	0.435
Mixed farming	0.124	0.082	0.536	0.375	0.660	0.453
Viticulture	0.122***	0.042	0.528**	0.226	0.650**	0.262
SEIFA	0.002***	0.000	-0.008***	0.003	-0.007**	0.003
Real commodity price index	0.001**	0.001	-0.011**	0.005	-0.010**	0.005
Urban accessibility index	0.077***	0.004	0.332***	0.081	0.409***	0.081
Remoteness areas index	0.008	0.023	0.033	0.101	0.040	0.124
Trend	0.022***	0.005	0.097***	0.017	0.120***	0.020
EP	0.499***	0.082	2.156***	0.650	2.655***	0.704
KI	-0.009	0.064	-0.037	0.276	-0.045	0.340
AMLR	0.275***	0.023	1.189***	0.302	1.464***	0.312
SE	0.281***	0.061	1.212***	0.375	1.493***	0.417
NY	0.426***	0.035	1.839***	0.460	2.265***	0.473
Spatio-temporal lag (ρ)	0.649***					
Pseudo R^2	0.874					
AIC	19681.650					
LR Test SDM vs. SAR	1041.45***					
LR Test SDM vs. SEM	275.90***					

Notes: The outcome variable is the per hectare real sale price of agricultural properties. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table D.8 Marginal effects of full sample SDM results of per hectare valuation price of South Australian agricultural properties, 1998-2013 (N=10,513)

	Direct effect	*Std. Err.*	*Indirect effect*	*Std. Err.*	*Total effect*	*Std. Err.*
Drought	-0.025	0.032	3.062	2.253	3.036	2.247
Native woody vegetation	-0.666***	0.080	124.350***	45.250	123.684***	45.252
Vegetation square	0.460***	0.095	11.898**	5.048	12.358**	5.095
Annual rainfall	0.002***	0.000	-0.016**	0.006	-0.014**	0.006
Annual maximum temperature	0.018	0.014	-6.066**	2.426	-6.048**	2.425
Soil organic carbon	0.066**	0.028	0.045	11.115	0.111	11.114
Silt	0.034***	0.007	13.224**	5.838	13.258**	5.838
Sand	0.002**	0.001	0.197	0.346	0.198	0.346
Clay	0.002*	0.001	2.943***	1.083	2.945***	1.084
Soil water holding capacity	0.087***	0.007	-8.576**	3.482	-8.488**	3.481
Soil erosion index	-0.010	0.006	15.472**	6.973	15.462**	6.973
Basic soil	0.060***	0.013	-11.294	7.938	-11.235	7.938
Elevation	0.000	0.000	-0.293***	0.107	-0.293***	0.107
Distance to coast	-0.055***	0.010	-1.416**	0.584	-1.471**	0.588
Distance to conservation reserve	0.019***	0.007	0.498*	0.256	0.517**	0.261
Distance to surface-water	0.004	0.009	0.091	0.246	0.094	0.255
Distance to highway	0.004	0.005	0.109	0.132	0.113	0.136
Lot size	-0.497***	0.005	6.662**	3.157	6.165*	3.157
Main rooms per hectare	0.209***	0.011	4.190	6.507	4.399	6.508
Structural improvements	0.149***	0.014	-46.183**	19.738	-46.034**	19.739
Irrigation	0.261***	0.033	128.786***	49.046	129.047***	49.049
Groundwater bore	0.042**	0.018	13.720	12.458	13.763	12.460
Cropping	0.068***	0.017	1.759**	0.779	1.827**	0.788
Horticulture	0.268***	0.033	6.942**	2.698	7.210***	2.708
Market garden	0.446***	0.053	11.531**	4.455	11.977***	4.471
Mixed farming	0.152**	0.075	3.922	2.419	4.074	2.479
Viticulture	0.221***	0.038	5.718**	2.367	5.939**	2.385
SEIFA	0.002***	0.000	-0.036**	0.016	-0.034**	0.016
Real commodity price index	0.002***	0.000	-0.112***	0.042	-0.110***	0.042
Urban accessibility index	0.094***	0.003	2.434***	0.904	2.528***	0.904
Remoteness areas index	0.056***	0.021	1.453*	0.777	1.510*	0.792
Trend	0.011**	0.004	0.283***	0.095	0.294***	0.097
EP	0.513***	0.075	13.262	5.333	13.774**	5.363
KI	-0.097*	0.059	-2.518	1.718	-2.615	1.767
AMLR	0.301***	0.021	7.791***	2.949	8.092***	2.954
SE	0.133**	0.056	3.447*	1.885	3.581*	1.927
NY	0.378***	0.032	9.771***	3.722	10.149***	3.730
Spatio-temporal lag (ρ)	0.776***					
Pseudo R^2	0.849					
AIC	17735.300					
LR Test SDM vs. SAR	1688.77***					
LR Test SDM vs. SEM	520.59***					

Notes: The outcome variable is the per hectare real valuation price of agricultural properties. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table D.9 Sensitivity analysis: Marginal effects of full sample SDM results of per hectare sales price (linear) of South Australian agricultural properties, 1998-2013

	Direct effect	*Std. Err.*	*Indirect effect*	*Std. Err.*	*Total effect*	*Std. Err.*
Drought	394.740	1494.156	2.30E+08	9.15E+08	2.30E+08	9.15E+08
Native woody vegetation	20051.240***	3726.237	-1.88E+10	5.82E+10	-1.88E+10	5.82E+10
Vegetation square	-5858.059	4403.966	-1.09E+09	3.50E+09	-1.09E+09	3.50E+09
Annual rainfall	8.799**	4.318	-91609.7	1063566	-91600.9	1063564
Annual maximum temperature	222.499	619.507	-1.41E+08	4.90E+08	-1.41E+08	4.90E+08
Soil organic carbon	3800.171***	1312.803	5.58E+09	1.75E+10	5.58E+09	1.75E+10
Silt	358.519	310.666	1.78E+09	5.55E+09	1.78E+09	5.55E+09
Sand	88.626**	35.797	1.55E+08	4.92E+08	1.55E+08	4.92E+08
Clay	-24.683	43.794	-1.31E+08	4.16E+08	-1.31E+08	4.16E+08
Soil water holding capacity	724.443**	299.455	-5.80E+08	1.86E+09	-5.80E+08	1.86E+09
Soil erosion index	-1340.510***	277.310	2.15E+09	6.76E+09	2.15E+09	6.76E+09
Basic soil	-651.403	601.545	-3.21E+09	1.01E+10	-3.21E+09	1.01E+10
Elevation	-3.618	5.199	-2.28E+05	9.24E+06	-2.28E+05	9.24E+06
Distance to coast	0.057***	0.022	10539.47	33121.85	10539.53	33121.85
Distance to conservation reserve	-0.039	0.041	-7271.07	24053.88	-7271.11	24053.89
Distance to surface-water	0.025	0.015	4626.661	14853.21	4626.686	14853.21
Distance to highway	-0.276***	0.035	-51435.4	160870.7	-51435.7	160870.7
Lot size	-3.525***	1.081	-2.11E+06	6.92E+06	-2.11E+06	6.92E+06
Main rooms per hectare	37322.590***	463.118	3.43E+09	1.06E+10	3.43E+09	1.06E+10
Structural improvements	2124.483***	675.069	-2.96E+09	9.69E+09	-2.96E+09	9.69E+09
Irrigation	1538.460	1562.598	-2.79E+09	9.78E+09	-2.79E+09	9.78E+09
Groundwater bore	-2983.897***	849.844	5.65E+09	1.77E+10	5.65E+09	1.77E+10
Cropping	-1268.882	772.809	-2.36E+08	7.54E+08	-2.36E+08	7.54E+08
Horticulture	13436.470***	1527.480	2.50E+09	7.82E+09	2.50E+09	7.82E+09
Market garden	16096.240***	2443.355	3.00E+09	9.37E+09	3.00E+09	9.37E+09
Mixed farming	-3656.877	3469.987	-6.81E+08	2.22E+09	-6.81E+08	2.22E+09
Viticulture	13313.060***	1748.149	2.48E+09	7.76E+09	2.48E+09	7.76E+09
SEIFA	66.891***	7.258	7.80E+06	2.50E+07	7.80E+06	2.50E+07
Real commodity price index	91.554***	21.320	6.42E+06	2.08E+07	6.42E+06	2.08E+07
Urban accessibility index	279482.000*	157221.100	5.20E+10	1.65E+11	5.20E+10	1.65E+11
Remoteness areas index	-405.871	948.493	-7.56E+07	2.94E+08	-7.56E+07	2.94E+08
Trend	-249.609	172.351	-4.65E+07	1.61E+08	-4.65E+07	1.61E+08
EP	10617.320***	3536.033	1.98E+09	6.21E+09	1.98E+09	6.21E+09
KI	1741.568	2769.358	3.24E+08	1.15E+09	3.24E+08	1.15E+09
AMLR	9087.058***	964.668	1.69E+09	5.29E+09	1.69E+09	5.29E+09
SE	5498.439**	2727.134	1.02E+09	3.22E+09	1.02E+09	3.22E+09
NY	6725.506***	1541.539	1.25E+09	3.92E+09	1.25E+09	3.92E+09
Spatio-temporal lag (ρ)	0.923***					
Pseudo R^2	0.022					
AIC	243588.2					

Note: The outcome variable is the per hectare real sale price of agricultural properties. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table D.10 Sensitivity analysis: Marginal effects of full sample SDM results of per hectare sales price (log-linear) of South Australian agricultural properties, 1998-2013

	Direct effect	*Std. Err.*	*Indirect effect*	*Std. Err.*	*Total effect*	*Std. Err.*	*Direct effect*
Drought	-0.076	0.050	0.295	0.444	0.219	0.431	0.612
Native woody vegetation	1.391***	0.122	-0.758	4.111	0.633	4.115	0.878
Vegetation square	-1.323***	0.144	-3.984**	1.629	-5.307***	1.673	0.002
Annual rainfall	0.001***	0.000	-0.002**	0.001	-0.001	0.001	0.245
Annual maximum temperature	-0.047**	0.021	-0.268	0.226	-0.316	0.221	0.152
Soil organic carbon	0.067	0.043	7.970**	3.412	8.037**	3.411	0.018
Silt	0.025**	0.010	2.104**	1.067	2.129**	1.067	0.046
Sand	0.000	0.001	-0.134	0.100	-0.134	0.100	0.18
Clay	0.004***	0.001	0.116	0.099	0.120	0.099	0.225
Soil water holding capacity	0.089***	0.010	-0.817	0.523	-0.727	0.520	0.162
Soil erosion index	-0.033***	0.009	2.580**	1.110	2.547**	1.110	0.022
Basic soil	0.122***	0.020	-3.484*	1.894	-3.362*	1.893	0.076
Elevation	-0.001***	0.000	-0.038***	0.014	-0.039***	0.014	0.006
Distance to coast	0.000**	0.000	0.000	0.000	0.000*	0.000	0.076
Distance to conservation reserve	0.000	0.000	0.000	0.000	0.000	0.000	0.619
Distance to surface-water	0.000	0.000	0.000	0.000	0.000	0.000	0.506
Distance to highway	0.000***	0.000	0.000**	0.000	0.000***	0.000	0.001
Lot size	-0.002***	0.000	-0.006**	0.002	-0.008***	0.002	0.002
Main rooms per hectare	0.806***	0.015	1.684	1.387	2.490*	1.389	0.073
Structural improvements	0.625***	0.022	-2.999	2.545	-2.375	2.547	0.351
Irrigation	0.228***	0.051	17.229***	6.211	17.457***	6.214	0.005
Groundwater bore	-0.110***	0.027	-4.826	3.129	-4.936	3.130	0.115
Cropping	-0.202***	0.025	-0.609**	0.255	-0.812***	0.264	0.002
Horticulture	0.732***	0.050	2.205**	0.877	2.938***	0.885	0.001
Market garden	0.754***	0.080	2.271**	0.918	3.025***	0.939	0.001
Mixed farming	0.218*	0.114	0.655	0.429	0.873*	0.524	0.096
Viticulture	0.693***	0.057	2.087**	0.846	2.780***	0.862	0.001
SEIFA	0.002***	0.000	-0.008**	0.003	-0.006*	0.003	0.089
Real commodity price index	0.002**	0.001	-0.008	0.005	-0.007	0.005	0.162
Urban accessibility index	17.296***	5.155	52.087**	25.793	69.384**	29.207	0.018
Remoteness areas index	-0.247***	0.031	-0.743**	0.306	-0.990***	0.317	0.002
Trend	0.027***	0.009	0.081***	0.019	0.108***	0.021	0
EP	0.888***	0.116	2.673**	1.139	3.560***	1.189	0.003
KI	-0.033	0.091	-0.100	0.274	-0.133	0.365	0.714
AMLR	0.323***	0.032	0.974**	0.397	1.297***	0.406	0.001
SE	0.225**	0.090	0.678*	0.368	0.904**	0.435	0.038
NY	0.538***	0.051	1.620**	0.657	2.158***	0.671	0.001
Spatio-temporal lag (ρ)	0.601***						
Pseudo R^2	0.759						
AIC	26640.0						

Note: The outcome variable is the per hectare real sale price of agricultural properties. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table D.11 Sensitivity analysis: Marginal effects of full sample SDM results of total sales price of South Australian agricultural properties, 1998-2013

	Direct effect	*Std. Err.*	*Indirect effect*	*Std. Err.*	*Total effect*	*Std. Err.*
Drought	-0.066*	0.035	0.901*	0.509	0.835*	0.501
Native woody vegetation	0.399***	0.088	14.277**	5.624	14.676***	5.625
Vegetation square	-0.625***	0.104	-2.699**	1.082	-3.324***	1.128
Annual rainfall	0.001***	0.000	-0.003***	0.001	-0.002**	0.001
Annual maximum temperature	0.013	0.015	-0.852**	0.351	-0.839**	0.347
Soil organic carbon	0.037	0.031	2.928	2.536	2.965	2.535
Silt	0.022***	0.007	1.926*	1.077	1.947*	1.077
Sand	0.001	0.001	-0.165	0.103	-0.164	0.103
Clay	0.000	0.001	0.341***	0.118	0.340***	0.118
Soil water holding capacity	0.069***	0.007	-2.016***	0.747	-1.947***	0.746
Soil erosion index	-0.012*	0.007	2.650**	1.121	2.637**	1.121
Basic soil	0.076***	0.014	-1.088	1.574	-1.011	1.574
Elevation	0.000	0.000	-0.042***	0.015	-0.042***	0.015
Distance to coast	-0.023**	0.011	-0.097*	0.059	-0.120*	0.067
Distance to conservation reserve	0.033***	0.008	0.142**	0.061	0.174***	0.065
Distance to surface-water	-0.025**	0.010	-0.108*	0.058	-0.133**	0.065
Distance to highway	-0.009*	0.005	-0.041	0.027	-0.050	0.031
Lot size	0.384***	0.006	1.388**	0.625	1.771***	0.625
Main rooms per hectare	0.290***	0.012	2.430*	1.424	2.720*	1.425
Structural improvements	0.483***	0.015	-2.816	2.389	-2.333	2.391
Irrigation	0.257***	0.037	25.008***	8.167	25.265***	8.170
Groundwater bore	0.082***	0.020	-1.084	2.711	-1.002	2.712
Cropping	0.025	0.018	0.109	0.087	0.135	0.104
Horticulture	0.220***	0.036	0.949**	0.377	1.169***	0.393
Market garden	0.311***	0.058	1.342**	0.543	1.653***	0.570
Mixed farming	0.124	0.082	0.536	0.404	0.660	0.478
Viticulture	0.122***	0.041	0.528*	0.269	0.650**	0.300
SEIFA	0.002***	0.000	-0.008**	0.003	-0.007**	0.003
Real commodity price index	0.001**	0.001	-0.011**	0.005	-0.010**	0.005
Urban accessibility index	0.077***	0.004	0.332***	0.123	0.409***	0.123
Remoteness areas index	0.008	0.023	0.033	0.102	0.040	0.125
Trend	0.022***	0.006	0.097***	0.021	0.120***	0.021
EP	0.499***	0.082	2.156**	0.901	2.655***	0.945
KI	-0.009	0.064	-0.037	0.276	-0.045	0.340
AMLR	0.275***	0.023	1.189***	0.449	1.464***	0.455
SE	0.281***	0.061	1.212**	0.507	1.493***	0.540
NY	0.426***	0.035	1.839***	0.685	2.265***	0.692
Spatio-temporal lag (ρ)	0.776***					
Pseudo R^2	0.656					
AIC	17735.3					

Note: The outcome variable is the total real sale price of agricultural properties. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table D.12 Sensitivity analysis: Marginal effects of full sample SDM results of per hectare valuation price (linear) of South Australian agricultural properties, 1998-2013

	Direct effect	***Std. Err.***	***Indirect effect***	***Std. Err.***	***Total effect***	***Std. Err.***
Drought	-103.993	682.454	8.98E+10	1.32E+11	8.98E+10	1.32E+11
Native woody vegetation	128.985	1682.052	-2.77E+11	4.55E+11	-2.77E+11	4.55E+11
Vegetation square	6199.513***	1969.928	1.83E+11	2.74E+11	1.83E+11	2.74E+11
Annual rainfall	13.795***	1.980	1.31E+07	4.38E+07	1.31E+07	4.38E+07
Annual maximum temperature	1073.496***	282.753	-1.22E+10	2.00E+10	-1.22E+10	2.00E+10
Soil organic carbon	1962.739***	605.183	9.65E+10	1.88E+11	9.65E+10	1.88E+11
Silt	219.590	145.485	-1.56E+10	4.51E+10	-1.56E+10	4.51E+10
Sand	49.068***	16.768	1.19E+10	1.80E+10	1.19E+10	1.80E+10
Clay	-5.697	20.563	1.62E+10	2.39E+10	1.62E+10	2.39E+10
Soil water holding capacity	454.786***	142.938	1.50E+10	2.96E+10	1.50E+10	2.96E+10
Soil erosion index	-675.526***	138.002	2.03E+11	2.98E+11	2.03E+11	2.98E+11
Basic soil	-756.942***	282.260	-8.31E+10	1.46E+11	-8.31E+10	1.46E+11
Elevation	1.693	2.492	-1.84E+08	4.38E+08	-1.84E+08	4.38E+08
Distance to coast	-0.003	0.010	-76861.1	306273	-76861.1	306273
Distance to conservation reserve	-0.030	0.019	-882605	1402848	-882605	1402848
Distance to surface-water	0.032***	0.007	943093.4	1384868	943093.4	1384868
Distance to highway	-0.132***	0.016	-3913600	5751172	-3913601	5751172
Lot size	-0.753	0.491	4.67E+07	1.16E+08	4.67E+07	1.16E+08
Main rooms per hectare	13389.630***	206.211	3.54E+10	8.45E+10	3.54E+10	8.45E+10
Structural improvements	-580.345*	311.380	-3.23E+11	4.86E+11	-3.23E+11	4.86E+11
Irrigation	730.446	710.329	1.91E+11	3.30E+11	1.91E+11	3.30E+11
Groundwater bore	-1853.654***	381.909	3.07E+10	1.33E+11	3.07E+10	1.33E+11
Cropping	-713.671**	345.599	-2.11E+10	3.24E+10	-2.11E+10	3.24E+10
Horticulture	3446.699***	683.266	1.02E+11	1.51E+11	1.02E+11	1.51E+11
Market garden	10295.000***	1094.648	3.04E+11	4.47E+11	3.04E+11	4.47E+11
Mixed farming	-663.141	1551.479	-1.96E+10	5.41E+10	-1.96E+10	5.41E+10
Viticulture	5014.452***	782.504	1.48E+11	2.18E+11	1.48E+11	2.18E+11
SEIFA	30.944***	3.299	9.81E+08	1.44E+09	9.81E+08	1.44E+09
Real commodity price index	59.579***	9.725	6.19E+08	9.27E+08	6.19E+08	9.27E+08
Urban accessibility index	233438.700***	70314.020	6.90E+12	1.03E+13	6.90E+12	1.03E+13
Remoteness areas index	516.197	424.124	1.53E+10	2.56E+10	1.53E+10	2.56E+10
Trend	-1121.234***	77.997	-3.32E+10	4.79E+10	-3.32E+10	4.79E+10
EP	2620.401*	1581.011	7.75E+10	1.23E+11	7.75E+10	1.23E+11
KI	507.168	1238.492	1.50E+10	4.21E+10	1.50E+10	4.21E+10
AMLR	4289.184***	432.201	1.27E+11	1.86E+11	1.27E+11	1.86E+11
SE	682.617	1219.178	2.02E+10	4.72E+10	2.02E+10	4.72E+10
NY	1173.353*	689.242	3.47E+10	5.48E+10	3.47E+10	5.48E+10
Spatio-temporal lag (ρ)	1.713***					
Pseudo R^2	0.0003					
AIC	227190.8					

Note: The outcome variable is the per hectare real valuation price of agricultural properties. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table D.13 Sensitivity analysis: Marginal effects of full sample SDM results of per hectare valuation price (log-linear) of South Australian agricultural properties, 1998-2013

	Direct effect	*Std. Err.*	*Indirect effect*	*Std. Err.*	*Total effect*	*Std. Err.*
Drought	-0.029	0.043	0.354	1.203	0.325	1.193
Native woody vegetation	0.128	0.107	29.238	22.638	29.366	22.641
Vegetation square	-0.103	0.127	-1.144	1.653	-1.247	1.762
Annual rainfall	0.001***	0.000	-0.005	0.003	-0.003	0.003
Annual maximum temperature	-0.041**	0.018	-1.800	1.476	-1.842	1.471
Soil organic carbon	0.110***	0.038	16.285	13.107	16.395	13.107
Silt	0.035***	0.009	6.168	4.687	6.203	4.687
Sand	0.001	0.001	0.092	0.229	0.093	0.229
Clay	0.005***	0.001	0.994	0.721	0.999	0.721
Soil water holding capacity	0.103***	0.009	-1.501	1.622	-1.398	1.620
Soil erosion index	-0.022***	0.008	8.439	6.383	8.417	6.384
Basic soil	0.094***	0.017	-13.398	9.971	-13.303	9.971
Elevation	-0.001***	0.000	-0.141	0.098	-0.141	0.098
Distance to coast	0.000	0.000	0.000	0.000	0.000	0.000
Distance to conservation reserve	0.000	0.000	0.000	0.000	0.000	0.000
Distance to surface-water	0.000	0.000	0.000	0.000	0.000	0.000
Distance to highway	0.000***	0.000	0.000	0.000	0.000	0.000
Lot size	-0.001***	0.000	-0.017	0.012	-0.019	0.012
Main rooms per hectare	0.635**	0.013	-0.768	4.186	-0.133	4.187
Structural improvements	0.268**	0.019	-21.918	16.601	-21.650	16.604
Irrigation	0.253**	0.045	65.889	46.717	66.141	46.721
Groundwater bore	-0.117**	0.024	-5.096	8.439	-5.213	8.441
Cropping	-0.120**	0.022	-1.336	1.044	-1.456	1.050
Horticulture	0.697***	0.044	7.759	5.846	8.456	5.848
Market garden	0.801***	0.070	8.928	6.739	9.729	6.746
Mixed farming	0.241**	0.100	2.679	2.300	2.920	2.350
Viticulture	0.694***	0.050	7.731	5.862	8.425	5.869
SEIFA	0.002***	0.000	-0.025	0.016	-0.023	0.016
Real commodity price index	0.002***	0.001	-0.055	0.038	-0.052	0.037
Urban accessibility index	16.866***	4.531	187.873	150.158	204.739	151.748
Remoteness areas index	-0.184***	0.027	-2.051	1.561	-2.235	1.566
Trend	0.015*	0.008	0.164**	0.073	0.179**	0.072
EP	0.818***	0.102	9.106	7.031	9.924	7.056
KI	-0.096	0.080	-1.070	1.138	-1.167	1.197
AMLR	0.355***	0.028	3.952	2.993	4.307	2.997
SE	0.087	0.079	0.972	1.116	1.059	1.177
NY	0.484***	0.044	5.390	4.098	5.874	4.105
Spatio-temporal lag (ρ)	0.733***					
Pseudo R^2	0.749					
AIC	23902.15					

Note: The outcome variable is the per hectare real valuation price of agricultural properties. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table D.14 Sensitivity analysis: Marginal effects of full sample SDM results of total valuation price of South Australian agricultural properties, 1998-2013

	Direct effect	*Std. Err.*	*Indirect effect*	*Std. Err.*	*Total effect*	*Std. Err.*
Drought	-0.025	0.032	3.062	3.626	3.036	3.621
Native woody vegetation	-0.666***	0.080	124.350	110.777	123.684	110.779
Vegetation square	0.460***	0.095	11.898	11.566	12.358	11.588
Annual rainfall	0.002***	0.000	-0.016	0.013	-0.014	0.013
Annual maximum temperature	0.018	0.014	-6.066	5.735	-6.048	5.732
Soil organic carbon	0.066**	0.028	0.045	11.115	0.111	11.114
Silt	0.034***	0.007	13.224	12.589	13.258	12.589
Sand	0.002**	0.001	0.197	0.352	0.198	0.352
Clay	0.002*	0.001	2.943	2.607	2.945	2.607
Soil water holding capacity	0.087***	0.007	-8.576	8.001	-8.488	8.001
Soil erosion index	-0.010	0.006	15.472	14.865	15.462	14.866
Basic soil	0.060***	0.013	-11.294	12.127	-11.235	12.127
Elevation	0.000	0.000	-0.293	0.268	-0.293	0.268
Distance to coast	-0.055***	0.010	-1.416	1.374	-1.471	1.377
Distance to conservation reserve	0.019***	0.007	0.498	0.503	0.517	0.506
Distance to surface-water	0.004	0.009	0.091	0.264	0.094	0.273
Distance to highway	0.004	0.005	0.109	0.165	0.113	0.169
Lot size	0.503***	0.005	6.662	6.523	7.165	6.524
Main rooms per hectare	0.209***	0.011	4.190	6.648	4.399	6.649
Structural improvements	0.149***	0.014	-46.183	43.077	-46.034	43.078
Irrigation	0.261***	0.034	128.786	118.334	129.047	118.337
Groundwater bore	0.042**	0.018	13.720	14.989	13.763	14.990
Cropping	0.068***	0.017	1.759	1.712	1.827	1.716
Horticulture	0.268***	0.033	6.942	6.619	7.210	6.623
Market garden	0.446***	0.053	11.531	10.977	11.977	10.982
Mixed farming	0.152**	0.075	3.922	4.192	4.074	4.227
Viticulture	0.221***	0.038	5.718	5.542	5.939	5.550
SEIFA	0.002***	0.000	-0.036	0.030	-0.034	0.030
Real commodity price index	0.002***	0.000	-0.112	0.099	-0.110	0.099
Urban accessibility index	0.094***	0.003	2.434	2.308	2.528	2.309
Remoteness areas index	0.056***	0.021	1.453	1.503	1.510	1.512
Trend	0.011*	0.006	0.283	0.169	0.294	0.167
EP	0.513***	0.075	13.262	12.868	13.774	12.885
KI	-0.097*	0.059	-2.518	2.721	-2.615	2.749
AMLR	0.301***	0.021	7.791	7.419	8.092	7.421
SE	0.133**	0.056	3.447	3.580	3.581	3.603
NY	0.378***	0.032	9.771	9.287	10.149	9.290
Spatio-temporal lag (ρ)	0.649***					
Pseudo R^2	0.583					
AIC	19681.65					

Note: The outcome variable is the total real valuation price of agricultural properties. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table D.15 Marginal effects of SDM results of per hectare sales price of South Australian agricultural properties by farm size (small farms – 2 to 12.23 ha; N=3,475), 1998-2013

	Direct effect	*Std. Err.*	*Indirect effect*	*Std. Err.*	*Total effect*	*Std. Err.*
Drought	-0.065	0.062	1.706**	0.748	1.641**	0.732
Native woody vegetation	1.271***	0.141	3.841	3.907	5.112	3.923
Vegetation square	-1.193***	0.157	-4.265***	1.521	-5.458***	1.588
Annual rainfall	0.000**	0.000	-0.003**	0.001	-0.002*	0.001
Annual maximum temperature	-0.039	0.025	0.023	0.256	-0.016	0.253
Soil organic carbon	0.116**	0.047	5.682	3.507	5.798*	3.514
Silt	0.000	0.011	0.442	0.974	0.441	0.974
Sand	0.001	0.001	-0.397**	0.161	-0.396**	0.161
Clay	-0.005***	0.002	-0.204	0.130	-0.210	0.130
Soil water holding capacity	0.062***	0.013	-1.434	0.872	-1.373	0.872
Soil erosion index	0.023**	0.011	-0.848	0.706	-0.825	0.707
Basic soil	0.089***	0.025	3.063	1.992	3.153	1.995
Elevation	0.000	0.000	-0.009	0.010	-0.010	0.010
Distance to coast	-0.099***	0.019	-0.355***	0.132	-0.454***	0.142
Distance to conservation reserve	0.016	0.013	0.058	0.050	0.075	0.062
Distance to surface-water	-0.005	0.019	-0.017	0.067	-0.022	0.086
Distance to highway	-0.024***	0.008	-0.087**	0.040	-0.111**	0.046
Lot size	-0.676***	0.024	-1.166	1.811	-1.842	1.815
Main rooms per hectare	0.161***	0.014	1.522	1.002	1.683*	1.004
Structural improvements	0.764***	0.038	-3.321	2.524	-2.556	2.528
Irrigation	0.075	0.048	14.144***	3.805	14.219***	3.809
Groundwater bore	0.026	0.037	-3.931	3.005	-3.905	3.011
Cropping	-0.008	0.034	-0.027	0.123	-0.035	0.157
Horticulture	0.018	0.045	0.063	0.162	0.081	0.207
Market garden	0.088	0.069	0.314	0.265	0.402	0.330
Mixed farming	0.023	0.141	0.081	0.504	0.103	0.644
Viticulture	0.047	0.054	0.168	0.202	0.214	0.254
SEIFA	0.001***	0.000	0.000	0.005	0.001	0.005
Real commodity price index	0.002***	0.001	0.009	0.008	0.012	0.008
Urban accessibility index	0.085***	0.006	0.303***	0.103	0.388***	0.105
Remoteness areas index	-0.057	0.051	-0.202	0.193	-0.259	0.241
Trend	0.017**	0.008	0.061***	0.023	0.078**	0.030
EP	0.163	0.129	0.583	0.498	0.747	0.619
KI	0.061	0.164	0.220	0.592	0.281	0.755
AMLR	0.203***	0.038	0.724***	0.277	0.927***	0.297
SE	-0.108	0.125	-0.387	0.473	-0.495	0.594
NY	0.140**	0.065	0.500*	0.281	0.640*	0.336
Spatio-temporal lag (ρ)	0.629***					
Pseudo R^2	0.684					
AIC	6450.695					
LR Test SDM vs. SAR	319.50***					
LR Test SDM vs. SEM	50.69***					

Notes: The outcome variable is the per hectare real sale price of agricultural properties. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table D.16 Marginal effects of SDM results of per hectare sales price of South Australian agricultural properties by farm size (medium farms – 12.24 to 64.48 ha; N=3,523), 1998-2013

	Direct effect	*Std. Err.*	*Indirect effect*	*Std. Err.*	*Total effect*	*Std. Err.*
Drought	-0.027	0.056	0.271	0.189	0.244	0.171
Native woody vegetation	0.978***	0.142	3.206**	1.394	4.185***	1.399
Vegetation square	-1.228***	0.168	-0.639**	0.261	-1.867***	0.350
Annual rainfall	0.001***	0.000	-0.001**	0.000	0.000	0.000
Annual maximum temperature	-0.040	0.024	0.008	0.119	-0.032	0.109
Soil organic carbon	0.067	0.050	-1.570**	0.721	-1.503**	0.718
Silt	0.018	0.011	1.601***	0.270	1.619***	0.270
Sand	0.002	0.001	-0.020	0.029	-0.018	0.029
Clay	0.002	0.002	-0.003	0.038	-0.001	0.038
Soil water holding capacity	0.035***	0.012	0.356**	0.179	0.392**	0.177
Soil erosion index	-0.023**	0.009	0.139	0.297	0.116	0.298
Basic soil	0.077***	0.021	0.201	0.558	0.278	0.559
Elevation	0.000	0.000	-0.015***	0.002	-0.015***	0.002
Distance to coast	-0.001	0.016	-0.001	0.008	-0.002	0.024
Distance to conservation reserve	0.034***	0.012	0.018*	0.009	0.052***	0.019
Distance to surface-water	-0.005	0.015	-0.003	0.008	-0.008	0.023
Distance to highway	0.010	0.008	0.005	0.005	0.015	0.013
Lot size	-0.655***	0.025	-1.305*	0.693	-1.960***	0.696
Main rooms per hectare	0.847***	0.075	-4.551*	2.422	-3.704	2.430
Structural improvements	0.415***	0.024	2.482***	0.667	2.896***	0.670
Irrigation	0.348***	0.064	-0.216	1.479	0.132	1.481
Groundwater bore	0.042	0.028	-1.560*	0.833	-1.518*	0.834
Cropping	-0.049*	0.027	-0.025	0.017	-0.074*	0.043
Horticulture	0.163**	0.067	0.084*	0.048	0.247**	0.107
Market garden	0.392***	0.106	0.204**	0.095	0.595***	0.178
Mixed farming	0.161*	0.098	0.084	0.060	0.244	0.152
Viticulture	0.360***	0.071	0.187**	0.082	0.548***	0.130
SEIFA	0.002***	0.000	-0.003*	0.002	-0.001	0.002
Real commodity price index	0.002**	0.001	0.003	0.003	0.006**	0.003
Urban accessibility index	0.079***	0.006	0.041**	0.016	0.120***	0.018
Remoteness areas index	-0.005	0.041	-0.003	0.021	-0.008	0.063
Trend	0.073***	0.011	0.038***	0.011	0.111***	0.009
EP	0.348***	0.113	0.181*	0.096	0.529***	0.191
KI	-0.116	0.099	-0.060	0.055	-0.176	0.150
AMLR	0.158***	0.031	0.082**	0.037	0.241***	0.058
SE	0.113	0.102	0.059	0.059	0.172	0.158
NY	0.143***	0.051	0.074*	0.040	0.217**	0.084
Spatio-temporal lag (ρ)	0.278***					
Pseudo R^2	0.732					
AIC	5781.67					
LR Test SDM vs. SAR	290.68***					
LR Test SDM vs. SEM	70.21***					

Notes: The outcome variable is the per hectare real sale price of agricultural properties. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table D.17 Marginal effects of SDM results of per hectare sales price of South Australian agricultural properties by farm size (large farms - 64.49 to 4944.87 ha; N=3,515), 1998-2013

	Direct effect	*Std. Err.*	*Indirect effect*	*Std. Err.*	*Total effect*	*Std. Err.*
Drought	-0.110**	0.055	3.504***	1.142	3.394***	1.134
Native woody vegetation	-0.983***	0.158	-9.811***	4.805	-10.794***	4.426
Vegetation square	0.065	0.202	0.261	0.815	0.326	1.017
Annual rainfall	0.003***	0.000	-0.012***	0.003	-0.010***	0.003
Annual maximum temperature	0.001	0.023	-0.726**	0.320	-0.724**	0.317
Soil organic carbon	-0.033	0.057	3.193	2.111	3.161	2.108
Silt	0.043***	0.014	-1.091	0.785	-1.048	0.784
Sand	0.000	0.001	0.045	0.061	0.045	0.061
Clay	0.010***	0.002	0.246**	0.104	0.256**	0.104
Soil water holding capacity	0.029***	0.010	0.226	0.312	0.255	0.309
Soil erosion index	-0.014	0.012	2.071*	1.093	2.057*	1.095
Basic soil	0.071***	0.024	-3.256*	1.724	-3.185*	1.725
Elevation	0.000	0.000	-0.023***	0.008	-0.023***	0.008
Distance to coast	0.009	0.017	0.038	0.069	0.047	0.086
Distance to conservation reserve	0.039***	0.012	0.156**	0.072	0.195**	0.081
Distance to surface-water	-0.049***	0.015	-0.195**	0.089	-0.244**	0.100
Distance to highway	-0.016	0.010	-0.064	0.046	-0.079	0.055
Lot size	-0.418***	0.015	-2.061**	0.901	-2.479***	0.902
Main rooms per hectare	3.666***	0.611	53.031	48.487	56.697	48.611
Structural improvements	0.250***	0.022	4.468*	2.318	4.718**	2.323
Irrigation	0.318***	0.097	-0.526	6.069	-0.208	6.086
Groundwater bore	0.139***	0.033	-1.432	2.244	-1.293	2.249
Cropping	0.183***	0.029	0.735***	0.269	0.919***	0.283
Horticulture	1.105***	0.396	4.434**	2.144	5.539**	2.448
Market garden	0.303	0.402	1.218	1.654	1.521	2.046
Mixed farming	0.594***	0.211	2.383**	1.153	2.977**	1.314
Viticulture	0.504***	0.161	2.024**	0.960	2.529**	1.081
SEIFA	0.001***	0.000	0.001	0.004	0.002	0.004
Real commodity price index	-0.001	0.001	-0.011*	0.006	-0.012**	0.006
Urban accessibility index	0.046***	0.007	0.184***	0.067	0.229***	0.071
Remoteness areas index	-0.032	0.028	-0.130	0.118	-0.163	0.144
Trend	0.041***	0.007	0.166***	0.042	0.208***	0.041
EP	0.029	0.111	0.118	0.451	0.147	0.562
KI	0.059	0.092	0.238	0.376	0.297	0.466
AMLR	0.317***	0.063	1.271**	0.501	1.588***	0.537
SE	0.370***	0.072	1.486***	0.571	1.856***	0.611
NY	0.420***	0.053	1.686***	0.599	2.106***	0.620
Spatio-temporal lag (ρ)	0.635***					
Pseudo R^2	0.759					
AIC	5807.391					
LR Test SDM vs. SAR	616.59***					
LR Test SDM vs. SEM	214.15***					

Notes: The outcome variable is the per hectare real sale price of agricultural properties. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table D.18 Marginal effects of SDM results of per hectare valuation price of South Australian agricultural properties by farm size (small farms – 2 to 12.23 ha; N=3,475), 1998-2013

	Direct effect	*Std. Err.*	*Indirect effect*	*Std. Err.*	*Total effect*	*Std. Err.*
Drought	-0.023	0.054	0.566	0.522	0.544	0.505
Native woody vegetation	0.342***	0.122	10.427***	3.494	10.769***	3.507
Vegetation square	-0.254*	0.135	-0.817*	0.489	-1.072*	0.613
Annual rainfall	0.001***	0.000	-0.004***	0.001	-0.003***	0.001
Annual maximum temperature	0.023	0.022	0.041	0.206	0.064	0.203
Soil organic carbon	0.185***	0.040	7.155**	2.871	7.340**	2.877
Silt	0.009	0.010	-0.351	0.757	-0.341	0.757
Sand	0.005***	0.001	-0.091	0.091	-0.087	0.091
Clay	-0.003*	0.001	-0.012	0.087	-0.015	0.087
Soil water holding capacity	0.085***	0.011	-0.074	0.569	0.011	0.568
Soil erosion index	0.031***	0.010	-1.106**	0.561	-1.075*	0.562
Basic soil	0.044**	0.022	0.638	1.444	0.683	1.446
Elevation	-0.001***	0.000	-0.007	0.007	-0.008	0.007
Distance to coast	-0.187***	0.017	-0.602***	0.165	-0.789***	0.169
Distance to conservation reserve	-0.009	0.011	-0.028	0.037	-0.037	0.048
Distance to surface-water	0.019	0.016	0.062	0.056	0.081	0.071
Distance to highway	-0.015**	0.007	-0.047*	0.025	-0.061*	0.031
Lot size	-0.645***	0.021	-3.365**	1.623	-4.010**	1.626
Main rooms per hectare	0.074***	0.012	0.436	0.819	0.510	0.821
Structural improvements	0.173***	0.033	-3.437*	2.003	-3.264	2.006
Irrigation	0.061	0.041	10.269***	2.417	10.330***	2.420
Groundwater bore	-0.007	0.032	5.172**	2.487	5.164**	2.493
Cropping	-0.054*	0.030	-0.175	0.108	-0.229*	0.135
Horticulture	0.065*	0.039	0.210	0.136	0.275	0.172
Market garden	0.208***	0.060	0.669**	0.260	0.877***	0.306
Mixed farming	0.275**	0.122	0.885*	0.456	1.160**	0.563
Viticulture	0.235***	0.047	0.756***	0.255	0.991***	0.286
SEIFA	0.002***	0.000	-0.003	0.004	-0.001	0.004
Real commodity price index	0.002***	0.001	-0.021***	0.007	-0.018**	0.007
Urban accessibility index	0.103***	0.005	0.331***	0.091	0.433***	0.092
Remoteness areas index	-0.080*	0.044	-0.258	0.157	-0.338*	0.197
Trend	0.046***	0.008	0.149***	0.027	0.195***	0.027
EP	0.128	0.111	0.412	0.372	0.540	0.480
KI	0.177	0.142	0.570	0.483	0.747	0.619
AMLR	0.125***	0.033	0.402***	0.153	0.528***	0.178
SE	-0.257**	0.108	-0.826*	0.429	-1.083**	0.524
NY	-0.062	0.056	-0.201	0.191	-0.264	0.245
Spatio-temporal lag (ρ)	0.614***					
Pseudo R^2	0.759					
AIC	5435.74					
LR Test SDM vs. SAR	436.93***					
LR Test SDM vs. SEM	89.12***					

Notes: The outcome variable is the per hectare real valuation price of agricultural properties. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table D.19 Marginal effects of SDM results of per hectare valuation price of South Australian agricultural properties by farm size (medium farms – 12.24 to 64.48 ha; N=3,523), 1998-2013

	Direct effect	*Std. Err.*	*Indirect effect*	*Std. Err.*	*Total effect*	*Std. Err.*
Drought	0.036	0.049	0.370**	0.184	0.406**	0.170
Native woody vegetation	0.166	0.123	6.822***	1.475	6.988***	1.478
Vegetation square	-0.336**	0.147	-0.232*	0.121	-0.568**	0.255
Annual rainfall	0.001***	0.000	-0.002***	0.001	-0.001**	0.000
Annual maximum temperature	-0.028	0.021	-0.182	0.125	-0.210*	0.116
Soil organic carbon	0.120***	0.043	-0.938	0.695	-0.818	0.692
Silt	0.038***	0.010	1.373***	0.253	1.411***	0.254
Sand	0.003***	0.001	0.064**	0.027	0.068**	0.027
Clay	0.003*	0.001	0.123***	0.040	0.125***	0.040
Soil water holding capacity	0.075***	0.011	0.341*	0.174	0.416**	0.173
Soil erosion index	-0.018**	0.008	-0.044	0.286	-0.062	0.287
Basic soil	0.053***	0.018	0.020	0.544	0.073	0.545
Elevation	0.000***	0.000	-0.015***	0.002	-0.016***	0.002
Distance to coast	-0.049***	0.014	-0.034**	0.014	-0.082***	0.026
Distance to conservation reserve	0.023**	0.010	0.016*	0.008	0.038**	0.018
Distance to surface-water	0.031**	0.013	0.021*	0.012	0.052**	0.024
Distance to highway	0.016**	0.007	0.011*	0.006	0.027**	0.013
Lot size	-0.563***	0.021	-0.865	0.665	-1.428**	0.668
Main rooms per hectare	0.247***	0.065	-6.303**	2.436	-6.057**	2.444
Structural improvements	0.035	0.021	1.597**	0.638	1.632**	0.641
Irrigation	0.464***	0.056	1.370	1.485	1.835	1.488
Groundwater bore	0.000	0.025	-0.623	0.782	-0.623	0.784
Cropping	0.001	0.024	0.001	0.016	0.002	0.040
Horticulture	0.268***	0.058	0.185***	0.070	0.453***	0.114
Market garden	0.339***	0.092	0.234**	0.095	0.574***	0.171
Mixed farming	0.082	0.085	0.057	0.061	0.139	0.145
Viticulture	0.135**	0.061	0.093*	0.051	0.227**	0.108
SEIFA	0.003***	0.000	-0.005***	0.002	-0.002	0.002
Real commodity price index	0.002***	0.001	-0.002	0.003	0.000	0.002
Urban accessibility index	0.096***	0.005	0.066***	0.021	0.163***	0.022
Remoteness areas index	-0.077**	0.036	-0.053*	0.028	-0.131**	0.061
Trend	0.079***	0.010	0.055***	0.012	0.134***	0.010
EP	0.294***	0.098	0.203**	0.096	0.497***	0.182
KI	-0.093	0.086	-0.064	0.061	-0.156	0.145
AMLR	0.176***	0.027	0.122***	0.043	0.298***	0.061
SE	-0.130	0.089	-0.090	0.065	-0.220	0.150
NY	0.054	0.044	0.037	0.033	0.091	0.076
Spatio-temporal lag (ρ)	0.331***					
Pseudo R^2	0.766					
AIC	4806.119					
LR Test SDM vs. SAR	454.31***					
LR Test SDM vs. SEM	110.08***					

Notes: The outcome variable is the per hectare real valuation price of agricultural properties. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table D.20 Marginal effects of SDM results of per hectare valuation price of South Australian agricultural properties by farm size (large farms - 64.49 to 4944.87 ha; N=3,515), 1998-2013

	Direct effect	*Std. Err.*	*Indirect effect*	*Std. Err.*	*Total effect*	*Std. Err.*
Drought	-0.089*	0.048	6.376***	2.299	6.287***	2.293
Native woody vegetation	-1.459***	0.140	-32.082***	11.755	-33.541***	11.768
Vegetation square	0.528***	0.179	4.049**	1.986	4.577**	2.111
Annual rainfall	0.003***	0.000	-0.024***	0.006	-0.021***	0.006
Annual maximum temperature	-0.103***	0.020	-1.033*	0.536	-1.136**	0.533
Soil organic carbon	-0.034	0.050	4.582	3.319	4.548	3.317
Silt	0.037***	0.013	-3.190**	1.480	-3.153**	1.479
Sand	-0.001	0.001	0.111	0.093	0.110	0.093
Clay	0.012***	0.002	0.378**	0.167	0.390**	0.167
Soil water holding capacity	0.047***	0.009	0.414	0.481	0.461	0.479
Soil erosion index	-0.020*	0.011	2.881*	1.702	2.861*	1.704
Basic soil	0.065***	0.021	-5.062*	2.803	-4.997*	2.805
Elevation	0.000	0.000	-0.043***	0.016	-0.044***	0.015
Distance to coast	0.046***	0.015	0.352**	0.172	0.397**	0.182
Distance to conservation reserve	0.044***	0.011	0.338**	0.150	0.382**	0.156
Distance to surface-water	-0.031**	0.013	-0.240*	0.136	-0.271*	0.146
Distance to highway	0.002	0.009	0.019	0.067	0.021	0.076
Lot size	-0.364***	0.013	-6.342***	2.206	-6.707***	2.208
Main rooms per hectare	0.821	0.544	18.392	73.045	19.213	73.176
Structural improvements	0.157***	0.020	11.237**	4.904	11.394**	4.909
Irrigation	0.219**	0.086	-3.316	9.387	-3.097	9.404
Groundwater bore	0.156***	0.029	-6.354	4.053	-6.198	4.058
Cropping	0.234***	0.026	1.797***	0.685	2.031***	0.693
Horticulture	1.571***	0.351	12.054**	5.111	13.624**	5.301
Market garden	0.411	0.356	3.154	2.941	3.565	3.272
Mixed farming	0.523***	0.186	4.013**	2.041	4.536**	2.175
Viticulture	0.565***	0.143	4.339**	1.967	4.905**	2.056
SEIFA	0.001***	0.000	0.005	0.006	0.006	0.006
Real commodity price index	-0.001	0.001	-0.028**	0.012	-0.029**	0.012
Urban accessibility index	0.062***	0.006	0.478***	0.181	0.541***	0.183
Remoteness areas index	0.043*	0.025	0.326	0.225	0.369	0.246
Trend	0.038***	0.005	0.288***	0.086	0.325***	0.085
EP	0.014	0.098	0.105	0.757	0.119	0.855
KI	0.003	0.082	0.022	0.626	0.025	0.707
AMLR	0.464***	0.055	3.562**	1.383	4.026***	1.403
SE	0.167***	0.064	1.279*	0.681	1.445**	0.729
NY	0.550***	0.047	4.224***	1.584	4.774***	1.597
Spatio-temporal lag (ρ)	0.702***					
Pseudo R^2	0.811					
AIC	4940.166					
LR Test SDM vs. SAR	1050.00***					
LR Test SDM vs. SEM	410.09***					

Notes: The outcome variable is the per hectare real valuation price of agricultural properties. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table D.21 Marginal effects of SDM results of per hectare sales price of South Australian agricultural properties by farming industry (cropping; N=4,041), 1998-2013

	Direct effect	*Std. Err.*	*Indirect effect*	*Std. Err.*	*Total effect*	*Std. Err.*
Drought	-0.110**	0.055	1.184*	0.716	1.074	0.704
Native woody vegetation	0.336*	0.174	-2.563	4.699	-2.227	4.717
Vegetation square	-0.914***	0.243	-2.627**	1.153	-3.542***	1.320
Annual rainfall	0.002***	0.000	-0.006***	0.002	-0.004***	0.002
Annual maximum temperature	0.024	0.026	-0.777**	0.328	-0.753**	0.326
Soil organic carbon	-0.095	0.064	2.198	2.323	2.103	2.319
Silt	0.025*	0.013	0.112	0.813	0.137	0.812
Sand	-0.001	0.002	0.031	0.068	0.030	0.068
Clay	0.010***	0.002	0.239**	0.096	0.249**	0.096
Soil water holding capacity	0.047***	0.011	-0.724*	0.422	-0.677	0.419
Soil erosion index	-0.004	0.014	1.898*	1.111	1.895*	1.112
Basic soil	0.049*	0.026	-0.065	1.523	-0.016	1.523
Elevation	0.000	0.000	-0.025***	0.009	-0.025***	0.009
Distance to coast	-0.029*	0.017	-0.082	0.057	-0.111	0.072
Distance to conservation reserve	0.054***	0.013	0.155**	0.064	0.209***	0.072
Distance to surface-water	-0.042***	0.016	-0.121*	0.062	-0.163**	0.074
Distance to highway	0.004	0.009	0.011	0.026	0.015	0.035
Lot size	-0.572***	0.009	1.035*	0.540	0.463	0.541
Main rooms per hectare	0.448***	0.035	1.377	2.633	1.825	2.640
Structural improvements	0.412***	0.022	-0.762	1.840	-0.350	1.845
Irrigation	0.271**	0.138	-5.618	8.786	-5.346	8.805
Groundwater bore	0.044	0.047	-3.107	3.455	-3.063	3.461
SEIFA	0.001***	0.000	-0.005**	0.003	-0.004	0.003
Real commodity price index	0.000	0.002	-0.007	0.005	-0.006*	0.004
Urban accessibility index	0.065***	0.006	0.188***	0.066	0.253***	0.068
Remoteness areas index	0.002	0.030	0.006	0.088	0.009	0.118
Trend	0.029***	0.008	0.083***	0.018	0.112***	0.020
EP	-0.097	0.115	-0.279	0.336	-0.376	0.447
KI	-0.093	0.149	-0.268	0.437	-0.361	0.584
AMLR	0.267***	0.054	0.767**	0.306	1.034***	0.337
SE	0.219**	0.089	0.629*	0.339	0.848**	0.412
NY	0.295***	0.053	0.847***	0.323	1.142***	0.351
Spatio-temporal lag (ρ)	0.586***					
Pseudo R^2	0.831					
AIC	7819.728					
LR Test SDM vs. SAR	375.50***					
LR Test SDM vs. SEM	107.54***					

Notes: The outcome variable is the per hectare real sale price of agricultural properties. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table D.22 Marginal effects of SDM results of per hectare sales price of South Australian agricultural properties by farming industry (grazing; N=5,320), 1998-2013

	Direct effect	*Std. Err.*	*Indirect effect*	*Std. Err.*	*Total effect*	*Std. Err.*
Drought	-0.026	0.050	0.514	0.380	0.489	0.368
Native woody vegetation	0.677***	0.107	4.242	3.079	4.919	3.080
Vegetation square	-0.816***	0.118	-2.289***	0.836	-3.105***	0.888
Annual rainfall	0.001***	0.000	-0.004***	0.001	-0.003***	0.001
Annual maximum temperature	0.077***	0.020	-0.385**	0.188	-0.308*	0.185
Soil organic carbon	0.074**	0.037	7.881***	2.828	7.955***	2.830
Silt	0.010	0.009	1.107	0.705	1.117	0.705
Sand	0.001	0.001	-0.206**	0.101	-0.205**	0.101
Clay	-0.003*	0.001	-0.205**	0.102	-0.207**	0.102
Soil water holding capacity	0.066***	0.011	-2.043***	0.699	-1.977***	0.699
Soil erosion index	-0.014*	0.008	0.535	0.602	0.521	0.602
Basic soil	0.113***	0.017	3.745**	1.647	3.858**	1.648
Elevation	0.001***	0.000	-0.013*	0.007	-0.012***	0.007
Distance to coast	-0.037***	0.014	-0.104**	0.052	-0.142**	0.062
Distance to conservation reserve	0.014	0.010	0.040	0.030	0.054	0.039
Distance to surface-water	-0.025*	0.014	-0.069	0.044	-0.094*	0.057
Distance to highway	-0.012*	0.007	-0.035	0.023	-0.048*	0.029
Lot size	-0.664***	0.008	0.570	0.570	-0.094	0.570
Main rooms per hectare	0.234***	0.013	2.562*	1.311	2.796**	1.313
Structural improvements	0.539***	0.022	1.824	1.670	2.363	1.672
Irrigation	0.173**	0.073	18.947***	7.088	19.120***	7.096
Groundwater bore	0.136***	0.023	-0.971	2.397	-0.835	2.401
SEIFA	0.001***	0.000	0.003	0.003	0.004	0.003
Real commodity price index	0.002	0.002	-0.010	0.007	-0.009	0.006
Urban accessibility index	0.058***	0.005	0.162***	0.057	0.220***	0.059
Remoteness areas index	-0.031	0.035	-0.088	0.104	-0.119	0.138
Trend	0.060***	0.009	0.168***	0.043	0.228***	0.041
EP	0.450***	0.111	1.264**	0.540	1.714***	0.615
KI	0.139	0.085	0.390	0.274	0.528	0.351
AMLR	0.230***	0.026	0.645***	0.233	0.875***	0.244
SE	0.682***	0.086	1.915***	0.691	2.598***	0.726
NY	0.297***	0.054	0.834**	0.323	1.131***	0.352
Spatio-temporal lag (ρ)	0.596***					
Pseudo R^2	0.886					
AIC	8993.014					
LR Test SDM vs. SAR	440.20***					
LR Test SDM vs. SEM	112.09***					

Notes: The outcome variable is the per hectare real sale price of agricultural properties. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table D.23 Marginal effects of SDM results of per hectare sales price of South Australian agricultural properties by farming industry (horticulture), 1998-2013

	Direct effect	*Std. Err.*	*Indirect effect*	*Std. Err.*	*Total effect*	*Std. Err.*
Drought	0.012	0.148	-0.835*	0.477	-0.823**	0.407
Native woody vegetation	0.580**	0.277	1.387	2.579	1.968	2.633
Vegetation square	-0.805**	0.372	-0.461	0.322	-1.266**	0.631
Annual rainfall	0.000	0.000	0.000	0.001	0.000	0.001
Annual maximum temperature	-0.074	0.059	-0.147	0.171	-0.221	0.157
Soil organic carbon	0.276***	0.103	1.093	2.065	1.369	2.084
Silt	-0.045*	0.022	-0.726	0.474	-0.771	0.478
Sand	-0.002	0.003	-0.187***	0.052	-0.189***	0.053
Clay	-0.004	0.003	0.001	0.056	-0.002	0.056
Soil water holding capacity	0.089***	0.023	-0.087	0.356	0.002	0.356
Soil erosion index	0.028	0.023	0.867**	0.439	0.895**	0.443
Basic soil	0.051	0.064	-3.532***	1.053	-3.481***	1.063
Elevation	0.000	0.001	0.006	0.005	0.005	0.005
Distance to coast	0.003	0.057	0.002	0.033	0.005	0.090
Distance to conservation reserve	0.012	0.024	0.007	0.014	0.019	0.038
Distance to surface-water	0.044	0.042	0.025	0.027	0.069	0.067
Distance to highway	-0.059***	0.017	-0.034*	0.020	-0.093***	0.032
Lot size	-0.549***	0.025	0.074	0.474	-0.476	0.478
Main rooms per hectare	0.260***	0.029	0.579	0.452	0.839*	0.456
Structural improvements	0.399***	0.085	2.679*	1.441	3.078**	1.445
Irrigation	0.099**	0.048	2.349***	0.816	2.447***	0.819
Groundwater bore	0.114**	0.056	1.691	1.478	1.805	1.496
Market garden	0.020	0.071	0.011	0.041	0.031	0.112
Mixed farming	-0.330	0.279	-0.189	0.188	-0.520	0.449
Viticulture	-0.043	0.066	-0.025	0.040	-0.068	0.105
SEIFA	0.002***	0.001	0.002	0.003	0.004	0.003
Real commodity price index	0.001	0.001	0.008	0.006	0.009	0.006
Urban accessibility index	0.082***	0.014	0.047*	0.027	0.129***	0.035
Remoteness areas index	-0.197*	0.111	-0.113	0.085	-0.310*	0.181
Trend	0.013	0.015	0.007	0.008	0.020	0.023
EP	0.062	0.673	0.035	0.386	0.097	1.058
KI	-0.532	0.403	-0.305	0.288	-0.837	0.662
AMLR	0.302***	0.093	0.173*	0.103	0.475***	0.168
SE	-0.267	0.266	-0.153	0.173	-0.420	0.427
NY	0.213	0.160	0.122	0.110	0.334	0.257
Spatio-temporal lag (ρ)	0.302***					
Pseudo R^2	0.679					
AIC	2187.566					
LR Test SDM vs. SAR	144.51***					
LR Test SDM vs. SEM	31.88***					

Notes: The outcome variable is the per hectare real sale price of agricultural properties. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table D.24 Marginal effects of SDM results of per hectare valuation price of South Australian agricultural properties by farming industry (cropping; N=4,041), 1998-2013

	Direct effect	*Std. Err.*	*Indirect effect*	*Std. Err.*	*Total effect*	*Std. Err.*
Drought	-0.038	0.049	2.222	1.947	2.184	1.938
Native woody vegetation	-1.199***	0.158	-22.656	16.418	-23.855	16.433
Vegetation square	0.772***	0.220	7.540*	3.945	8.312**	4.065
Annual rainfall	0.003***	0.000	-0.018**	0.007	-0.015**	0.007
Annual maximum temperature	-0.009	0.023	-3.155**	1.473	-3.164**	1.471
Soil organic carbon	-0.118**	0.058	-4.632	6.002	-4.750	6.000
Silt	0.010	0.012	0.404	2.060	0.414	2.061
Sand	0.000	0.001	0.579**	0.276	0.579**	0.276
Clay	0.016***	0.002	1.010**	0.418	1.026**	0.418
Soil water holding capacity	0.063***	0.010	1.331	1.048	1.394	1.046
Soil erosion index	0.019	0.013	6.353*	3.512	6.372*	3.514
Basic soil	0.053**	0.024	0.541	3.796	0.594	3.798
Elevation	0.000*	0.000	-0.112**	0.047	-0.112**	0.047
Distance to coast	-0.054***	0.016	-0.531*	0.283	-0.585**	0.291
Distance to conservation reserve	0.046***	0.012	0.451**	0.229	0.497**	0.235
Distance to surface-water	-0.045***	0.014	-0.444*	0.243	-0.489*	0.251
Distance to highway	0.003	0.008	0.033	0.080	0.036	0.088
Lot size	-0.420***	0.008	2.855*	1.696	2.434	1.697
Main rooms per hectare	0.284***	0.032	2.543	6.700	2.827	6.708
Structural improvements	0.114***	0.021	-8.075	5.818	-7.962	5.822
Irrigation	0.398***	0.126	4.585	21.676	4.983	21.700
Groundwater bore	0.114***	0.043	-6.071	8.781	-5.957	8.789
SEIFA	0.001***	0.000	-0.023**	0.009	-0.022**	0.010
Real commodity price index	0.003**	0.001	-0.033**	0.015	-0.029**	0.014
Urban accessibility index	0.079***	0.006	0.773**	0.350	0.852**	0.351
Remoteness areas index	0.010	0.028	0.096	0.275	0.106	0.302
Trend	0.012*	0.006	0.114**	0.046	0.125**	0.049
EP	-0.430***	0.104	-4.197**	2.054	-4.627**	2.100
KI	-0.200	0.136	-1.950	1.563	-2.149	1.677
AMLR	0.412***	0.049	4.020**	1.864	4.432**	1.877
SE	0.003	0.081	0.031	0.794	0.035	0.876
NY	0.284***	0.048	2.770**	1.320	3.054**	1.338
Spatio-temporal lag (ρ)	0.715***					
Pseudo R^2	0.828					
AIC	7019.203					
LR Test SDM vs. SAR	724.96***					
LR Test SDM vs. SEM	232.85***					

Notes: The outcome variable is the per hectare real valuation price of agricultural properties. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table D.25 Marginal effects of SDM results of per hectare valuation price of South Australian agricultural properties by farming industry (grazing; N=5,320), 1998-2013

	Direct effect	***Std. Err.***	***Indirect effect***	***Std. Err.***	***Total effect***	***Std. Err.***
Drought	0.013	0.045	2.207**	1.099	2.220**	1.093
Native woody vegetation	0.028	0.096	18.381**	8.684	18.409**	8.687
Vegetation square	-0.149	0.106	-1.138	0.924	-1.287	1.017
Annual rainfall	0.001***	0.000	-0.009***	0.003	-0.008**	0.003
Annual maximum temperature	0.062***	0.018	-0.700*	0.407	-0.639	0.404
Soil organic carbon	0.130***	0.033	31.675***	11.779	31.804***	11.782
Silt	0.027***	0.008	-1.271	1.460	-1.244	1.460
Sand	0.000	0.001	-0.698**	0.308	-0.698**	0.309
Clay	-0.003***	0.001	-0.623**	0.287	-0.626**	0.287
Soil water holding capacity	0.081***	0.009	-6.879***	2.627	-6.798**	2.627
Soil erosion index	-0.026***	0.007	1.444	1.316	1.418	1.316
Basic soil	0.103***	0.016	13.665**	5.478	13.768**	5.479
Elevation	0.000**	0.000	-0.011	0.013	-0.011	0.013
Distance to coast	-0.073***	0.013	-0.558**	0.242	-0.631**	0.247
Distance to conservation reserve	0.016*	0.009	0.121	0.082	0.137	0.090
Distance to surface-water	0.006	0.013	0.045	0.099	0.051	0.111
Distance to highway	-0.005	0.006	-0.041	0.050	-0.047	0.056
Lot size	-0.548***	0.007	1.653	1.254	1.105	1.254
Main rooms per hectare	0.180***	0.012	6.857**	3.088	7.038**	3.090
Structural improvements	0.161***	0.019	1.959	3.386	2.120	3.389
Irrigation	0.302***	0.065	43.958**	18.478	44.260**	18.487
Groundwater bore	0.111***	0.021	-0.624	4.805	-0.513	4.809
SEIFA	0.002***	0.000	0.023**	0.011	0.025**	0.011
Real commodity price index	0.004***	0.002	-0.040**	0.018	-0.036**	0.018
Urban accessibility index	0.082***	0.005	0.625**	0.259	0.707***	0.260
Remoteness areas index	-0.031	0.032	-0.238	0.261	-0.269	0.291
Trend	0.064***	0.008	0.488***	0.166	0.552***	0.163
EP	0.342***	0.100	2.608*	1.335	2.950**	1.398
KI	0.107	0.076	0.818	0.673	0.926	0.740
AMLR	0.261***	0.023	1.987**	0.840	2.248***	0.846
SE	0.638***	0.077	4.867**	2.081	5.505***	2.106
NY	0.165***	0.048	1.255*	0.640	1.420**	0.670
Spatio-temporal lag (ρ)	0.713***					
Pseudo R^2	0.889					
AIC	7800.799					
LR Test SDM vs. SAR	761.26***					
LR Test SDM vs. SEM	250.32***					

Notes: The outcome variable is the per hectare real valuation price of agricultural properties. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table D.26 Marginal effects of SDM results of per hectare valuation price of South Australian agricultural properties by farming industry (horticulture; N=1,152), 1998-2013

	Direct effect	*Std. Err.*	*Indirect effect*	*Std. Err.*	*Total effect*	*Std. Err.*
Drought	-0.155	0.099	0.294	0.298	0.139	0.248
Native woody vegetation	-0.096	0.185	0.670	1.543	0.575	1.578
Vegetation square	0.109	0.249	0.049	0.115	0.157	0.362
Annual rainfall	0.001***	0.000	-0.001	0.001	0.000	0.000
Annual maximum temperature	0.131***	0.040	-0.328***	0.109	-0.197**	0.100
Soil organic carbon	0.128*	0.069	-2.254	1.305	-2.126	1.316
Silt	-0.005	0.015	0.206	0.272	0.200	0.274
Sand	0.005**	0.002	-0.067**	0.029	-0.063**	0.029
Clay	0.002	0.002	0.128**	0.039	0.129***	0.039
Soil water holding capacity	0.059***	0.015	0.057	0.220	0.116	0.219
Soil erosion index	0.018	0.016	-0.315	0.259	-0.297	0.261
Basic soil	-0.093**	0.043	-1.318	0.577	-1.411**	0.582
Elevation	0.000	0.000	0.001***	0.003	0.001	0.003
Distance to coast	0.048	0.044	0.021**	0.023	0.069	0.065
Distance to conservation reserve	0.003***	0.000	0.006***	0.002	0.009***	0.002
Distance to surface-water	0.001**	0.001	0.008***	0.004	0.009**	0.004
Distance to highway	-0.110***	0.038	-0.049**	0.031	-0.160***	0.061
Lot size	-0.513***	0.017	0.566	0.293	0.053	0.295
Main rooms per hectare	0.129***	0.019	0.634	0.271	0.763***	0.274
Structural improvements	0.110*	0.057	1.220	0.880	1.329	0.882
Irrigation	0.046	0.032	0.723	0.484	0.769	0.486
Groundwater bore	0.049	0.037	-0.897	0.882	-0.848	0.893
Market garden	0.098**	0.048	0.044**	0.032	0.142*	0.073
Mixed farming	0.158	0.187	0.071*	0.093	0.229	0.275
Viticulture	-0.015	0.016	-0.007***	0.008	-0.022	0.024
SEIFA	-0.013	0.028	-0.006**	0.013	-0.018	0.041
Real commodity price index	0.003	0.011	0.001***	0.005	0.005	0.017
Urban accessibility index	0.074***	0.010	0.033**	0.019	0.108***	0.024
Remoteness areas index	0.010	0.074	0.004**	0.033	0.014	0.108
Trend	0.086***	0.013	0.038**	0.017	0.124***	0.016
EP	-0.769*	0.451	-0.344	0.270	-1.112*	0.672
KI	-0.416	0.270	-0.186	0.158	-0.602	0.405
AMLR	0.159**	0.062	0.071**	0.048	0.229**	0.099
SE	0.019	0.178	0.008	0.080	0.027	0.258
NY	-0.303***	0.108	-0.135	0.084	-0.438***	0.166
Spatio-temporal lag (ρ)	0.257***					
Pseudo R^2	0.796					
AIC	1265.773					
LR Test SDM vs. SAR	187.78***					
LR Test SDM vs. SEM	54.10***					

Notes: The outcome variable is the per hectare real valuation price of agricultural properties. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table D.27 Sensitivity analysis: Marginal effects of full sample SDM results of per hectare sales price of South Australian agricultural properties (2 years spatio-temporal inverse distance matrix with 11 km cut-off), 1998-2013

	Direct effect	*Std. Err.*	*Indirect effect*	*Std. Err.*	*Total effect*	*Std. Err.*
Drought	-0.047	0.032	0.378**	0.169	0.331**	0.163
Native woody vegetation	0.525***	0.090	0.503	1.698	1.029	1.705
Vegetation square	-0.710***	0.106	-0.326***	0.123	-1.035***	0.192
Annual rainfall	0.001***	0.000	-0.001***	0.000	-0.001**	0.000
Annual maximum temperature	-0.071***	0.012	0.082	0.070	0.011	0.068
Soil organic carbon	0.097***	0.031	4.223***	1.205	4.320***	1.206
Silt	0.040***	0.007	-0.639*	0.355	-0.598*	0.355
Sand	0.002*	0.001	-0.037	0.045	-0.035	0.045
Clay	0.000	0.001	-0.016	0.044	-0.017	0.044
Soil water holding capacity	0.047***	0.007	-0.222	0.260	-0.175	0.261
Soil erosion index	-0.008	0.007	0.443	0.310	0.434	0.311
Basic soil	0.075***	0.015	1.832***	0.643	1.908***	0.643
Elevation	-0.001***	0.000	-0.007*	0.004	-0.007**	0.004
Distance to coast	0.025**	0.010	0.011*	0.006	0.036**	0.015
Distance to conservation reserve	0.020***	0.007	0.009*	0.005	0.029**	0.011
Distance to surface-water	-0.052***	0.009	-0.024**	0.009	-0.076***	0.015
Distance to highway	-0.015***	0.005	-0.007**	0.003	-0.022***	0.008
Lot size	-0.623***	0.006	-0.132	0.180	-0.755***	0.181
Main rooms per hectare	0.285***	0.012	0.890*	0.499	1.175**	0.500
Structural improvements	0.512***	0.016	0.811	0.770	1.323*	0.771
Irrigation	0.304***	0.037	2.295*	1.336	2.598*	1.339
Groundwater bore	0.087***	0.020	-2.639***	1.009	-2.552**	1.010
Cropping	0.031	0.019	0.014	0.010	0.045	0.027
Horticulture	0.248***	0.036	0.114***	0.042	0.362***	0.065
Market garden	0.344***	0.059	0.158***	0.060	0.502***	0.101
Mixed farming	0.114	0.084	0.052	0.042	0.166	0.124
Viticulture	0.174***	0.042	0.080**	0.034	0.254***	0.067
SEIFA	0.002***	0.000	-0.004***	0.001	-0.002*	0.001
Real commodity price index	0.001**	0.000	-0.006***	0.002	-0.005***	0.002
Urban accessibility index	0.079***	0.004	0.036***	0.013	0.115***	0.014
Remoteness areas index	-0.069***	0.020	-0.031**	0.014	-0.100***	0.031
Trend	0.080***	0.008	0.037***	0.011	0.117***	0.009
EP	-0.121***	0.047	-0.056*	0.029	-0.177**	0.071
KI	-0.284***	0.062	-0.130**	0.053	-0.414***	0.101
AMLR	0.289***	0.022	0.133***	0.047	0.422***	0.056
SE	0.020	0.038	0.009	0.018	0.029	0.056
NY	0.263***	0.028	0.121***	0.044	0.383***	0.058
Spatio-temporal lag (ρ)	0.234***					
Pseudo R^2	0.872					
AIC	20308.110					

Notes: The outcome variable is the per hectare real sale price of agricultural properties. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table D.28 Sensitivity analysis: Marginal effects of full sample SDM results of per hectare valuation price of South Australian agricultural properties (2 years spatio-temporal inverse distance matrix with 11 km cut-off), 1998-2013

	Direct effect	*Std. Err.*	*Indirect effect*	*Std. Err.*	*Total effect*	*Std. Err.*
Drought	-0.025	0.030	0.415***	0.155	0.389***	0.150
Native woody vegetation	-0.481***	0.084	1.006	1.469	0.524	1.475
Vegetation square	0.322***	0.099	0.110**	0.053	0.431***	0.140
Annual rainfall	0.001***	0.000	-0.002***	0.000	-0.001***	0.000
Annual maximum temperature	-0.111***	0.011	0.253***	0.062	0.142**	0.060
Soil organic carbon	0.122***	0.029	2.664***	1.009	2.786***	1.010
Silt	0.055***	0.007	-0.782**	0.309	-0.727**	0.310
Sand	0.004***	0.001	-0.038	0.039	-0.034	0.039
Clay	0.002**	0.001	-0.025	0.038	-0.023	0.038
Soil water holding capacity	0.056***	0.006	-0.205	0.223	-0.149	0.224
Soil erosion index	-0.008	0.006	-0.026	0.261	-0.034	0.261
Basic soil	0.058***	0.014	1.301**	0.544	1.359**	0.545
Elevation	-0.001***	0.000	0.000	0.003	-0.001	0.003
Distance to coast	0.011	0.009	0.004	0.003	0.015	0.012
Distance to conservation reserve	0.004	0.007	0.001	0.002	0.005	0.009
Distance to surface-water	-0.053***	0.008	-0.018**	0.007	-0.072***	0.013
Distance to highway	-0.006	0.005	-0.002	0.002	-0.008	0.007
Lot size	-0.506***	0.005	-0.160	0.155	-0.666***	0.155
Main rooms per hectare	0.203***	0.011	0.679	0.428	0.882**	0.429
Structural improvements	0.191***	0.015	1.003	0.666	1.193*	0.667
Irrigation	0.306***	0.035	1.469	1.144	1.774	1.147
Groundwater bore	0.049***	0.019	-1.536*	0.839	-1.486*	0.840
Cropping	0.075***	0.017	0.026**	0.011	0.101***	0.025
Horticulture	0.317***	0.034	0.108***	0.042	0.425***	0.060
Market garden	0.516***	0.055	0.176***	0.068	0.692***	0.097
Mixed farming	0.141*	0.079	0.048	0.032	0.189*	0.107
Viticulture	0.254***	0.039	0.087**	0.035	0.341***	0.062
SEIFA	0.003***	0.000	-0.004***	0.001	-0.001	0.001
Real commodity price index	0.001***	0.000	-0.007***	0.002	-0.006***	0.001
Urban accessibility index	0.092***	0.004	0.031***	0.012	0.123***	0.013
Remoteness areas index	-0.074***	0.019	-0.025**	0.011	-0.100***	0.027
Trend	0.100***	0.008	0.034***	0.011	0.134***	0.008
EP	-0.299***	0.044	-0.102**	0.041	-0.401***	0.070
KI	-0.390***	0.058	-0.133**	0.053	-0.524***	0.091
AMLR	0.335***	0.021	0.114***	0.043	0.449***	0.051
SE	-0.158***	0.036	-0.054**	0.023	-0.212***	0.051
NY	0.208***	0.027	0.071**	0.028	0.279***	0.044
Spatio-temporal lag (ρ)	0.192***					
Pseudo R^2	0.866					
AIC	18914.360					

Notes: The outcome variable is the per hectare real valuation price of agricultural properties. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table D.29 Sensitivity analysis: Marginal effects of full sample SDM results of per hectare sales price of South Australian agricultural properties (3 years spatio-temporal inverse distance matrix with 22 km cut-off), 1998-2013

	Direct effect	*Std. Err.*	*Indirect effect*	*Std. Err.*	*Total effect*	*Std. Err.*
Drought	-0.047	0.032	0.378**	0.169	0.331**	0.163
Native woody vegetation	0.525***	0.090	0.503	1.698	1.029	1.705
Vegetation square	-0.710***	0.106	-0.326***	0.123	-1.035***	0.192
Annual rainfall	0.001***	0.000	-0.001***	0.000	-0.001**	0.000
Annual maximum temperature	-0.071***	0.012	0.082	0.070	0.011	0.068
Soil organic carbon	0.097***	0.031	4.223***	1.205	4.320***	1.206
Silt	0.040***	0.007	-0.639*	0.355	-0.598*	0.355
Sand	0.002*	0.001	-0.037	0.045	-0.035	0.045
Clay	0.000	0.001	-0.016	0.044	-0.017	0.044
Soil water holding capacity	0.047***	0.007	-0.222	0.260	-0.175	0.261
Soil erosion index	-0.008	0.007	0.443	0.310	0.434	0.311
Basic soil	0.075***	0.015	1.832***	0.643	1.908***	0.643
Elevation	-0.001***	0.000	-0.007*	0.004	-0.007**	0.004
Distance to coast	0.025**	0.010	0.011*	0.006	0.036**	0.015
Distance to conservation reserve	0.020***	0.007	0.009*	0.005	0.029**	0.011
Distance to surface-water	-0.052***	0.009	-0.024**	0.009	-0.076***	0.015
Distance to highway	-0.015***	0.005	-0.007**	0.003	-0.022***	0.008
Lot size	-0.623***	0.006	-0.132	0.180	-0.755***	0.181
Main rooms per hectare	0.285***	0.012	0.890*	0.499	1.175**	0.500
Structural improvements	0.512***	0.016	0.811	0.770	1.323*	0.771
Irrigation	0.304***	0.037	2.295*	1.336	2.598*	1.339
Groundwater bore	0.087***	0.020	-2.639***	1.009	-2.552**	1.010
Cropping	0.031	0.019	0.014	0.010	0.045	0.027
Horticulture	0.248***	0.036	0.114***	0.042	0.362***	0.065
Market garden	0.344***	0.059	0.158***	0.060	0.502***	0.101
Mixed farming	0.114	0.084	0.052	0.042	0.166	0.124
Viticulture	0.174***	0.042	0.080**	0.034	0.254***	0.067
SEIFA	0.002***	0.000	-0.004***	0.001	-0.002*	0.001
Real commodity price index	0.001**	0.000	-0.006***	0.002	-0.005***	0.002
Urban accessibility index	0.079***	0.004	0.036***	0.013	0.115***	0.014
Remoteness areas index	-0.069***	0.020	-0.031**	0.014	-0.100***	0.031
Trend	0.080***	0.008	0.037***	0.011	0.117***	0.009
EP	-0.121***	0.047	-0.056*	0.029	-0.177**	0.071
KI	-0.284***	0.062	-0.130**	0.053	-0.414***	0.101
AMLR	0.289***	0.022	0.133***	0.047	0.422***	0.056
SE	0.020	0.038	0.009	0.018	0.029	0.056
NY	0.263***	0.028	0.121***	0.044	0.383***	0.058
Spatio-temporal lag (ρ)	0.238***					
Pseudo R2	0.871					
AIC	20308.11					

Notes: The outcome variable is the per hectare real sale price of agricultural properties. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table D.30 Sensitivity analysis: Marginal effects of full sample SDM results of per hectare valuation price of South Australian agricultural properties (3 years spatio-temporal inverse distance matrix with 22 km cut-off), 1998-2013

	Direct effect	*Std. Err.*	*Indirect effect*	*Std. Err.*	*Total effect*	*Std. Err.*
Drought	-0.025	0.030	0.415***	0.155	0.389***	0.150
Native woody vegetation	-0.481***	0.084	1.006	1.469	0.524	1.475
Vegetation square	0.322***	0.099	0.110**	0.053	0.431***	0.140
Annual rainfall	0.001***	0.000	-0.002***	0.000	-0.001***	0.000
Annual maximum temperature	-0.111***	0.011	0.253***	0.062	0.142**	0.060
Soil organic carbon	0.122***	0.029	2.664***	1.009	2.786***	1.010
Silt	0.055***	0.007	-0.782**	0.309	-0.727**	0.310
Sand	0.004***	0.001	-0.038	0.039	-0.034	0.039
Clay	0.002**	0.001	-0.025	0.038	-0.023	0.038
Soil water holding capacity	0.056***	0.006	-0.205	0.223	-0.149	0.224
Soil erosion index	-0.008	0.006	-0.026	0.261	-0.034	0.261
Basic soil	0.058***	0.014	1.301**	0.544	1.359**	0.545
Elevation	-0.001***	0.000	0.000	0.003	-0.001	0.003
Distance to coast	0.011	0.009	0.004	0.003	0.015	0.012
Distance to conservation reserve	0.004	0.007	0.001	0.002	0.005	0.009
Distance to surface-water	-0.053***	0.008	-0.018**	0.007	-0.072***	0.013
Distance to highway	-0.006	0.005	-0.002	0.002	-0.008	0.007
Lot size	-0.506***	0.005	-0.160	0.155	-0.666***	0.155
Main rooms per hectare	0.203***	0.011	0.679	0.428	0.882**	0.429
Structural improvements	0.191***	0.015	1.003	0.666	1.193*	0.667
Irrigation	0.306***	0.035	1.469	1.144	1.774	1.147
Groundwater bore	0.049***	0.019	-1.536*	0.839	-1.486*	0.840
Cropping	0.075***	0.017	0.026**	0.011	0.101***	0.025
Horticulture	0.317***	0.034	0.108***	0.042	0.425***	0.060
Market garden	0.516***	0.055	0.176***	0.068	0.692***	0.097
Mixed farming	0.141*	0.079	0.048	0.032	0.189*	0.107
Viticulture	0.254***	0.039	0.087**	0.035	0.341***	0.062
SEIFA	0.003***	0.000	-0.004***	0.001	-0.001	0.001
Real commodity price index	0.001***	0.000	-0.007***	0.002	-0.006***	0.001
Urban accessibility index	0.092***	0.004	0.031***	0.012	0.123***	0.013
Remoteness areas index	-0.074***	0.019	-0.025**	0.011	-0.100***	0.027
Trend	0.100***	0.008	0.034***	0.011	0.134***	0.008
EP	-0.299***	0.044	-0.102**	0.041	-0.401***	0.070
KI	-0.390***	0.058	-0.133**	0.053	-0.524***	0.091
AMLR	0.335***	0.021	0.114***	0.043	0.449***	0.051
SE	-0.158***	0.036	-0.054**	0.023	-0.212***	0.051
NY	0.208***	0.027	0.071**	0.028	0.279***	0.044
Spatio-temporal lag (ρ)	0.192					
Pseudo R2	0.866					
AIC	18914.36					

Notes: The outcome variable is the per hectare real valuation price of agricultural properties. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table D.31 Sensitivity analysis: Marginal effects of full sample SDM results of per hectare sales price of South Australian agricultural properties (5 years spatio-temporal inverse distance matrix with 22 km cut-off), 1998-2013

	Direct effect	***Std. Err.***	***Indirect effect***	***Std. Err.***	***Total effect***	***Std. Err.***
Drought	-0.075**	0.036	2.075**	0.943	2.000**	0.934
Native woody vegetation	0.395***	0.088	21.810***	8.375	22.205***	8.376
Vegetation square	-0.624***	0.104	-4.381***	1.572	-5.005***	1.622
Annual rainfall	0.001***	0.000	-0.007***	0.002	-0.006***	0.002
Annual maximum temperature	0.037**	0.016	-1.486***	0.545	-1.449***	0.542
Soil organic carbon	0.030	0.031	6.434	4.231	6.464	4.229
Silt	0.020***	0.007	2.752*	1.542	2.772*	1.542
Sand	0.001	0.001	-0.394**	0.178	-0.393**	0.178
Clay	0.000	0.001	0.536***	0.189	0.536***	0.189
Soil water holding capacity	0.071***	0.007	-3.463***	1.140	-3.392***	1.139
Soil erosion index	-0.013**	0.007	4.782**	1.945	4.768**	1.945
Basic soil	0.077***	0.014	-0.257	2.527	-0.180	2.526
Elevation	0.000***	0.000	-0.072***	0.023	-0.072***	0.023
Distance to coast	-0.022**	0.011	-0.157*	0.091	-0.179*	0.100
Distance to conservation reserve	0.033***	0.008	0.234**	0.091	0.267***	0.096
Distance to surface-water	-0.026**	0.010	-0.185**	0.092	-0.211**	0.100
Distance to highway	-0.008	0.005	-0.059	0.041	-0.068	0.046
Lot size	-0.617***	0.006	2.168**	0.944	1.551	0.943
Main rooms per hectare	0.288***	0.012	3.206	2.436	3.495	2.437
Structural improvements	0.484***	0.015	-1.992	3.668	-1.509	3.669
Irrigation	0.251***	0.037	37.067***	11.551	37.319***	11.553
Groundwater bore	0.080***	0.020	-7.010	4.861	-6.930	4.862
Cropping	0.028	0.018	0.197	0.142	0.225	0.159
Horticulture	0.226***	0.036	1.589***	0.560	1.815***	0.576
Market garden	0.314***	0.058	2.203***	0.800	2.517***	0.830
Mixed farming	0.132	0.082	0.926	0.646	1.058	0.720
Viticulture	0.125***	0.041	0.879**	0.417	1.004**	0.448
SEIFA	0.002***	0.000	-0.003	0.005	-0.002	0.005
Real commodity price index	0.001**	0.001	-0.017*	0.009	-0.016*	0.009
Urban accessibility index	0.076***	0.004	0.534***	0.172	0.610***	0.173
Remoteness areas index	-0.002	0.023	-0.015	0.164	-0.017	0.188
Trend	0.018***	0.006	0.130***	0.032	0.148***	0.035
EP	0.465***	0.083	3.264***	1.213	3.729***	1.258
KI	-0.013	0.064	-0.089	0.451	-0.102	0.515
AMLR	0.276***	0.023	1.942***	0.646	2.218***	0.653
SE	0.262***	0.062	1.840***	0.695	2.102***	0.730
NY	0.420***	0.036	2.947***	0.968	3.367***	0.978
Spatio-temporal lag (ρ)	0.645***					
Pseudo R^2	0.874					
AIC	19667.710					

Notes: The outcome variable is the per hectare real sale price of agricultural properties. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

Table D.32 Sensitivity analysis: Marginal effects of full sample SDM results of per hectare valuation price of South Australian agricultural properties (5 years spatio-temporal inverse distance matrix with 22 km cut-off), 1998-2013

	Direct effect	*Std. Err.*	*Indirect effect*	*Std. Err.*	*Total effect*	*Std. Err.*
Drought	-0.034	0.032	8.920**	4.364	8.886*	4.357
Native woody vegetation	-0.670***	0.080	265.524***	56.185	264.854***	56.188
Vegetation square	0.459***	0.094	25.124***	6.794	25.583***	6.866
Annual rainfall	0.002***	0.000	-0.040***	0.009	-0.038***	0.009
Annual maximum temperature	0.044***	0.014	-12.157***	2.686	-12.113***	2.684
Soil organic carbon	0.060**	0.028	0.668	23.479	0.728	23.478
Silt	0.033***	0.007	27.495***	9.838	27.528***	9.837
Sand	0.002**	0.001	-0.579	0.734	-0.578	0.734
Clay	0.002*	0.001	6.220***	1.248	6.222***	1.248
Soil water holding capacity	0.090***	0.007	-19.640***	5.193	-19.550***	5.192
Soil erosion index	-0.011*	0.006	36.613***	9.116	36.602***	9.116
Basic soil	0.062***	0.013	-11.725	15.420	-11.663	15.419
Elevation	0.000	0.000	-0.684***	0.134	-0.684***	0.134
Distance to coast	-0.055	0.010	-3.020***	0.746	-3.075***	0.753
Distance to conservation reserve	0.021***	0.007	1.139***	0.426	1.160***	0.432
Distance to surface-water	0.000	0.009	-0.001	0.512	-0.001	0.522
Distance to highway	0.006	0.005	0.301	0.269	0.307	0.274
Lot size	-0.498***	0.005	13.930***	4.952	13.432***	4.952
Main rooms per hectare	0.208***	0.011	12.489	14.593	12.697	14.594
Structural improvements	0.150***	0.014	-83.561***	25.517	-83.411***	25.518
Irrigation	0.251***	0.033	240.368***	49.719	240.618***	49.720
Groundwater bore	0.039**	0.018	-9.845	25.809	-9.806	25.811
Cropping	0.070***	0.017	3.853***	1.142	3.923***	1.155
Horticulture	0.271***	0.033	14.822***	3.213	15.093***	3.232
Market garden	0.447***	0.053	24.478***	5.208	24.925***	5.237
Mixed farming	0.161**	0.074	8.819**	4.367	8.980**	4.436
Viticulture	0.224***	0.038	12.259***	2.983	12.483***	3.009
SEIFA	0.002***	0.000	-0.018	0.028	-0.016	0.028
Real commodity price index	0.002***	0.000	-0.277***	0.061	-0.276***	0.061
Urban accessibility index	0.093***	0.004	5.110***	0.925	5.203***	0.926
Remoteness areas index	0.042*	0.021	2.286*	1.233	2.328*	1.253
Trend	0.007*	0.004	0.358	0.239	0.365	0.243
EP	0.477***	0.076	26.131***	6.456	26.609***	6.509
KI	-0.112*	0.059	-6.142*	3.377	-6.254*	3.433
AMLR	0.301***	0.021	16.448***	3.157	16.748***	3.165
SE	0.103*	0.056	5.662*	3.226	5.765*	3.280
NY	0.368***	0.033	20.161***	4.025	20.529***	4.040
Spatio-temporal lag (ρ)	0.764***					
Pseudo R^2	0.518					
AIC	17705.010					

Notes: The outcome variable is the per hectare real valuation price of agricultural properties. *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels, respectively.

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