Calibration and Validation of Remotely Sensed Ground Cover Maps

Thesis submitted for the degree of

Doctor of Philosophy

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ABSTRACT

Calibration and validation is essential in the development of remotely sensed fractional ground cover maps to ensure their reliability and provide users with confidence. Field measurements of fractional cover (FC) are typically collected through surveys where participants have the potential to introduce biases as they categorise ground cover. Environmental factors also have potential to influence the reliability of image-derived products. FC maps have been found to provide poor estimates of cover in arid regions of Australia, and it has been suggested that this may be due to soil colour. Further investigation is required to determine if soil colour influences satellite-derived FC products and there is scope to explore other methods of collecting field measurements in order to reduce errors.

The aim of this thesis was to investigate methods of improving fractional ground cover mapping in Australia. The objectives were to (1) trial hyperspectral ground cover sampling in arid Australia by determining how spectral surveys and traditional sampling compare at the same scale and to compare these field methods to satellite-derived FC products, (2) examine observer consistency when classifying vegetation as photosynthetic or non-photosynthetic and to examine how spectral classification of vegetation compares to observer results, and (3) determine if the Australian MODIS FC product is influenced by soil colour.

For objective one a sampling design suitable for the evaluation of coarse resolution imagery was developed. Sites were sampled collecting hyperspectral reflectance measurements and step-point observations of ground cover that were later compared to Australian MODIS and Landsat FC products. The results showed a strong relationship between the field sampling methods, that the Landsat FC product was strongly correlated to non-photosynthetic vegetation and soil and the MODIS product was

strongly correlated to photosynthetic vegetation. This study demonstrated the hyperspectral field sampling's improved objectivity, ease of use, and ability to produce results comparable to traditional transect measures.

Objective two examined photographs and reflectance measurements of vegetation transitioning from 100% photosynthetic to 100% non-photosynthetic. Observers classified leaves as either photosynthetic or non-photosynthetic (as required in field fractional cover methods), while spectral unmixing was used to decompose the reflectance measurements into photosynthetic and non-photosynthetic proportions. At the extremes (≤ 25 % or ≥ 75 %) photosynthetic observers tended to agree and assigned the leaf to the correct category. However, for leaves in transition (> 25 % or < 75 % photosynthetic) decisions differed more widely and classifications showed little agreement with the spectral proportions of photosynthetic and non-photosynthetic vegetation. This study increased our understanding of the limitations of field data collected using traditional observation methods, of observer variation, and of when observer data may become unreliable.

Objective three compared MODIS and TERN AusPlot field estimates of FC at 250 sites across Australia and examined the effect of soil colour (represented by Munsell hue) on the FC values. Overall, there was a significant difference between all 250 sites based on hue suggesting that soil colour has a significant effect on the MODIS product. This evaluation provided insights into the association of specific soil colours with bias in MODIS ground cover fractions and highlighted hues that are associated with under- or overestimation of MODIS FC. Future research may utilise this information to help develop methods of minimising the effects of soil colour in future FC products.

This thesis has contributed toward efforts to improve the collection of ground cover measurements for the validation of remotely sensed products, using spectral transect surveys as an alternative to traditional surveys, for photosynthetic activity, provided insight into observer classification consistency and determined how observer-based classification and hyperspectral unmixing compare, and contributed to our understanding of the effects of soil colour on the MODIS FC product. This knowledge will allow informed consumption of the current MODIS FC product, and assist future efforts to calibrate and validate FC products ensuring end-users have reliable and consistent ground cover data for research and decision making.

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 ONE

INTRODUCTION

1.1 Background

Natural resource managers at regional, state and national levels require good quality environmental information for the effective assessment and monitoring of land condition (Bastin et al. 2009). Increasingly these decision-makers are seeking extensive data with detailed spatial coverages and high temporal frequencies for the assessment of land condition trends, states and transitions (Thackway and Lesslie 2006; Thackway et al. 2013). This information is especially important for managers of remote arid regions. The Australian arid zone covers approximately 48% of Australia's land mass (3,697,109.29 km^2) (Department of the Environment 2015), and there is significant variability in ecosystems and climate across the continent. Monitoring such large and variable regions solely using traditional on-ground survey methods is logistically impractical. Therefore, agencies in Australia and internationally have moved towards using remote sensing for broad-scale assessment of land condition (Bastin et al. 2009).

Earth observation provides an efficient and effective means to map and monitor the natural and built environment. Analysis of remotely sensed imagery can provide continuous and consistent observations at a range of spectral, spatial and temporal scales (Congalton et al. 2014). These observations are critical for researchers and decision-makers across a range of sectors including research institutes, private and non-government organisations as well as at various levels of government (Held et al. 2015; Tasman 2008). Analysing temporal data, such as that derived from Moderate-Resolution Imaging Spectroradiometer (MODIS) or the Landsat time series, can provide vital information on a range of natural and anthropogenic phenomena that affect the Earth's surface (Okin 2007). Urban growth (Stefanov et al. 2001), flood detection (Sakamoto et al. 2007), detecting fire danger, fuel loads (Yebra et al. 2008), monitoring vegetation phenology (Ma et al. 2013; Zhang et al. 2003) and land use land cover change (Klein et al. 2012) are just a few examples of applications that can benefit from spatial and temporal data derived from remote sensing.

Dynamic land cover information extracted from time series analysis of satellite imagery provides a means to meet the demands of users and can be used to focus the efforts of natural resource managers in Australia. The relative proportion of vegetation and soil exposure (fractional cover) is a frequently used indicator of land condition, stability and the success of land management practices. For example, vegetation cover is stated to maximise the productivity of the landscape as well as reduce the risk of soil erosion (Leys et al. 2009). It is also considered the single most important factor in determining soil erosion risk (McKenzie and Dixon 2006). Therefore fractional land cover information is a critical factor for land managers. McKenzie and Dixon (2006) report that the lack of fractional land cover data hinders the assessment of the environment, especially identification of land management outcomes, soil erosion modelling and risk assessments (Leys et al. 2009). To date most applications of remote sensing for land management assessment have relied on spectral indices such as the Normalised Difference Vegetation Index (Abuzar et al. 2017; De Keersmaecker et al. 2017; Wessels et al. 2004), Enhanced Vegetation Index (Lobell et al. 2010; Phompila et al. 2015), or the University of Adelaide Land Cover Index (Clarke et al. 2011; Clarke et al. 2004), as indicators for vegetation or soil cover. Alternative algorithms capable of estimating sub-pixel proportions of cover types, such as spectral mixture analysis (SMA) (Adams et al. 1993; Adams et al. 1986) or multiple endmember spectral mixture analysis (MESMA) (Quintano et al. 2013; Roberts et al. 1998), provide an alternative approach.

In Australia, scientists and agencies have developed fractional cover measures that can be produced from Landsat and MODIS time series datasets. Scarth et al. (2010) produced a time series analysis based on 15 years of monthly Landsat-derived fractional cover imagery. This was conducted over Northern Queensland on land that had undergone an intense grazing trial and the results were an improved method to recover key indicators for rangeland condition monitoring. The Scarth et al. (2010) method was then applied nationally and the Landsat fractional ground cover dataset is now available across Australia as part of Digital Earth Australia's online platform (Geoscience Australia 2018). It works in conjunction with the Open Data Cube (https://www.opendatacube.org/) and has imagery from Landsat 5, 7 and 8 available for analysis. Guerschman et al. (2009) produced a fractional cover product from MODIS imagery, initially developed to monitor the northern tropical savanna region of the Northern Territory, and later implemented nationally (Stewart et al. 2011). Guerschman's model produced a quantitative estimate of fractional green vegetation (GV), non-photosynthetic (NPV) and bare soil (BS) by unmixing the spectral space defined by the Normalized Difference Vegetation Index (Tucker 1979) (NDVI) and a Cellulose Absorption Index (CAI) (Nagler et al. 2003) proxy. In the process of implementing this model nationally, Guerschman et al. (2012) improved the model conducting further assessment of the output product and later in 2018 updated the product to use the latest MODIS MCD43A4 collection 6 imagery (Guerschman and Hill 2018). Examples of the current application of the MODIS product include its use in the Australian State of the Environment Reports (https://soe.environment.gov.au/), as part of the DustWatch Australia (https://www.dustwatch.edu.au/) monitoring program and viewing through the Australian National University's Environment Explorer (http://wenfo.org/ausenv). Researchers have also utilised the MODIS product to study vegetation dynamics (Zhou et al. 2016), forest decline (Evans et al. 2013) and rainfall erosivity and hillslope erosion (Zhu et al. 2019). This along with the development of other fractional cover products is a step forward in providing critical land condition data to natural resource managers, but as Lawley et al. (2014) found the MODIS product currently fails to represent accurately all rangeland conditions found across Australia.

Scarth et al. (2015) stated this failure was not unexpected but highlights the need for further work in the area.

Another measure developed for the monitoring of land cover dynamics using coarse multispectral data is the Relative Spectral Mixture Analysis (RSMA) (Okin 2007). RSMA is an index of the amount of GV, NPV, BS and snow relative to a reference time. This model differs from Scarth et al. (2010) and Guerschman et al. (2013) in two significant ways. Firstly, the RSMA uses three representative reference signatures of GV, NPV and snow to unmix multi-temporal reflectance data (i.e. MODIS imagery) but does not use a soil endmember, while the Landsat and MODIS models use image-derived endmembers for all three cover components (GV, NPV and soil). Secondly, the ground cover components from the RSMA are defined so that the resulting index is positive when the fractional cover of the ground component is greater than at the reference time and negative when the fractional cover is less than the reference time. A limitation of this method is that it does not produce an absolute measure of vegetation cover but a relative index. Therefore, if a user requires absolute fractional cover values Guerschman et al. (2013), Scarth et al. (2010) or other conventional SMA products are recommended, but if a user is more interested in the change of ground cover over time, then RSMA is a good alternative. Further work was conducted by Okin et al. (2013) to calibrate RSMA to an absolute measure of fractional cover produce comparable results to SMA and MESMA but does not necessarily provide the best estimates of ground cover dynamics.

Evaluation of fractional ground cover maps and any image-derived product is critical to ensure the accuracy of the product and provide users with confidence in the data they are using. A problem that arises especially for areas like the South Australian arid lands is that fractional cover products were not specifically designed for arid environments and there is some doubt over the accuracy of these methods in South Australia. Lawley et al. (2014) evaluated the soil component of the MODIS product (Guerschman et al. 2012) and found that it struggled to accurately monitor arid landscapes with significant soil exposure. Meyer and Okin (2015) and Lawley et al. (2014) evaluation of fractional cover measures found that the soil component these products poorly represents on-ground soil exposure, which as stated earlier, is an important indicator of land condition. This may be due to any of several factors, including the spectral similarity and therefore difficulty of separating BS and NPV (Okin 2007); confounding influences of soil colour, brightness, texture or moisture; or landscape structural complexity leading to where multiple scattering and mutual shadowing complicating reflectance signals (Ray and Murray 1996). This is a problem common to many fractional cover products that requires a solution, either in the form of new and better fractional cover measures, or by better calibration of current measures. Understanding the influences of soil colour on fractional ground cover products was identified as a key gap in current research and is examined as part of this thesis.

An important consideration when natural resource managers or other users employ remotely sensed products is the reliability of the data. This often depends on the quality of on-ground measurements used to calibrate and validate these products. The collection of field data over a variety of different environments, along with coincident imagery, is important to continue efforts to further calibrate and validate these products (Scarth et al. 2010). In the past this data has been collected on a needs basis by individual groups and organisations. More recently in Australia, the collection of some of this data has been coordinated by a national network of organisations including the Terrestrial Ecosystem Research Network (TERN) AusPlots and the Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES), within the Australian Department of Agriculture and Water Resources. The AusPlots facility within TERN is a plot-based surveillance monitoring program aiming to '*establish and maintain a* *national network of plots that enable consistent ecological assessment and ongoing monitoring'* (TERN 2016). Ecological data collected as part of these programs include detailed vegetation and soil surveys that are outlined in full in the AusPlot Rangelands Survey Protocols Manual (White et al. 2012). The ABARES program developed and utilises the Muir et al. (2011) technical handbook for ground cover monitoring in Australia.

Ground cover field measurements are extremely useful but costly and time-consuming to collect and have limited spatial and temporal coverage. It is therefore critical when these surveys are conducted that the information collected is optimal, efficient and of good quality to ensure that it can be utilised for a range of applications. Another challenge is to match the scale of the field data with that of broad-scale remote sensing fractional cover products (Guerschman et al. 2012; Morisette et al. 2002; Turner et al. 2004; Turner et al. 2006). This is particularly relevant to the evaluation of MODIS derived products where the MODIS pixel size is greater than the current size of AusPlots or ABARES nationally consistent survey sites.

The AusPlots methodology surveys plots 100 m by 100 m, one-twenty-fifth the size of a 500 m MODIS pixel. This is not ideal for calibration and validation but has been deemed acceptable under the assumption that the surveyed plots are placed within a homogeneous landscape and can, therefore, be up-scaled as they are representative of the wider landscape (Held et al. 2015). It is suggested that sampling should ideally occur over a cluster of pixels (3 x 3) (Congalton and Green 2008; Muir et al. 2011) in order to reduce errors related to geo-rectification but when analysing imagery with a spatial resolution of 500 m the sampling area becomes logistically infeasible. This is the reason why up-scaling, the integration of field measurements and high-resolution imagery to produce high resolution maps of the parameters measured in the field, has been used in the past and is why other techniques should be explored (Held et al. 2015).

Currently, the Muir et al. (2011) technical guide for field measurements of fractional ground cover and AusCover Good Practice Guidelines (Held et al. 2015) are Australia's only survey techniques specifically designed for the validation of fractional cover datasets and these methods are considered reliable for measuring ground cover components.

A key problem with this method of estimating cover is in the categorisation of ground cover into defined categories. Categories such as soil and rock are simple for field observers to distinguish but the distinction between green (photosynthetic) and dry (non-photosynthetic) vegetation can introduce subjective decision making and multiple observers may vary in their distinction of these cover types. There has been little examination of observer reliability when conducting field assessments of fractional cover. However, bare soil and non-photosynthetic vegetation have been demonstrated to be the least and most challenging categories (respectively) for observers to categorise, regardless of observer experience; while photosynthetic vegetation proved challenging for inexperienced observers (Trevithick et al. 2012). Other than the Trevithick et al. (2012) study there is a lack of research that explores the variation in decisions among field observers and how this can influence the reliability of calibration and validation. A key knowledge gap that is addressed in this thesis is identifying the degree of inter-observer variation when classifying vegetation as either photosynthetic vegetation (PV) or non-photosynthetic vegetation (NPV), as well as examining how observer and spectral classification of PV and NPV compare.

Currently, field-based reflectance data is rarely used for the validation of fractional cover maps but is used to calibrate or validate other satellite products. Digital Earth Australia has developed an initiative in order to collect standardised validation data for the assessment of surface reflectance data. This initiative takes a community approach to data collection around Australia in order to collect data across a variety of surface types and landscapes (Malthus 2019). This data has the potential to not just be used for calibration of surface reflectance products but could be used to calibrate and validate a variety of other satellite derived ground cover products and is an area for future research.

A promising spectral field method, the Meyer and Okin (2015) spectral line point intercept transect (SLPIT), is capable of rapidly collecting field data over long transects and could potentially remove the need for observers to categorise ground cover in the field. This technique samples transects similar to the Muir et al. (2011) approach but instead records continuous surface reflectance measurements with a portable high spectral resolution spectroradiometer, aiming to reduce human error by removing the need for the human classification of ground cover in the field. The SPLIT method has demonstrated strong correlation with satellite fractional cover, but poor correlation with field step-point data. However, the later poor correlation is likely a result of a scale mismatch between the SPLIT transect length (500 m) and the step-point transect length (100 m). Thus, the SPLIT method appears promising, by being both rapid and quantitative. However, the SPLIT technique has not yet been trialled in other environments, and the inconsistency between SPLIT and step-point data has not been resolved. More widespread testing is required in order to establish confidence in and refine the sampling design. The SPLIT techniques shows a considerable promise and is worth exploring to determine its suitability as a field method for the collection of calibration and validation data in the Australian landscape context. Therefore, testing hyperspectral field sampling in Australia is examined in the thesis.

1.2 Research Aims & Objectives

Established in section 1.1 were three key knowledge gaps in the current literature. These were: a need to understand the effect of soil properties on fractional ground cover estimates derived from remotely sensed imagery; the need to improve our understanding of observer variation when categorising vegetation as photosynthetic or non-photosynthetic in the field and lastly; the need for more quantitative field methods, potentially hyperspectral field sampling of ground cover, for the calibration and validation remotely sensed ground cover maps.

Therefore, the overarching aim of this thesis is to investigate methods of improving fractional ground cover mapping in Australia. This aim is approached from two angles; studying the collection of validation data (objective 1 and 2) and a systematic evaluation of soil colour influence on satellite-derived fractional cover estimates (objective 3). The objectives of the thesis are:

1. To trial hyperspectral ground cover sampling in arid Australia by determining how spectral surveys and traditional sampling compare at the same scale and to compare these field methods to current satellite-derived fractional cover products.
2. To examine observer consistency when classifying vegetation as photosynthetic or non-photosynthetic and to examine how spectral classification of vegetation compares to observer results.
3. To determine if the Australian MODIS fractional cover product is influenced by soil colour.

1.3 Thesis Structure

The following thesis is divided into five chapters. Chapter one outlines key literature relevant to this research, highlights gaps in the literature, provides a study context and outlines the research aims and motivations behind the thesis. Chapters two, three and four cover the principal bodies of research which are presented as stand-alone published papers or manuscripts intended for publication. Chapter five is composed of the discussion and conclusions which highlight key results, significance and contributions of the thesis as well as future research opportunities. The following provides a brief summary of the content presented in each chapter.

Chapter Two: Fisk, C., Clarke, K.D., & Lewis, M.M. (2019). Comparison of Hyperspectral Versus Traditional Field Measurements of Fractional Ground Cover in the Australian Arid Zone. *Remote Sensing, 11*, 2825, https://doi.org/10.3390/rs11232825.

This chapter explores the use of hyperspectral field sampling in order to improve the measurement of fractional ground cover for the purpose of calibration and validation of fractional ground cover maps in Australia. The aim of this study was to develop an effective sampling design for spectral ground cover surveys in order to estimate fractional ground cover in the Australian arid zone. To meet this aim two objectives are addressed: (1) determining how spectral surveys and traditional step-point sampling compare when conducted at the same spatial scale and (2) comparing these two methods to current Australian satellite-derived fractional ground cover products. From this study we developed a new sampling design for field-based hyperspectral sampling of ground cover, demonstrated the significant potential of hyperspectral transect sampling and tested the relationship between the field methods and two current satellite-derived fractional cover products.

Chapter Three: Fisk, C., Clarke, K.D., Delean, S., & Lewis, M.M. (2019). Distinguishing Photosynthetic and Non-Photosynthetic Vegetation: How do traditional observations and spectral classification compare? *Remote Sensing*, *11*, 2589, https://doi.org/10.3390/rs11212589.

This chapter explores the decisions observers make when classifying vegetation in the field as photosynthetic or non-photosynthetic and the potential problems associated with these techniques. The aim of this study was to examine how multiple observers compare when categorising vegetation over the full range of photosynthetic levels and how the classification of hyperspectral reflectance measurements compare to human observations of the same vegetation samples. Understanding how observers' decisions may compare is essential when creating consistent datasets and when understanding the potential limitations of the data. This chapter provides an explanation of when people are more likely to differ when classifying vegetation in relation to the percentage of photosynthetic or non-photosynthetic material and highlights the benefits of collecting hyperspectral measurements of vegetation.

Chapter Four: Fisk, C., Clarke, K.D. & Lewis, M.M. (2019). Evaluating the influence of soil colour on the MODIS Fractional Cover product in Australia (unpublished).

The first two chapters of the thesis relate to the validation of fractional cover mapping whereas this chapter addresses the third aim by investigating the potential influence soil colour may have on the MODIS fractional cover product. Early in the development of the Australia-wide MODIS product soil moisture and soil colour or more specifically soil brightness was thought to cause errors in the fractions of ground cover reported. Since then soil moisture and soil brightness have been investigated and studies have reported that these properties do not influence the product. A concern with these results is that the soil colour maps used are not direct soil colour measurements and that the maps were so coarse (5 km pixels) that these factors may have influenced results. The aim of this study was to perform a systematic evaluation to determine if soil colour has any influence on the relative cover fractions derived from the MODIS unmixing model. We sought to understand (1) the possible influence of soil colour on the MODIS product and if there is an influence, (2) whether there is an observable pattern or a specific colour affecting the ground cover fractions. This will enable conclusions to be made regarding why these errors may be occurring. Future research can then build on these findings to work towards mitigating the influence, if negative, soil colour has on satellite-derived fractional cover products.

Chapter Five: Discussion

This chapter highlights and further explores the key findings from chapters two, three and four. It outlines contributions this work has made to the field of earth observation sciences and also provides recommendations for future research.

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CHAPTER TWO

Comparison of Hyperspectral versus Traditional Field Measurements of Fractional Ground Cover in the Australian Arid Zone

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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: 29/11/2019

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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

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Abstract

The collection of high-quality field measurements of ground cover is critical for calibration and validation of fractional ground cover maps derived from satellite imagery. Field-based hyperspectral ground cover sampling is a potential alternative to traditional *in situ* techniques. This study aimed to develop an effective sampling design for spectral ground cover surveys in order to estimate fractional ground cover in the Australian arid zone. To meet this aim, we addressed two key objectives: (1) Determining how spectral surveys and traditional step-point sampling compare when conducted at the same spatial scale and (2) comparing these two methods to current Australian satellite-derived fractional cover products. Across seven arid, sparsely vegetated survey sites, six 500-m transects were established. Ground cover reflectance was recorded taking continuous hyperspectral readings along each transect while step-point surveys were conducted along the same transects. Both measures of ground cover were converted into proportions of photosynthetic vegetation, non-photosynthetic vegetation, and bare soil for each site. Comparisons were made of the proportions of photosynthetic vegetation, non-photosynthetic vegetation, and bare soil derived from both *in situ* methods as well as MODIS and Landsat fractional cover products. We found strong correlations between fractional cover derived from hyperspectral and step-point sampling conducted at the same spatial scale at our survey sites. Comparison of the *in situ* measurements and image-derived fractional cover products showed that overall, the Landsat product was strongly related to both *in situ* methods for non-photosynthetic vegetation and bare soil whereas the MODIS product was strongly correlated with both *in situ* methods for photosynthetic vegetation. This study

demonstrates the potential of the spectral transect method, both in its ability to produce results comparable to the traditional transect measures, but also in its improved objectivity and relative logistic ease. Future efforts should be made to include spectral ground cover sampling as part of Australia's plan to produce calibration and validation datasets for remotely sensed products.

2.1 Introduction

Satellite image-derived fractional ground cover mapping has proven to be an essential source of information for applications, including analysis of spatial and temporal vegetation dynamics (Ma et al. 2013), monitoring urban greenness (Gan et al. 2014), mapping bushfire burn severity levels (Quintano et al. 2013), forest cover change (Mayes et al. 2015), and deforestation (Karimi et al. 2016). Algorithms, including spectral mixture analysis (Adams et al. 1986; Settle and Drake 1993; Smith et al. 1990), multiple endmember spectral mixture analysis (Roberts et al. 1998), and relative spectral mixture analysis (Okin 2007), are used to produce fractional cover (FC) maps. These algorithms can be applied to multispectral and hyperspectral imagery, decomposing each image pixel into a measure of similarity to two or more spectrally distinct land cover types. These typically include photosynthetic vegetation (PV), non-photosynthetic vegetation (NPV), bare soil (BS), shadow, and snow (Okin 2007; Settle and Drake 1993), with the resulting maps providing quantitative estimates of the proportion of the cover types comprising each pixel.

Fractional cover mapping has been performed across a range of scales, including global mapping projects as such the Copernicus Global Land Service, which has produced a 300-m and a 1-km fraction of green vegetation cover product based on PROBA-V and SPOT-VGT imagery (Baret et al. 2013; Camacho et al. 2013). Local studies have used FC products to assist water quality management of catchments (Awad et al. 2018), urban land cover mapping (Powell et al. 2007), and the study of savanna vegetation morphology (Guerschman et al. 2009; Mishra et al. 2014). In Australia, time series of fractional cover have been produced from MODIS (Thomas et al. 2003) and Landsat (Artigas and Yang 2005; Guerschman et al. 2012) and are being used widely for environmental assessment and monitoring applications.

Calibration and validation are essential for ensuring the reliability and consistency of FC products. Data used for calibration and validation of fractional cover are derived from a variety of sources and techniques, and there is currently no international standard. Lawley et al. (2014), Montesano et al. (2009), Morisette et al. (2003), and Xiao and Moody (2005) all utilised remotely sensed imagery with high spatial resolution to validate FC products with lower spatial resolution. The advantages of this approach are that high-spatial resolution imagery provides an objective record at the time of the region being assessed and may allow for the validation of areas that cannot be easily accessed. Alternative evaluations have sought to avoid subjective on-ground assessments of ground cover and instead have used a combination of qualitative and quantitative data for assessment. For example, Guerschman et al. (2009) utilised two qualitative datasets to calibrate the Australian MODIS fractional cover product: (1) A general description of vegetation type and condition, including photographs of each site, and (2) a vectorized fire scar map that classified areas of the landscape as either burnt or unburnt.

Common approaches to *in situ* measurement of ground cover, demonstrated by Scarth et al. (2010), Asner and Heidebrecht (2002), and Lewis (1998), have utilised variants of point-based sampling techniques that were initially developed for vegetation ecology and rangeland assessment (Evans and Love 1957; Graham 1989; Winkworth et al. 1962). These methods include line-point intercept transects, step-point surveys, and wheel-point surveys, where observers walk across a study area making point-based observations at defined intervals. Across a survey area, hundreds of point-based observations are used to estimate FC. Point observations generally categorise ground cover into defined classes, such as rock, disturbed soil, green leaf, and dry leaf, which are later aggregated into broader classes, such as PV, NPV, and BS, matching the field classes with the image product being assessed. Muir et al. (2011) developed an Australian national standard for field measurements of fractional ground cover, which provides a well-documented, easily repeatable method that is now widely used.

Although field protocols have been developed to improve consistency and reduce the potential for errors, subjective human judgements are still required, and these may affect the data significantly (Trevithick et al. 2012). In such surveys, observers are required to make hundreds of rapid decisions, only having a few seconds to observe and record the cover type before moving on. Most cover types are relatively easy to discriminate in the field but distinguishing between PV and NPV can be a difficult task. PV and NPV are better thought of as extremes of a continuum, rather than binary categories, and hence distinguishing between PV and NPV can be difficult for observers (Fisk et al. 2019).

A technique that has the potential to help reduce subjectivity is to estimate the relative fractions of PV, NPV, and BS from field-based hyperspectral reflectance measurements. While *in situ* hyperspectral measurements have been used for radiometric and spectral calibration and validation of remotely sensed products (Li et al. 2010; Liang et al. 2002), and may provide reference signatures for image analyses (Artigas and Yang 2005; Thomas et al. 2003), they have not been used explicitly for the validation of fractional ground cover products until Meyer and Okin (2015). This method records many *in situ* spectra over a study area, which in their aggregate, capture the combined spectral response of the site. The relative proportions of PV, NPV, and BS can then be unmixed from the field spectra. Using this approach (Meyer and Okin 2015) demonstrated a stronger agreement between FC values derived from field-based reflectance measurements and their image-based product than between traditional line-point intercept observations and their image-based product, which showed low correlations. In our paper, hyperspectral ground surveys refer to the collection of spectral measurements over an area for the purpose of estimating ground cover fractions (Li et al. 2010), quite a different application to the use of *in situ* spectroscopic measurements for radiometric calibration of imagery.

Another challenge for calibration and validation is to match the scale of field data with that of broad-scale FC products. When validating products developed from coarse resolution imagery (e.g., 500 m), it is common to up-scale field data recorded at a finer scale (e.g., 100 m) in order to determine the accuracy of the coarse resolution products. This is usually conducted under the assumption that the area around the sample site is homogenous and similar to that surveyed. For example, Meyer and Okin (2015) conducted spectral sampling over 500-m transects to correspond to a MODIS pixel and compared the results to line-point intercept sampling that was conducted over smaller 100-m transects. A potential reason for the low correlation between the sampling methods is that the 100-m transects were insufficient to gain an adequate estimate of the ground cover for a 500-m pixel. (Meyer and Okin 2015) were following the Muir et al. (2011) field sampling layout, where transects were placed in a radiating star pattern that was designed to relate field measurements to Landsat imagery. The Muir et al. (2011) design samples three 100-m transects, which covers approximately 3 × 3 Landsat pixels, making it ideal for validating Landsat-based products but not necessarily adequate for coarser resolution products (MODIS).

The layout of transects also has the potential to affect how an area is sampled. For instance, the star-transect method includes a sampling bias that over-represents cover towards the centre of the plot. Three transects are placed in a star pattern with the result being that observation points are concentrated in the centre of the star and increasingly dispersed as the distance from the centre increases. Therefore, a sampling pattern that provides a more even distribution across a site may provide a better representation of the ground cover. Other studies have placed parallel transects evenly across sample sites (Lewis 2000; Lewis 1998) or placed transects in a grid pattern in order to more evenly sample the area (White et al. 2012).

Field-based hyperspectral ground cover sampling is a potential alternative to traditional techniques that may assist with the calibration and validation of remotely sensed products. The motivation for this research is to expand upon the work of Meyer and Okin (2015) and trial hyperspectral ground cover sampling in Australia, with the ultimate aim of incorporating spectral sampling as part of Australia's national effort to collect validation and calibration data to meet our remote sensing needs. Our aim was to develop an effective sampling design for spectral ground cover surveys in order to estimate fractional ground cover. Our objectives were (1) to determine how spectral surveys and traditional step-point sampling compare when conducted at the same spatial scale, and (2) determine how these *in situ* methods compare to current Australian satellite-derived FC products.

2.2 Materials & Methods

Currently, *in situ* validation data collected using the Muir et al. (2011) method is used to assess the accuracy of both the MODIS and Landsat products. Meyer and Okin (2015) found that the *in situ* spectral measurements they collected could be used to validate fractional ground cover mapping developed from MODIS imagery over Botswana, but this has not been tested across other environments. To meet our objectives, we therefore completed ground cover surveys before inspecting how our *in situ* measurements would compare with the MODIS and Landsat products. Figure 1 provides an overview of the methods used in this study.

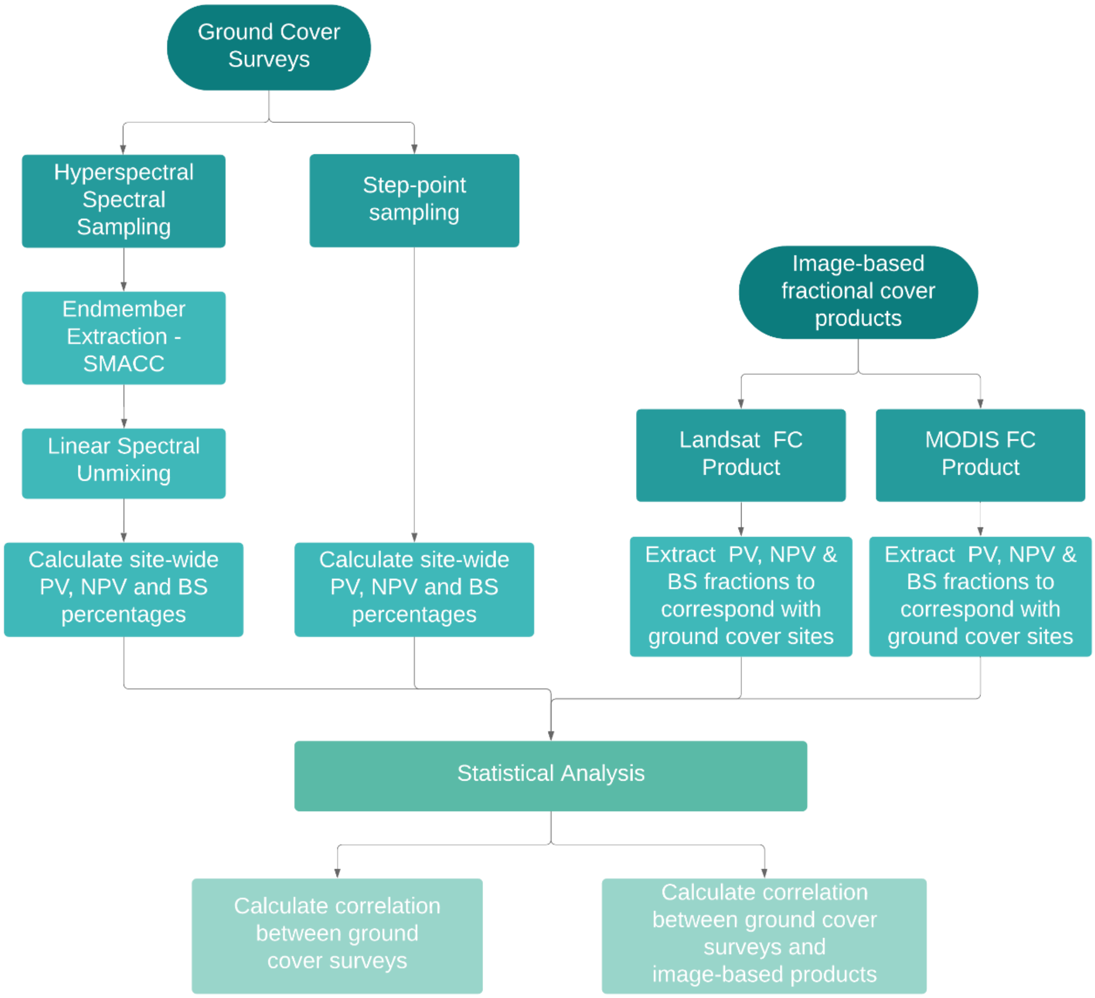

Figure 1 Flowchart outlining the methodological approach taken in this paper.

2.2.1 Study Area

The study was conducted in New South Wales (NSW), Australia within the arid zone (Figure 2). Sites FG1–FG4 (Figure 3a,b) were situated at Fowlers Gap Arid Research Station, 110 km north of Broken Hill, NSW, while sites BH1–BH3 (Figure 3c,d) were located surrounding the City of Broken Hill. The climate for both regions is hot and persistently dry (Stern et al. 2000). Fowlers Gap has a mean annual rainfall of 240 mm, a mean annual minimum temperature of 13 °C, and a mean annual maximum temperature of 26.9 °C (Bureau of Meteorology 2019b). The vegetation at Fowlers Gap comprises low open chenopodiaceous shrublands, some low open Acacia and Casuarina woodland as well as grasslands on the plains (Mabbutt et al. 1973). Broken Hill has a mean annual rainfall of 250 mm with a mean annual minimum temperature of 11.8 °C and a mean annual maximum temperature of 24.7 °C (Bureau of Meteorology 2019a). The vegetation around Broken Hill is also composed of chenopod shrublands that includes saltbush and bluebush communities as well as Mulga (Acacia *aneura*) (Benson 1999).

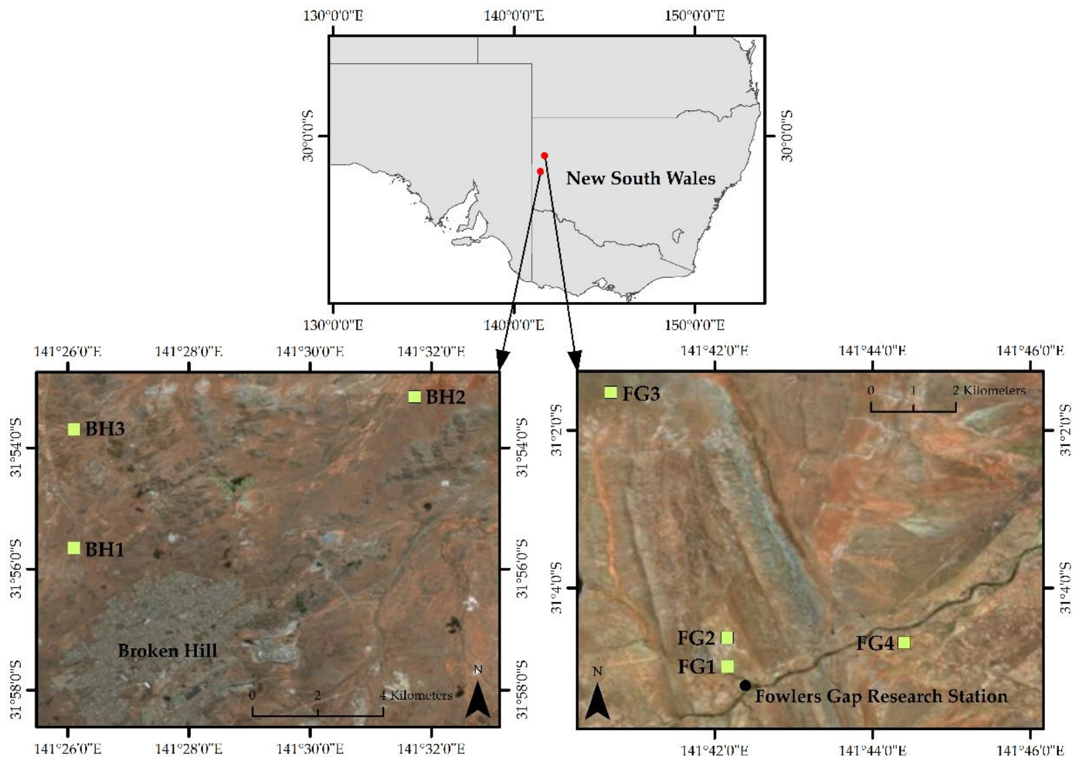

Figure 2 Site map displaying the locations of survey sites surrounding Broken Hill and Fowlers Gap Research Station, NSW. Base map: true colour satellite image accessed from ESRI, 2019.

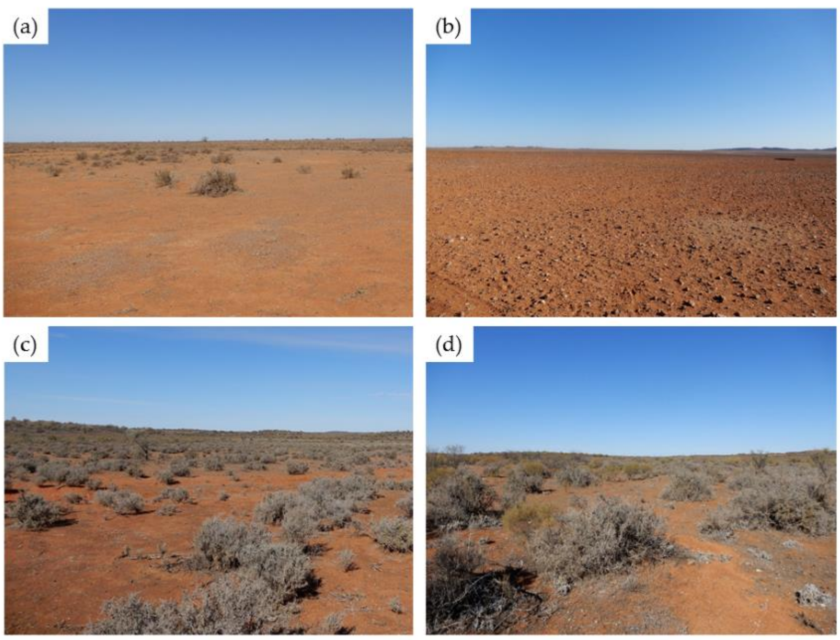

Figure 3 Site photographs from Fowlers Gap Research Station **(a,b)** and Broken Hill **(c,d)**.

2.2.2 Ground Cover Surveys

To survey ground cover, six 500 m transects oriented north–south and spaced 100 m apart were established at each site. Across the six transects, two survey methods were used. Firstly, ground cover reflectance was recorded using an Analytical Spectral Devices Inc. FieldSpec 3 spectroradiometer (ASD) that measures the visible to shortwave infrared (350 - 2500 nm) parts of the electromagnetic spectrum. The sensor has 2150 bands with a spectral resolution of 3 nm from 350 - 1000 nm and 10 nm from 1000 - 2500 nm. An 8-degree field of view fore-optic was held 1 m above the ground, creating a 0.14 m diameter ground field of view. At the start of each transect, and as required, the device was optimized and white reference measurements taken following the recommended protocols (Analytical Spectral Devices 2008). The operator of the ASD walked along each transect at a consistent pace taking continuous readings of ground cover reflectance. The continuous readings were averaged by the ASD and 10 averaged spectra were recorded for each 25 m segment of the transect, totalling 200 spectra per transect (1200 measurements per site).

The second method used was step-point sampling, where an observer collected point-based observations of ground cover along the six transects. The observer marked a point on a boot tip and at 5 m intervals recorded the cover that intersected the point. Cover was categorised into a set number of cover types, including crust, rock, litter, green leaf, and dry leaf, as outlined in the Muir et al. (2011) protocol. The cover for each of these categories was calculated as the proportion of the total number of point observations at the site (n = 600). These categories were grouped into three broad classes, PV, NPV, and BS, to give their FC percentage within the site.

2.2.3 Endmember Extraction & Spectral Unmixing

The hyperspectral reflectance measurements for each transect were converted into single raster files enabling them to be processed in ENVI 5.3.1 (Exelis Visual

Information Solutions, Boulder, Colorado). The Sequential Maximum Angle Convex Cone (SMACC) tool was used to extract endmembers from the transect rasters and to perform linear spectral unmixing (Gruninger et al. 2004). The SMACC tool automatically defines the most extreme point (i.e., the brightest pixel in multi-dimensional space) as the first endmember in the raster using a convex cone model. The next endmember is identified based on the angle it makes with the existing cone (i.e., the pixel that is most different from the brightest), which is then added to the cone to derive the next endmember. This process continues until a specific tolerance is reached or until a specific number of endmembers are identified.

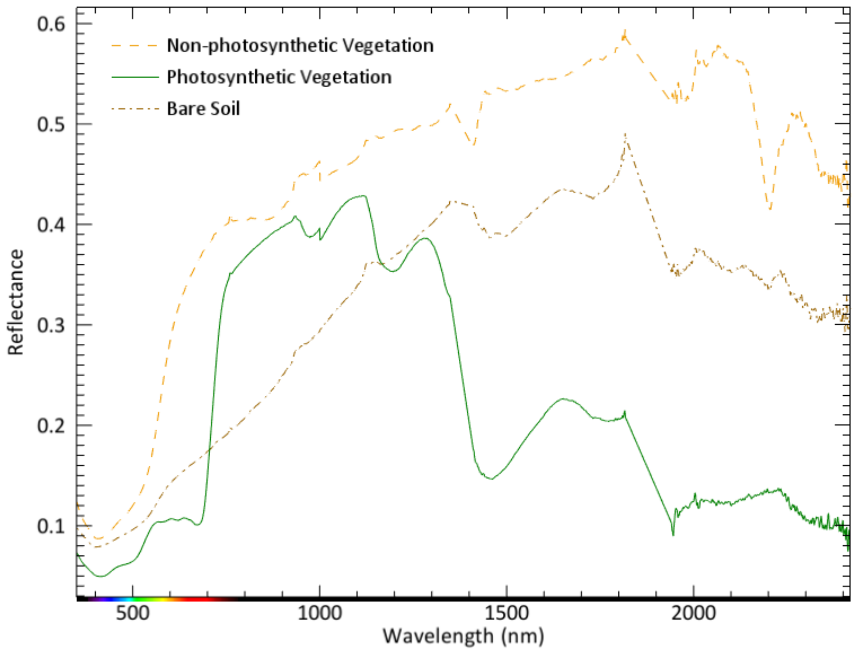

Figure 4 Example of image-derived endmembers for non-photosynthetic vegetation, photosynthetic vegetation, and bare soil.

For each of the transects, PV, NPV, and BS endmembers (Figure 4) were extracted and abundance images of PV, NPV, BS, and shadow were produced, with each image displaying the proportion a specific endmember contributes to each pixel. These images were produced using a fully constrained linear spectral unmixing algorithm:

$$DN_b = \sum_{i=1}^{n} F_i \, DN_{i,b} + E_b \text{ and } \sum_{i=1}^{n} F_i = 1 \quad (1)$$

where DN_b is the apparent surface reflectance of a pixel in band b of an image; F_i is the fraction of endmember i; $DN_{i,b}$ is the relative reflectance of endmember i in band b; n is the number of endmembers; and E_b is the error for band b of the fit of n spectral endmembers, that of (Adams et al. 1993; Adams et al. 1986; Smith et al. 1990). The proportions of PV, NPV, and BS across each site were calculated as the averages of the unmixed fractions derived from each transect spectrum.

2.2.4 Comparison to Image-Based Fractional Cover Products

The field-based FC estimates were compared to two Australian image-derived FC products based on MODIS (Guerschman and Hill 2018) and Landsat imagery (Geoscience Australia 2015). The MODIS FC product was initially developed for monitoring the tropical savanna region of the Northern Territory, Australia (Guerschman et al. 2009) and was later applied across the continent by the Commonwealth Scientific and Industrial Research Organisation (CSIRO) (Guerschman et al. 2012). This product uses MODIS imagery and describes the proportion of PV, NPV, and BS Australia-wide. The Landsat product was developed by the Joint Remote Sensing Research Program (JRSRP) also as a national FC product utilising the Landsat archive. Initially developed for rangeland monitoring in Queensland, Australia, the product is now being implemented nationally by Geoscience Australia (Scarth et al. 2010; Schmidt et al. 2010). Key differences between the two products include their spatial and temporal resolutions. The MODIS product has a moderate resolution of 500 m while the Landsat product is at a finer scale of 25 m. The latest version of the MODIS product uses MODIS MC43A4 version 6 imagery, which is a 16-day composition of daily captures from 2000 to 2019 (on-going) (Guerschman and Hill 2018). The Landsat product utilises data from the Landsat archive from 1986 to the present. Recent versions of the Landsat and MODIS FC products use a similar unmixing process (Guerschman et al. 2015) that incorporates endmembers of PV, NPV, and BS derived from field spectra and the imagery itself. For this study, the Guerschman and Hill (2018) version 3.1.0 MODIS product and the Landsat FC25 version 1.5 were used (Geoscience Australia 2015). The MODIS and Landsat FC products were acquired for dates that corresponded with the collection of *in situ* ground cover measurements. The Landsat FC image is based on a single date (17 August 2018) while the MODIS FC product is developed from a 16-day composite of imagery collected from the 13 to 28 August 2018. The PV, NPV, and BS values for each of the seven sites were extracted from a single pixel for the MODIS product while an average of 400 Landsat pixels across the same 500 × 500 m area were calculated. These extracted values were then compared to both the step-point and the spectral PV, NPV, and BS fractions.

2.2.5 Statistical Analysis

To determine the relationship between the *in situ* FC estimates and the image-based estimates, two metrics were used: Spearman's rank-order correlation (r_s) to measure the relationship between methods and the mean absolute error (MAE) to measure the average error. MAE was calculated as follows:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} | f_1 - f_2 | \tag{2}$$

where f_1 and f_2 represent the two FC measures being tested and n is the number of measurements. MAE is an average of the absolute difference between FC measure 1 and FC measure 2 (i.e., the absolute error). MAE is calculated in the same units as the variables and is a negatively oriented score, with lower values indicating lower errors.

2.3 Results

The *in situ* methods showed strong positive relationships across all three ground cover types (Table 1). While r_s was high, the MAE for NPV (r_s = 0.61, MAE = 19.82) and BS (r_s = 0.82, MAE = 19.26) was also relatively high. PV (r_s = 0.87, MAE = 1.37) showed a high correlation with low errors. Overall, low errors were observed for all comparisons made for PV. When the *in situ* methods were compared to the image-based models (MODIS and Landsat), spectral transect sampling showed a strong relationship to the MODIS image for PV and was the strongest relationship observed (r_s = 0.91, MAE = 4.21). For BS, the correlation between the MODIS imagery and the *in situ* methods was moderate and moderate to low for NPV. In comparison, the Landsat imagery showed a strong to moderate relationship with both *in situ* methods for BS, NPV, and PV.

Table 1 Summary of correlations and errors for each ground cover type based on comparisons between *in situ* and image-based fractional cover methods (step-point, spectral, MODIS, and Landsat).

	Step-point		Spectral	
Bare Soil				
	r_s	MAE	r_s	MAE
Step-point				
Spectral	0.82	19.26		
MODIS	0.58	20.31	0.56	26.43
Landsat	0.79	13.85	0.79	19.95
Non-photosynthetic Vegetation				
	Step-point		Spectral	
	r_s	MAE	r_s	MAE
Step-point				
Spectral	0.61	19.82		
MODIS	0.43	19.62	0.16	19.61
Landsat	0.68	15.79	0.71	14.86
Photosynthetic Vegetation				
	Step-point		Spectral	
	r_s	MAE	r_s	MAE
Step-point				
Spectral	0.87	1.37		
MODIS	0.86	4.24	0.91	4.21
Landsat	0.5	4.68	0.45	4.71

The percent cover of PV, NPV, and BS calculated for the *in situ* and image-based method at each field site (Figure 5) shows the *in situ* methods varied significantly. For Fowlers Gap sites 2 - 4, the step-point and spectral PV, NPV, and BS were very similar, whereas at the Fowlers Gap site 1 and the Broken Hill sites, PV followed a similar pattern but NPV and BS varied significantly from one another. Overall, PV was low across all sites and especially low for the Fowlers Gap sites, with approximately 10% less PV than the Broken Hill sites. As shown in Figure 3a,b, Fowlers Gap vegetation was extremely sparse with vast areas of exposed soil, and while the Broken Hill sites were also sparely vegetated, they still had considerably more vegetation than the Fowlers Gap sites.

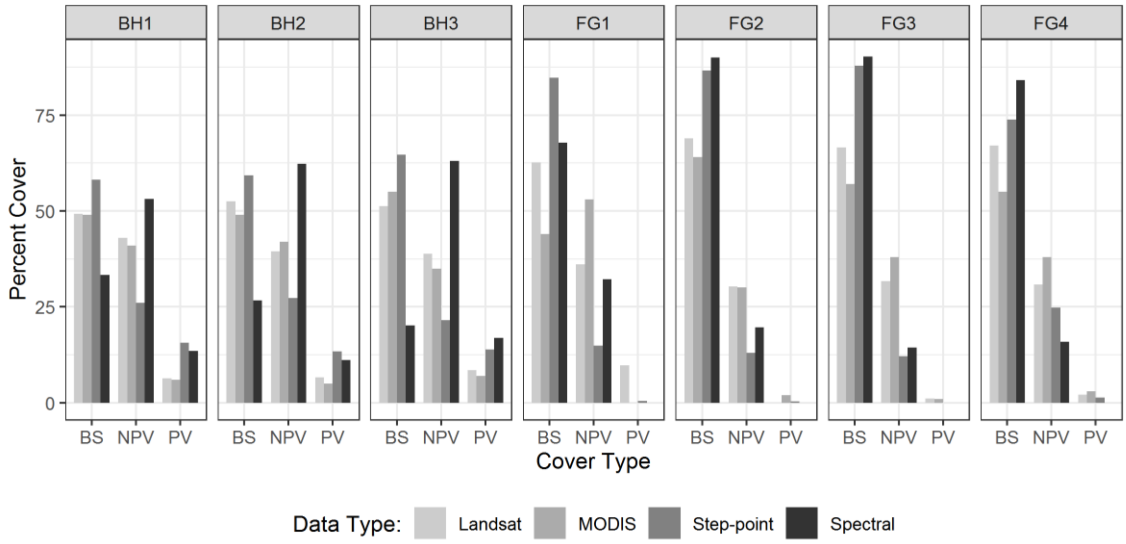

Figure 5 Summary of the fractional cover at each survey site calculated for each survey method.

2.4 Discussion

The motivation for this study was to test field-based hyperspectral ground cover sampling as a method of calibrating and validating image-based fractional ground cover products in Australia. By developing an alternative survey design for spectral transect sampling and comparing this method to step-point sampling at the same spatial scale, we developed an insight into the relationship between our two field methods and how they compare to current Australian image-derived fractional ground cover products.

Overall, the *in situ* methods were positively correlated with each other. Though neither method is truly ‘ground truth’, this strong positive linear relationship between the *in situ* methods suggests they provided relatively accurate estimates of ground cover at each field site. In contrast, Meyer and Okin (2015) found little to no correlation between their two field methods. This is likely due to a scale mismatch in the Meyer and Okin study (the line point transects were 100 m, and the spectral transects were 500 m), whereas we avoided this mismatch by conducting both surveys over the same 500-m transects. Additionally, by avoiding a star-transect layout, our grid sample design more evenly distributed sample points across each site, ensuring that that we were not over sampling a specific area and collecting data evenly across each site.

Overall, there was relatively good correlation between both *in situ* methods and the image-based products. Previous validation of the MODIS and Landsat methods using *in situ* measurements similar to our step-point sampling reported good correlation between *in situ* measurements and the image-based products (Guerschman and Hill 2018; Scarth et al. 2010), but very few of these sites were located in areas with a very low percentage of vegetation. MAE was consistently low between the *in situ* measurements and image-based values for PV compared to BS and NPV, which showed considerably higher errors (Table 1). This pattern of errors is also consistent with past studies, where PV has been successfully unmixed due to being spectrally unique, whereas BS and NPV are typically harder to distinguish due to their spectral similarity (Meyer and Okin 2015; Mishra et al. 2014).

The observer and the spectral field data recorded less than 1.3% PV at the Fowlers Gap site, MODIS PV values ranged from 0% to 3%, and Landsat ranged from 0% to 9.72% PV. Considering the finer resolution of the Landsat product, we would have expected PV to be better correlated with the Landsat values rather than the MODIS values. A reason for this could be related to the image products. The Landsat FC product is based on a single image captured on one day, whereas the MODIS MCD43A4 product calculates the weighted estimate of albedo over a 16-day period. The Landsat image was captured during this 16-day composite period.

This comparison was conducted with a small number of samples located in the arid zone where we know these products tend to fail (Guerschman et al. 2012; Scarth et al. 2010). More extensive surveys are needed to determine if this pattern is more widespread in arid areas. It is also important to remember that we compared single MODIS pixels with an average of 400 Landsat pixels. Sampling a cluster of pixels is preferable for accuracy assessment to remove errors associated with positional accuracy (Congalton and Green 2008). This is feasible for image products with resolutions of 5, 10, or 30 m but becomes logistically taxing for clusters of MODIS pixels at 500 m. This is why the upscaling of field data is regularly used. Currently, the MODIS product is validated using upscaled *in situ* data initially collected over 100-m transects. Sampling the area of a single pixel in the field has limitations. We argue that overall, surveying the area of a single MODIS pixel is preferable to comparing upscaled field data to a MODIS pixel.

Arid shrublands and desert zone cover 48% of the Australian continent (Department of the Environment 2015). Having reliable long-term fractional cover data at varying scales is crucial for those managing or studying these regions, especially for areas that are inaccessible or unsafe to travel. The *in situ* methods used have both benefits and shortcomings. Step-point sampling has been developed over time as a simple and easily repeatable method of collecting fractional ground cover estimates. Limitations of this technique include the time-consuming collection of field observations and the potential for human subjectivity and bias to be introduced, especially when classifying PV and NPV (Fisk et al. 2019). Utilizing standardized definitions and methods (Muir et al. 2011) may reduce subjective error but cannot remove it entirely. In order to further reduce human bias, spectral transect sampling provides a solution. This method allows for continuous, quantitative hyperspectral measurements to be taken over an area, providing an objective record of ground cover without the need for observers to make categorical decisions in the field. This hyperspectral record of ground cover may also have the potential to calibrate and validate a range of other remotely sensed products and this is an area of future research. With the continued demand for high-quality ground cover products, it is critical to ensure that we are collecting high-quality calibration and validation data for the assessment of these sought-after products.

2.5 Conclusions

Field-based estimation of fractional ground cover is critical for ensuring the accuracy and consistency of remotely sensed ground cover maps. Currently, Australia's national standard for the collection of field estimates of ground cover uses traditional field sampling techniques, but hyperspectral reflectance sampling of ground cover has considerable potential to improve field measurements collected for calibration and validation purposes. This study trailed the use of hyperspectral reflectance sampling in the sparsely vegetated NSW arid zone. Comparison of step-point and spectral transect sampling across the same transects, at the same spatial scale, demonstrated the significant potential of the spectral transect method, both in is ability to produce results comparable to the traditional transect measures and also in the improved objectivity and relative logistic ease of the method.

Overall, we found the *in situ* step-point and spectral sampling techniques to be positively correlated across the three ground cover classes. Comparing the *in situ* data and current Australian image-derived fractional cover products showed that overall, the Landsat product was strongly related to both *in situ* methods for non-photosynthetic vegetation and bare soil whereas the MODIS product was strongly correlated with both *in situ* methods for photosynthetic vegetation. These results are specific to our survey sites and further work is required to test their wider applicability.

While a limitation of spectral sampling is the availability and cost of the spectroradiometer itself, overall, the benefits outweigh the limitations. Spectral sampling is especially beneficial for repeat surveys or multi-temporal studies. Future efforts should be made to include spectral ground cover sampling as part of Australia's efforts to produce calibration and validation datasets for remotely sensed products and should further test this method to develop a national or global standard.

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CHAPTER THREE

Distinguishing Photosynthetic and Non-Photosynthetic Vegetation: How do Traditional Observations and Spectral Classification Compare?

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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

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Abstract

Remotely sensed ground cover maps are routinely validated using field data collected by observers who classify ground cover into defined categories such as photosynthetic vegetation (PV), non-photosynthetic vegetation (NPV), bare soil (BS), and rock. There is an element of subjectivity to the classification of PV and NPV, and classifications may differ between observers. An alternative is to estimate ground cover based on *in situ* hyperspectral reflectance measurements (HRM). This study examines observer consistency when classifying vegetation samples of wheat (Triticum aestivum var. Gladius) covering the full range of photosynthetic activity, from completely senesced (0% PV) to completely green (100% PV), as photosynthetic or non-photosynthetic. We also examine how the classification of spectra of the same vegetation samples compares to the observer results. We collected HRM and photographs, over two months, to capture the transition of wheat leaves from 100% PV to 100% NPV. To simulate typical field methodology, observers viewed the photographs and classified each leaf as either PV or NPV, while spectral unmixing was used to decompose the HRM of the leaves into proportions of PV and NPV. The results showed that when a leaf was ≤25% or ≥75% PV observers tended to agree, and assign the leaf to the expected category. However, as leaves transitioned from PV to NPV (i.e., PV ≥ 25% but ≤ 75%) observers' decisions differed more widely and their classifications showed little agreement with the spectral proportions of PV and NPV. This has significant implications for the reliability of data collected using binary methods in areas containing a significant proportion of vegetation in this intermediate range such as the over/underestimation of PV and NPV

vegetation and how reliably this data can then be used to validate remotely sensed products.

3.1 Introduction

Remotely sensed fractional cover maps are critically important for understanding a variety of environmental issues such as the impacts of land use change, climate change variability, ecosystem function, and desertification (Asner and Heidebrecht 2002; Guerschman et al. 2009). Algorithms used to produce fractional cover maps decompose each pixel in an image into a measure of similarity to two or more spectrally distinct land cover types, typically including photosynthetic vegetation (PV), non-photosynthetic vegetation (NPV), bare soil (BS), shadow, and snow (Okin 2007; Settle and Drake 1993). This results in quantitative estimates of the fraction or proportion of the cover types that comprise image pixels.

During the production of these fractional cover maps some form of reference data is required for calibration and validation, typically derived from on-ground measurements. Commonly-used field methods for estimating fractional ground cover require observers to walk across a study area and make point-based observations at defined intervals. These methods use variants of point-based sampling techniques that were initially developed for vegetation ecology and rangeland assessment (Evans and Love 1957; Graham 1989; Winkworth et al. 1962). They can also be used for more detailed surveys such as determining the presence or abundance of plant species across a survey area (Lewis 1994; Peterson and Reich 2008).

When estimating fractional cover within a defined sampling area observers typically make hundreds of point-based assessments which are collated to produce overall estimates of fractional cover for each cover type across the site. Some cover types are discrete, well defined classes (e.g., “rock”, “cryptogam”, or “litter”) that are easily discriminated with high accuracy. However, PV and NPV are more accurately thought of as the extremes of a continuum, rather than binary categories, and therefore, distinguishing between PV and NPV can be a difficult task for observers. Moreover, there is little information on how consistently different observers categorise samples across the PV/NPV continuum.

This uncertainty is widely acknowledged and dealt with to some degree in standard field methods. For instance, Muir et al. (2011) technical handbook outlines a simple, systematic and repeatable method to ensure the collection of consistent observations of fractional ground cover. This method has been implemented in Australia across a national network of ground cover sites and is used to calibrate and validate a variety of remotely sensed fractional cover datasets including the Commonwealth Scientific and Industrial Research Organisation (CSIRO) fractional cover product (Guerschman and Hill 2018) and the Joint Remote Sensing Research Program (JRSRP) Landsat fraction cover product (Scarth et al. 2010). Muir's method surveys 100 m transects and was designed initially to validate Landsat products allowing the average fractional cover values from a cluster of Landsat pixels (90 m) to be compared to *in situ* fractions. When this field method is used to validate the CSIRO product, which has a spatial resolution of 500 m, it requires the field observations to be up-scaled. In order for these sites to be up-scaled the area surrounding the site needs to fit a specific criteria; (1) the species composition and cover should be spatially consistent and (2) that minimal topographic variation should occur across the site and surrounding area (Guerschman et al. 2012; Muir et al. 2011).

Field measurements for validating satellite-derived land cover products come with a number of limitations. Firstly, the data is often thought of as 'ground truth', but because of the sampling techniques involved, there is the potential to introduce errors. Secondly, acquiring calibration and validation data is often time-consuming and costly due to the number of sites required, the labour needed and distance required to travel to sites that may be dispersed across large areas. Thirdly, human subjectivity is known to be a significant contributing factor in the variability of vegetation field estimates, particularly when identifying NPV.

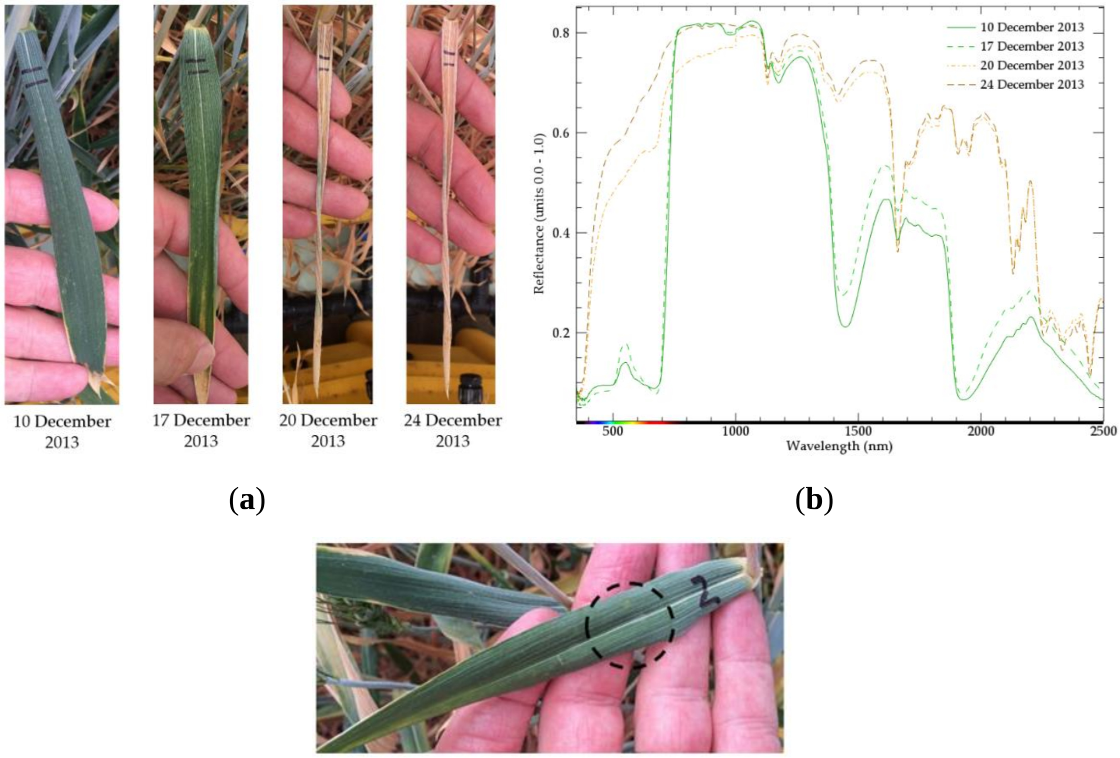
A potential solution to help reduce human error is to estimate the relative fractions of PV, NPV, and BS from field-based hyperspectral reflectance measurements. This method allows for many spectra to be recorded over a defined area, which capture the combined spectral response of the site in their aggregate. These spectra can then be unmixed to estimate the relative fractions of PV, NPV, and BS. Using this approach Meyer and Okin (2015) demonstrated stronger agreement between fractional cover derived from field-based reflectance measurements and remotely sensed imagery than between traditional line-point intercept observations and remotely sensed imagery. However, as there was no ultimate point of truth for field cover, it was not possible to tell which measurements best represented reality. Thus, the collection of field spectral reflectance is a potential alternative to observer surveys, but we have a limited understanding of how this data compares when categorising PV and NPV. We are especially uncertain how spectral fractional cover estimates compare to human assessments as vegetation transitions from photosynthetic (green) to non-photosynthetic (dry). For the purpose of this study the spectral samples were considered a less subjective method of classifying vegetation and therefore used as a point of truth for the comparisons though acknowledge that there still remains uncertainties in the spectral measurements.

The overall aim of this study was to examine how human assessments compare to spectral fractional cover estimates, with a particular focus on how humans categorise vegetation across the PV/NPV continuum. Specifically, the research compared how vegetation is classified as photosynthetic and non-photosynthetic through observer surveys, replicating decisions made during field surveys, versus spectral unmixing of hyperspectral vegetation spectra. The key objectives were to understand when observers categorise vegetation as green or dry, determine the amount of variation between observers (if any) and to analyse how spectral classification compares to observation-based classification of vegetation.

3.2 Materials & Methods

3.2.1 Wheat Plants

Wheat plants (Triticum *aestivum* var. Gladius) sown during August 2013 were grown in pots and monitored throughout their development in a glasshouse at the South Australian Research and Development Institute Plant Research Centre, University of Adelaide. Once the wheat reached maturity, single leaves from 12 separate plants were selected and labelled. To capture plant transition from maturity through to the end of senescence each of the 12 leaves was sampled over a two month period. During this period, the 12 leaves were photographed to create a visual record (Figure 6a), and hyperspectral measurements of reflectance (Figure 6b) were taken using an ASD Inc. (Analytical Spectral Devices) FieldSpec 3 spectroradiometer. This instrument measures the visible to shortwave infrared (350 - 2500 nm) parts of the electromagnetic spectrum in 2150 bands with a spectral sampling interval of 3 nm for 350–1000 nm and 10 nm for 1000 - 2500 nm. Leaf spectra were recorded with an ASD leaf-clip, an accessory specifically designed for recording leaf spectra under controlled lighting and geometry. Measurements were taken from the same part of each leaf, approximately 3 cm from the base of the leaf, on each sample date (Figure 6c).



(c)

Figure 6 (a) An example of wheat photographs taken over four dates. **(b)** Hyperspectral reflectance measurements of the four leaves in Figure 6a. **(c)** Black dashed circle indicates the reflectance sample location for each leaf.

3.2.2 Observer-Based Binary Classification

A questionnaire was developed to simulate observer field classifications of vegetation samples as either a green leaf (PV) or dry leaf (NPV) when using the Muir et al. (2011) technique and definitions. From the photographs taken over a two month period, 74 were randomised and developed into the survey, with the leaves chosen to ensure a mix of different stages of senescence. Thirty-two observers were asked to perform a binary classification of each leaf as either green or dry. The observers consisted of university staff and students ranging from experienced field observers with a background in remote sensing and ecology to staff and students with no experience in the field or in remote sensing. Prior to the survey, all observers read the Muir et al. (2011) definitions of a green leaf and a dry leaf (Table 2) and subsequently classified the 74 leaves in a closed format survey based on their interpretation of the definitions provided. The classifications were based on observations of the small area of leaves where the spectral samples were taken (Figure 6c) and each leaf was viewed individually and classified before moving on to the next leaf.

Table 2 Definition of a green and dry leaf according to Muir et al. (2011).

Category	Definition
Green Leaf	• A leaf with green pigmentation (one that is actively photosynthesising) attached to a plant. • Leaves may appear more yellow than green.
Dry Leaf	• A leaf with non-green pigmentation (one that is not actively photosynthesising). • Includes senescing (but still living vegetation) and dead vegetation. • Leaf must be attached to a plant or the ground.

3.2.3 Spectral Unmixing

Photosynthetic and non-photosynthetic fractions of the 74 leaf spectral samples were derived by spectral unmixing. Reference spectra (endmembers) for the unmixing were selected from leaves not included in the survey (Figure 7).

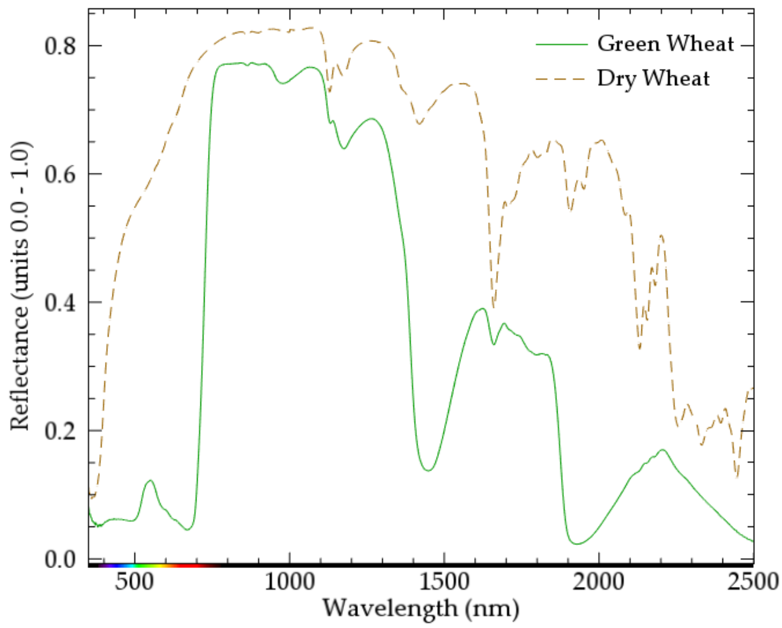


Figure 7 Green and dry leaf endmembers selected for spectral unmixing.

The individual leaf spectra were converted into a single raster-like file which was processed using the linear spectral unmixing tool in ENVI 5.3.1 (Exelis Visual Information Solutions, Boulder, Colorado) and the reference spectra were used to decompose each of the spectral samples into relative proportions of green and dry. The partially constrained linear spectral unmixing algorithm (Adams et al. 1993; Adams et al. 1986; Smith et al. 1990) used was:

$$DN_b = \sum_{i=1}^{n} F_e \, DN_{e,b} + E_b \text{ and } \sum_{i=1}^{n} F_e = 1 \tag{1}$$

where DN_b is the apparent surface reflectance of a pixel in band b of an image; F_e is the fraction of endmember e; $DN_{e,b}$ is the relative reflectance of endmember e in band b; n is the number of endmembers, and E_b is the error for band b of the fit of n spectral endmembers. The unmixing resulted in three values for each leaf; the PV fraction, NPV fraction, and the root mean squared error (RMSE). Overall, the RMSE for each leaf showed very low errors with the highest RMSE reported as 0.08%. This provides confidence in the fractions of PV and NPV derived from the unmixing. Past studies show that PV can be predicted with high accuracy from spectral unmixing while typically NPV is harder to estimate (Li et al. 2017; Okin et al. 2013). The reflectance measurements were taken in a way to ensure no other materials such as soil or litter would be recorded by the sensor which can cause confusion during unmixing. Considering these factors, we can have a high degree of confidence in the spectral unmixing. In this paper PV and NPV is used to refer to the spectral classification of the leaves while 'green' and 'dry' refers the observer classifications. PV/ green leaf are equivalent categories, as are NPV/ dry leaf.

3.2.4 Statistical Analysis

To summarise the individual green and dry observations, descriptive statistics were used to calculate the total number of green observations and dry observations as a percentage of the total number of leaves (n = 74). Based on these totals, the grouped mean was calculated for both green and dry classes along with the standard deviation. These summary statistics were repeated for the spectral measurements of each leaf, calculating the average PV and NPV percentage based on the PV and NPV fractions derived for each leaf from the linear unmixing.

To test the relationship between the PV fractions and the green observations the raw individual observations and spectral unmixing fractions were analysed. Logistic regression was used to model the binary observer response variable (i.e., green or not green). PV was the single, linear, fixed effects predictor in the model, and observer identity was fitted as a random intercept effect to account for the repeated measures by observers in scoring all photographs. The regression was calculated in R using a generalized linear mixed effect model (GLMM) (Bates et al. 2015). A detailed explanation of the GLMM can be found in (Chambers et al. 2001). Using the GLMM output parameters the confidence intervals (CI) were calculated.

3.3 Results

Firstly, we explored the observers' classifications to determine their variation within the green and dry categories. Individual observers categorised 32 - 49% of the leaves in our sample as green and 51 - 65% as dry. The majority (73%) of observer responses were situated within the 91 - 100% range representing 54 of the 74 leaves analysed (Figure 8). These 54 leaves (Figure 9a) were unanimously classified as either a green or dry leaf by the observers. Of the remaining 20 leaves, 11 showed 90 - 99% agreement between the observers, while the remaining 9 leaves (Figure 9b) had the most substantial variation in observer response.

The grouped mean proportions of green and dry leaves within the sample were 42% green and 58% dry, with a standard deviation of 3.82% for both green and dry showing that overall there is little variation amongst the observers. The average fractions of PV and NPV were 44.68% and 55.31%. The green and dry observational data, and PV and

NPV fractions are both inverse of each other. From here on we will report only the green and PV results.

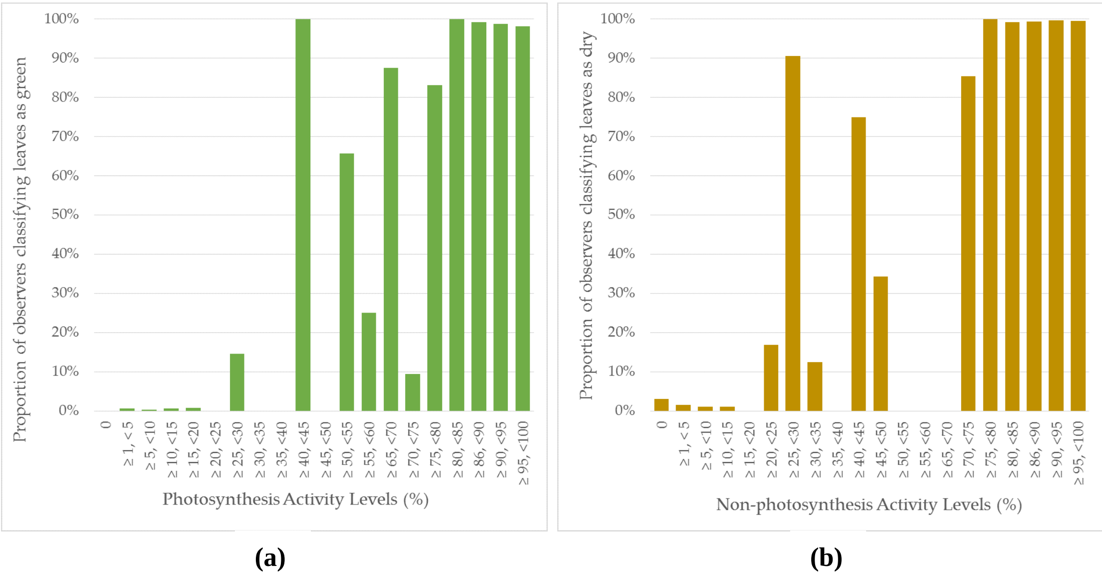


Figure 8 (a) Distributions of green observation vs. the photosynthetic vegetation (PV) fractions (photosynthesis activity levels) and **(b)** the distribution of dry observations vs. the non-photosynthetic vegetation (NPV) fractions (non-photosynthesis activity levels).

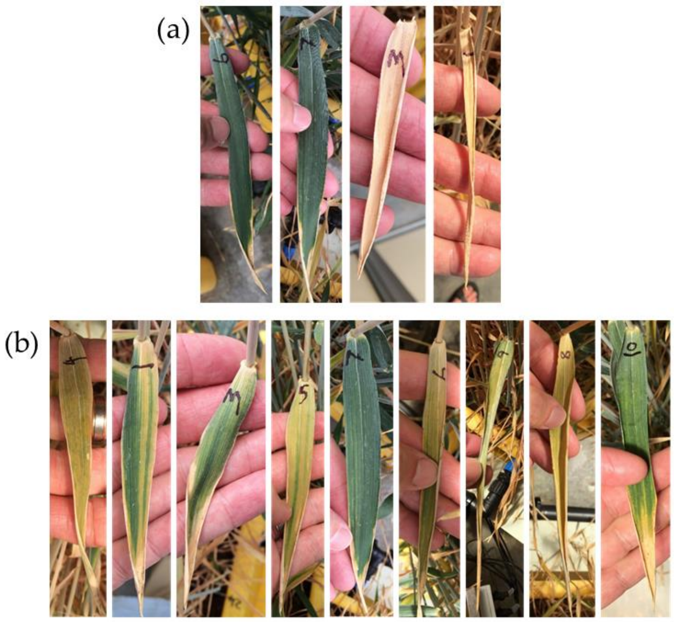


Figure 9 (a) Example of leaves unanimously classified as green or dry by observers. **(b)** Leaves with significant variation amongst observers.

The GLMM likelihood ratio test between the spectral and observer results showed a strong positive linear relationship between the PV fractions and green observations (χ2

= 2358.2, df = 1, $p < 0.001$). The GLMM also provided a value for the odds of an observer classifying a leaf as green. In this case, the odds of an observer scoring green increased by 10% with every one percent increase in the PV fraction (95% CI = 9.3%, 10.9%). It is important to note that this increase is relative to each observer. For example, some observers classify leaves as green, on average, at lower PV values, thereby reaching 100% PV more slowly, while others classify a leaf as green much later in the continuum and will reach 100% very quickly.

Based on the GLMM, the predicted mean observer values were calculated and represented as a line of best fit along with its confidence intervals (Figure 10). This confirms that at the extremes, when a leaf is extremely dry (0 - ~25%)) or extremely green (PV ~75 - 100%) as classified by spectral unmixing, observers were almost all in agreement, and made the most appropriate classification. In the middle of the PV/NPV continuum (between ~25% and ~75% green) there is a zone of uncertainty where we saw observer decisions considerably differed from one another.

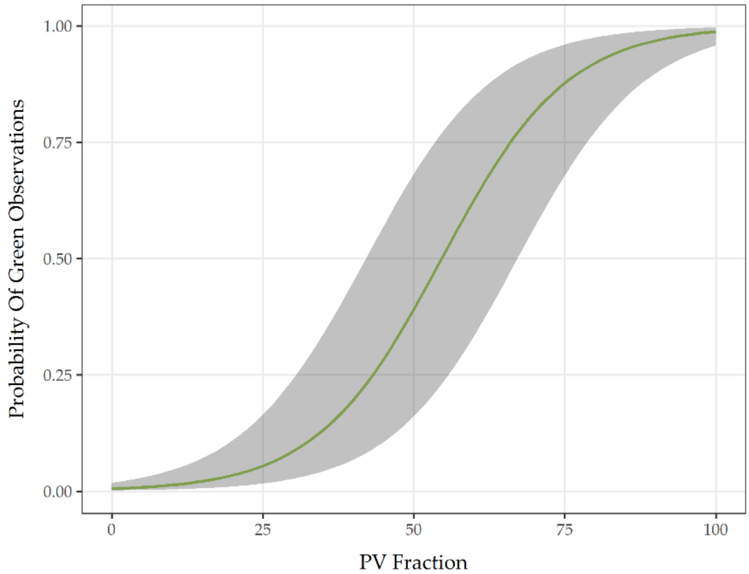


Figure 10 Relationship between predicted green observations and the percentage of photosynthetic vegetation. The green line represents the mean predicted observer values and the 95% confidence interval range is represented by the grey shaded area.

3.4 Discussion

The aim of this study was to investigate how human assessments compare to spectral estimates of fractional cover. By having multiple observers assess the same samples, we have developed an insight into the consistency of observer classifications and have also clarified the relationship between human and spectral assessments of PV and NPV.

When assessing the variation in the human observation of green and dry classes, there was a 17% difference between the minimum and maximum green proportions and a 14% difference between the dry proportions. Comparison of variation between observer results is not something that can be done routinely in the field because, typically, a single person would survey a specific area or transect due to time and cost. One study that examined the variability of fractional ground cover reference data between experienced and inexperienced observers found that there was no significant difference between mean estimates of cover based on experience level (Trevithick et al. 2012). They noted that variation did increase between experienced and inexperienced observers for PV and NPV and that, for all observers NPV was the hardest to identify. It is important to note this variation when comparing these observed estimates to PV and NPV from satellite-derived fractional cover maps. While this variation is small, it is important to recognise when designing field methods and may influence cover estimates when multiple observers are contributing to one larger dataset.

Unanimous agreement between observers does not necessarily mean that the observers were correct but does suggest strong agreement among the observers for those specific leaves. When observers perform these classifications, they are required to make binary decisions, and in order to gain consistent data, it is vital that all observers have the same understanding of the definitions they are using. After our survey, observers provided feedback on the definitions (Table 2) upon which they based their decisions. A comment expressed by many was that the green and dry leaf definitions were not clear and that they appeared contradictory. When using these definitions it can be difficult for observers to define the point at which they should classify a leaf as green or dry and for this decision to be consistent between a group of observers. If an observer chooses to honour the dry leaf definition, anything with non-green pigmentation should be considered dry, meaning that an observer potentially would only classify a leaf as green if it was entirely green even though the green leaf definition stated that it could be more yellow than green. Another potential confounding factor is that a leaf may still be photosynthesising even if it has patches of yellow or appears dry, which was observed in a small number of leaves in the survey. An area of future research would be to improve these definitions clarifying how to classify any leaf into the green/dry categories.

There was a strong positive linear relationship between observer decisions and the spectral classification of each leaf. A limitation of this study is that the majority of the leaves fell within the top and bottom 25% of the photosynthetic continuum with few leaves spread across the mid 50% range: This distribution is likely to have influenced the results of the GLMM. When leaves were close to being completely green or dry, both the observers and spectral unmixing results were strongly related, but as the leaf transitioned this relationship became unclear. This is consistent with past studies that extract PV from in remotely sensed imagery using spectral unmixing techniques finding that PV can be reliably extracted (Mishra et al. 2014; Trevithick et al. 2012). The classification of leaves by observers within this 50% range can occur as follows; (1) a leaf that is classified as ~25% PV might be assessed as green by 0%, 5%, or 35% of observers, (2) a leaf that is ~55% PV might be assessed as green by 30% or 100% of observers and (3) a leaf that is ~70% PV might be assess as green by 0%, 20%, or 85% of human observers. Therefore, human classification of leaves with a mixture of PV and

NPV (i.e., within the mid 50% of the spectral range) shows little agreement with the spectral proportions of PV and NPV. To examine these results further, a survey including more leaves within the mid-range of the PV/ NPV continuum would be desirable and is a potential area for future research. The GLMM also tested the odds of the relationship between the observer and spectral results and showed that the odds of an observer classifying a leaf as green increases by 10% for every 1% increase in the PV fraction relative to the observer's last decision.

The use of wheat (*Triticum aestivum* var. Gladius) was an ideal choice to visually capture the transition of leaves from green to dry. Growing wheat in a controlled environment ensured that photographs and reflectance measurements of the same leaves could be taken over time with the results providing a baseline understanding of how observers can react when categorizing vegetation. No work was performed to test if these results could be generalized across other plant species but our results should be generalizable across other spectrally similar C3 plants as well as other green plants that lack any other significant source of pigmentation.

Spectral sampling provided a continuous and objective means to collect the reflectance of vegetation for spectral unmixing. The linear spectral unmixing results showed that very few leaves were entirely classified as PV or NPV and highlights the benefit of a survey method that can record continuous, rather than binary data. The ability to measure and analyse reflectance of vegetation or ground cover is a key advantage of this technique as it removes the need for observers to make binary decisions in the field. A recommendation for future studies is that if all vegetation is expected to be <75% PV or NPV either spectral sampling or observer surveys are appropriate. If the majority of the vegetation is situated between ~25% and ~75% PV, observer surveys are likely to introduce uncertainty and therefore we recommend spectral sampling. Spectral sampling enables the collection of more quantitative information to be collected over a study area and may allow for a more accurate assessment of relative PV or NPV status of vegetation to be attained for the purpose of training and evaluating earth observation products.

3.5 Conclusions

The collection of field-based calibration and validation data is critical for ensuring the accuracy and consistency of remotely sensed fractional ground cover products. This study provides a greater understanding of the variation that may occur between observer decisions and when this data may become less reliable. In addition, it clarifies the relationship between human and spectral assessment of PV and NPV, highlighted by the follow key findings. Firstly, when comparing the proportions of PV and NPV between observers, there was up to 17% variation between observers for PV and up to 14% variation for NPV. This variation can have implications for the consistency of data collected using multiple observers and how accurately satellite-derived ground cover products can be calibrated and validated using this data. Secondly, the GLMM suggests that the PV and NPV values for the observer and spectral data were similar but shows that observers overestimated NPV and underestimated PV. Lastly, at the extremes of leaf photosynthetic expression there was strong agreement between observer decisions and spectral classification but as the leaves transitioned this relationship weakened, with little agreement for leaves close to 50%.

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CHAPTER FOUR

Evaluating the influence of soil colour on MODIS fractional cover estimation in Australia

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Statement of Authorship

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Contribution to the paper	Conceptualization, Methodology, data curation, formal analysis, writing – original draft preparation, writing – review and editing.	
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: 22/12/2019

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	Kenneth D. Clarke	
Contribution to the Paper	Conceptualization, Methodology, formal analysis, writing – review and editing.	
Signature		9/01/2020

Name of Co-Author	Megan M. Lewis	
Contribution to the Paper	Conceptualization, Methodology, formal analysis, writing – review and editing.	
Signature		8/01/2020

Abstract

Soil colour is a significant factor that influences soil reflectance and is believed to negatively influence fractional ground cover estimates derived from MODIS imagery. MODIS fractional cover estimates of ground cover play an important role in ecosystem monitoring across Australia. While past assessments suggest that soil colour or soil brightness does not influence these ground cover estimates some doubts remain. This study aimed to perform a systematic evaluation of fractional ground cover estimates derived from MODIS imagery across Australia to determine if soil colour has any influence on the product. To meet this aim, we addressed two key objectives: (1) to compare fractional ground cover estimates from the Australian MODIS fractional ground cover product and the Australia-wide AusPlot program field measurements, providing a baseline understanding of how the image-derived estimates compared to field estimates; (2) to examine if soil colour has any influence of the MODIS product using quantitative and qualitative methods. Two hundred and fifty AusPlot sites distributed across Australia that contained field measurements of fractional ground cover of bare soil, photosynthetic and non-photosynthetic vegetation along with Munsell soil colour descriptors were selected for the analysis. Relationships were established between the MODIS and AusPlot fractional cover values using Munsell hue as an indicator of soil colour. Linear relationships were established for the soil colour groups and a visual assessment of the graphs produced was performed to uncover any observable pattern in the data based on hue and the Munsell colour notation as a whole. Overall the MODIS and AusPlot fractional cover values for BS and PV were strongly correlated while NPV displayed a weak relationship but was still statistically significant. There was a significant difference between the five hues analysed, showing an observable effect of hue within the MODIS product at the 250 sites. For the majority of hues there was some over or underestimation of MODIS fractional cover relative to

AusPlot estimates. For example, for sites with a hue of 10R bare soil tended to be overestimated and photosynthetic vegetation underestimated. It is our hope that understanding the effect of soil colour on MODIS fractional cover estimates will assist future calibration efforts to improve the product, and provide the context to enable more accurate consumption of the current product in cases where precision might be of the utmost importance.

4.1 Introduction

Ground cover is a frequently used indicator of soil condition, soil erosion, the health and function of rangelands as well as the success or failures of land management practices (Bastin et al. 2012; Stewart et al. 2011). Mapping and monitoring ground cover using remotely sensed imagery provides a consistent means of recording and monitoring ground cover over time and a practical way to monitor broad regions or entire continents as a whole. In Australia, efforts have been made to develop fractional cover products that support temporal analysis of ground cover change (i.e. seasonal, monthly or yearly).

The MODIS fractional ground cover product provides relative estimates of the proportion of bare soil (BS), photosynthetic (PV) and non-photosynthetic vegetation (NPV) and has become a vital component of the Australian Government Ground Cover project (Guerschman and Hill 2018; Stewart et al. 2011). This project was established in 2009 after recognising the need for nationally consistent ground cover data that can be utilised for land management and the assessment of soil condition. Fractional ground cover estimates were derived from MODIS imagery and initially developed to monitor the tropical savanna region of the Northern Territory (Guerschman et al. 2009). It used MODIS Nadir Bidirectional Reflectance Distribution Function Adjusted Reflectance (NBAR MCD43A4) collection 5 imagery which was an 8-day product with a spatial resolution of 500 m. The Guerschman et al. (2009) method was later applied nationally, creating a continent-wide fractional cover product utilising the MODIS archives available from 2000 to present (Guerschman et al. 2015). In 2018, the MODIS NBAR MCD43A4 dataset was updated to collection 6, and with it the MODIS fractional cover product was also updated undergoing further calibration and validation (Guerschman and Hill 2018). Applications of the MODIS fractional cover dataset are a part of the Australian National University Explorer (Van Dijk 2016) which is a web application developed to summarise spatial data in order to report on the condition and changes occurring to the Australia landscape, the DustWatch program (DustWatch Australia 2019) and State of the Environment Reports (Department of the Environment and Energy 2018). It is therefore vital to ensure the accuracy of the MODIS product when it is used to inform a variety of end-users such as researchers studying rainfall erosivity and hillslope erosion (Zhu et al. 2019), forest decline (Evans et al. 2013) or vegetation dynamics (Zhou et al. 2016).

Soil colour has a significant influence on the variability of soil reflectance (Escadafal et al. 1989; Viscarra Rossel et al. 2010). Across a landscape such as Australia soil properties including moisture, texture and soil colour can vary considerably over short distances (Mouazen et al. 2005; Viscarra Rossel et al. 2006; Whiting et al. 2004). Past evaluations of the MODIS fractional cover estimates found that the bare soil component performs poorly in arid regions of Australia, where vegetation is sparse (Lawley et al. 2014). Other studies have explored soil properties to determine if they affect the production of fractional cover maps. Specifically, Guerschman et al. (2012) evaluated the accuracy of fractional cover estimates derived from the MODIS model across Australia. Evaluation of the effects of soil properties included soil colour data derived from the Digital Soil Atlas of Australia (Australian Soil Resource Information System 2009) and hyperspectral reflectance measurements of soil collected in the field at varying moisture conditions. This study highlighted that bright soils were associated with poor model performance in particular for the BS and NPV layers, but that soil colour in general did not affect the model. Soil moisture was also found to affect the estimation of cover especially in areas with a high proportion of exposed wet soil, finding that these areas are likely to be wrongly classified as non-photosynthetic vegetation. Guerschman et al. (2015) later explored the influence of soil moisture and soil brightness as a proxy for soil colour and found that there was no substantial influence on model performance. That analysis used digital soil colour maps developed from over 4000 hyperspectral soil measurements collected across Australia (Rossel and Chen 2011; Viscarra Rossel et al. 2010). Munsell hue, value and chroma maps at 5km resolution were derived from an RGB map produced using principal component analysis applied to hyperspectral measurements of surficial soil and interpolated from these across Australia to develop a full coverage map. It was noted that the coarse resolution of the information may have influenced results (Guerschman et al. 2015). Furthermore, these digital Munsell soil colour maps do not represent direct soil colour measurements but rather inferred colour based on spectral measurements that have been transformed and substantially interpolated. Therefore an area for future research is the use of direct *in situ* soil colour measurements to explore the effects of soil colour on MODIS fractional cover estimates.

As part of the 2009 Australian Government Ground Cover initiative, the Terrestrial Ecosystem Research Network (TERN) was established in order to provide standardised and integrated measurements of change to Australia's land-based ecosystem biodiversity. This is being delivered by providing open-access data and tools for researchers and infrastructure in order to contribute to a broader understanding of Australia's ecosystems (TERN 2017). AusPlots is a branch of TERN responsible for the plot-based surveillance monitoring program. The aim of AusPlots is to establish and maintain a network of plots for ecological assessment and on-going monitoring of ecosystems across Australia (TERN AusPlots 2017). The AusPlots Rangeland Survey Protocol (White et al. 2012) outlines the field methods used for surveillance and the data that is available. Point intercept ground cover surveys have been used to calculate the percentage of bare soil and photosynthetic and non-photosynthetic vegetation across each plot. This has the potential to be used to validate and calibrate image-based fractional cover products along with other satellite-derived products. Recording of soil properties at AusPlots sites was introduced late into the program therefore is only available for parts of the growing dataset. Soil information that is available includes soil characteristics, Munsell soil colour classification, soil cores, bulk density and soil samples. Soil samples collected are later stored as part of the CSIRO National Soils archive (White et al. 2012).

Other than Rossel and Chen (2011) digital soil colour maps and the AusPlots Munsell soil colour data, there is no other suitable national soil colour database available in Australia. Now that there is a larger number of surveillance sites with soil data available, the motivation of this study was to explore the potential effect of soil colour on the MODIS fractional cover product utilising this newly collected AusPlots data. The principal aim was to perform a systematic evaluation of fractional ground cover estimates derived from MODIS imagery to determine if soil colour had any influence on the product. The following objectives were used to address this aim and motivation: (1) to compare the fractional cover values derived from the MODIS product and the AusPlots ground measurements, thus providing a baseline understanding of how the image (MODIS) and field (AusPlots) estimates compare prior to the soil colour analysis, and (2) to examine if soil colour has any influence on the MODIS fractional cover product using qualitative and quantitative methods.

4.2 Materials & Methods

4.2.1 Field data

AusPlots field measurements were used as our *in situ* dataset and were accessed using the R package ausplotR (TERN 2019). Basic site information, fractional cover values for percentage green (photosynthetic vegetation), brown (non-photosynthetic vegetation) and bare (bare soil) and soil colour were calculated using the default settings (cryptogram assigned to NPV) and extracted from the AusPlots database. Each AusPlots site covers 100 by 100 m and is located in a homogenous area to enable upscaling of the data. At each site the latitude and longitude are recorded at the centre and four corners of the plot and a 1 m soil pit is dug in the south-west corner of the plot in order to record the soil profile and provide a general description of the soil for the site. Full details of the data collection protocols are provided in the AusPlots Rangeland Survey Protocol (White et al. 2012).

AusPlots data extracted from ausplotR was filtered to keep only surficial soil colour measurements collected from the soil pits. Sites that did not contain soil colour or contained soil data with errors were removed. This left 250 sites situated around Australia and surveyed between 2011 - 2018 (Figure 11) available for the analysis.

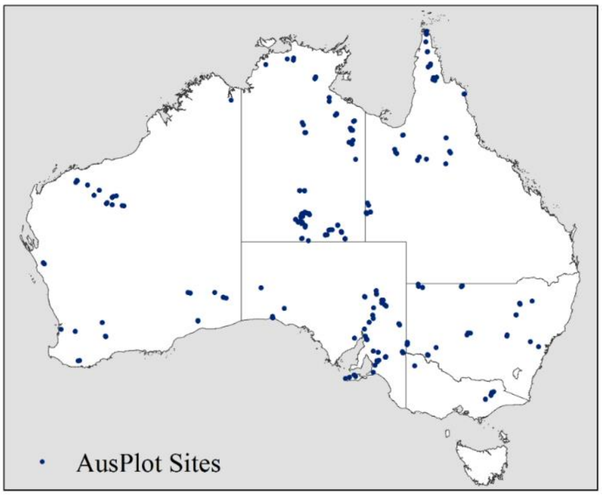

Figure 11 Location across Australia of 250 AusPlot sites used in the analysis.

Each of these 250 sites contains a Munsell soil colour classification which describes the hue, value and chroma of the soil sample taken at the site. The Munsell Soil Colour Charts (Munsell Colour 1992) were developed from the Munsell (1912) Colour System and Notation and are used to visually match soil samples with standard colour chips contained in the charts in order to provide a soil sample with a soil name. The Munsell colour notation is a traditional and reliable method that soil scientists use to provide an internationally consistent colour name that does not require translation. Munsell soil colour names consist of three components; hue, value and chroma. Hue is defined by the principal hues such red (R) and yellow (Y) and intermediate hues such as YR between the adjacent principal hues. The hue is preceded by a number ranging from 0 - 10, (i.e. 10YR) and as this number increases the hue becomes more yellow and less red. The value represents the lightness or darkness of the colour and is denoted by numbers ranging from 0 representing black to 10 representing white. Chroma defines the saturation of the colour and is represented by a number ranging from 0 – 20 in the Munsell (1912) colour charts but in the soil charts typically stops at a chroma of 8. An example of a complete Munsell colour classification from one of the AusPlots sites is 10YR 4/2 (hue = 10YR, value = 4 and chroma = 2). In this study hue was used as the key descriptor of colour as it represents the principal colour of the soil. Munsell colour can differ if the soil is wet or dry.

At the time of AusPlots sampling, surface soil is recorded as dry or moist (wet). Typically if the soil is dry (i.e. no moisture observed) the dry Munsell colour is determined before wetting the soil and recording wet soil colour. If the soil if already wet due to rain only a wet soil colour is recorded. The majority of the 250 sites available had both wet and dry soil classifications while others had only a wet classification. For the purpose of this study wet and dry soil colours were analysed separately.

4.2.2 MODIS Fractional Cover Product

The MODIS fractional cover product version 3.1.0 (Guerschman 2018) was used for this analysis and is developed from the MODIS MCD43A4 NBAR collection 6 (Schaaf and Wang 2015) imagery. The MODIS product is available from 2000 to present, hence we were able to match the AusPlot site field collection dates (2011 – 2018) to the MODIS product date and extract the corresponding MODIS fractional cover values. The MODIS product provides a centre date for each 16 day composite therefore AusPlots dates were matched to the 16 day date range and the corresponding MODIS fractional cover values were extracted.

4.2.3 Statistical Analysis

The R package Standardised Major Axis Estimation and Testing Routines (SMATR) (Warton et al. 2012) was used to test the relationship between the fractional cover values derived from the AusPlots data and the MODIS image product using the standardised major axis (SMA) function. Unlike typical regression models where the user is attempting to predict a dependent (Y) from and independent variable (X), the SMA model analyses a pair of variables, for example Y1 (i.e. AusPlots BS fractions) and Y2 (i.e. MODIS BS fractions) and determines how they relate to one another. The first analysis compared all sites with a wet soil colour classification and tested the relationship between the AusPlots and the MODIS fractional cover values. This was necessary in order to gain a baseline understanding of how the MODIS and AusPlot fractional cover values compared. The test was performed for the three ground cover categories PV, NPV and BS and this process was then repeated for sites with a dry soil colour.

The second analysis stratified the sites by wet soil Munsell hue and the SMA function was used to establish linear relationships between AusPlots and MODIS fractions for each hue. The linear relationships for all hues were then tested using the common slopes test for bivariate lines that is included in SMA function when requested. The common slope test examines the slope and elevation of the line of best fit for each group to determine if they differed from each other. This was again conducted separately for the BS, NPV and PV values as well as for wet and dry soil colours. A qualitative interpretation of the plots was conducted in order to visualise any observable patterns or trends in the data. This was assisted by the use of the R package Algorithms for Quantitative Pedology (AQP) (Beaudette et al. 2013) to colour each of the sample points with their associated soil colour chip from the Munsell soil colour charts.

4.3 Results

At the highest level, ignoring soil colour and just examining the relationship between the MODIS and AusPlots fractional cover estimates, our results demonstrate strong and statistically significant correlations for BS and PV, and weaker but still statistically significant correlations for NPV (Table 3) for sites with either wet or dry soil colour classifications.

Table 3 Relationships between MODIS and AusPlots BS, NPV and PV fractional cover for sites with wet (n = 250) and dry (n = 139) soil colour classifications.

	BS		NPV		PV	
	Wet	Dry	Wet	Dry	Wet	Dry
r^2	0.633	0.668	0.077	0.045	0.635	0.679
p-value	< 2.22e-16	< 2.22e-16	9.9042e-06	0.012	< 2.22e-16	< 2.22e-16

When beginning to examine the impact of hue, our results demonstrated slopes significantly different from 1 for almost all hues (Figure 12 and 13), but that the elevation of the line for most categories is not offset. This occurred for both wet and dry soil colour except for BS and NPV in the dry soil category. Comparison of the linear relationships for the wet soil colours and the PV dry soil colours shows that the slopes were significantly different while the elevation of the lines did not significantly differ except for the dry BS and NPV categories (Table 4) where the slope and elevation for each significantly differed.

Table 4 Comparison of linear relationships between hue groups for wet and dry soil colour classifications.

	BS		NPV		PV	
	Wet	Dry	Wet	Dry	Wet	Dry
Slope comparisons among groups (p-value)	0.004	0.538	0.010	0.003	0.034	0.078
Elevation comparisons among groups (p-value)	0.119	1.7613e-05	0.178	3.4126e-05	0.111	0.873

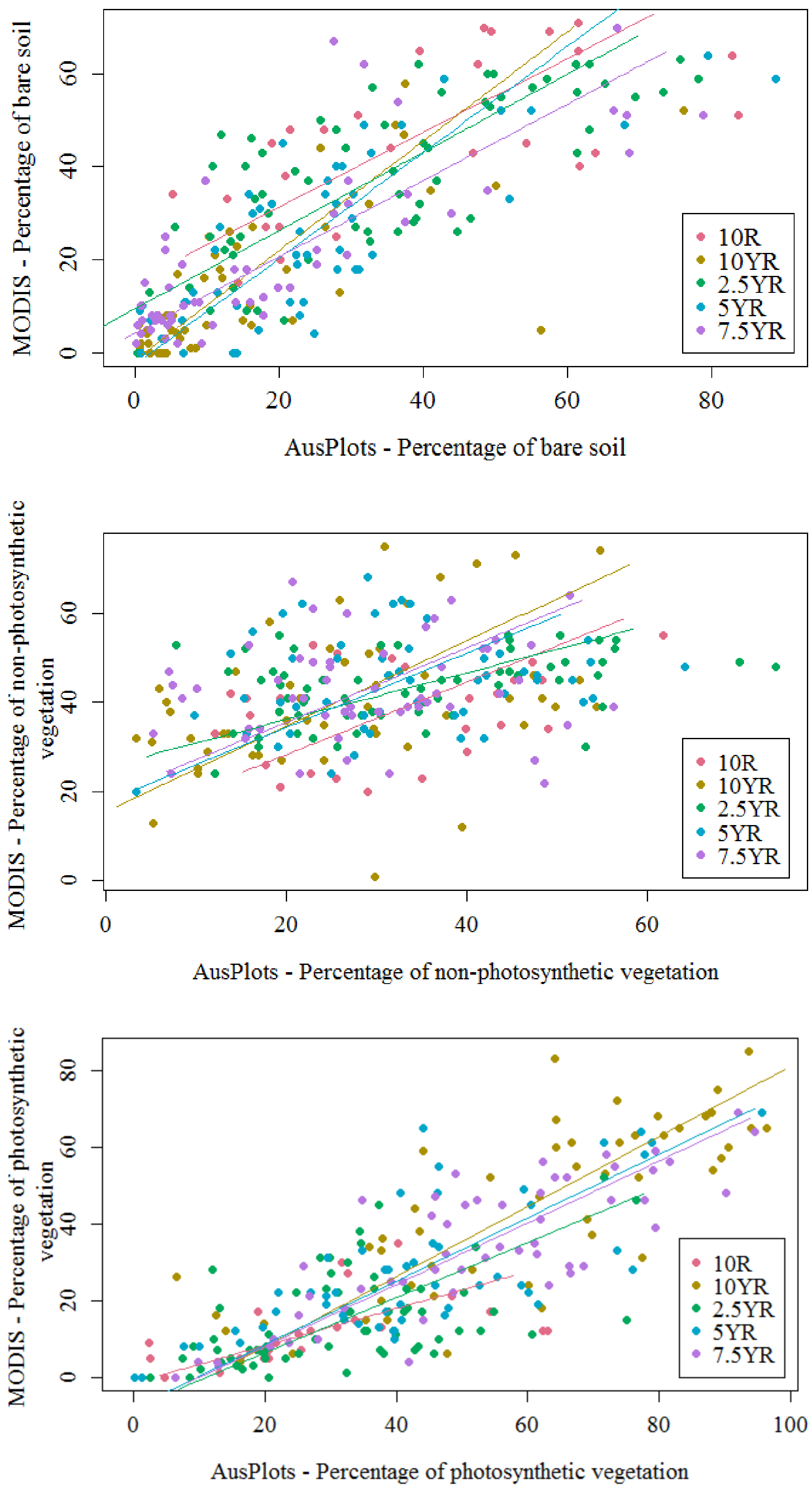

Figure 12 Lines of best fit for wet soil hues.

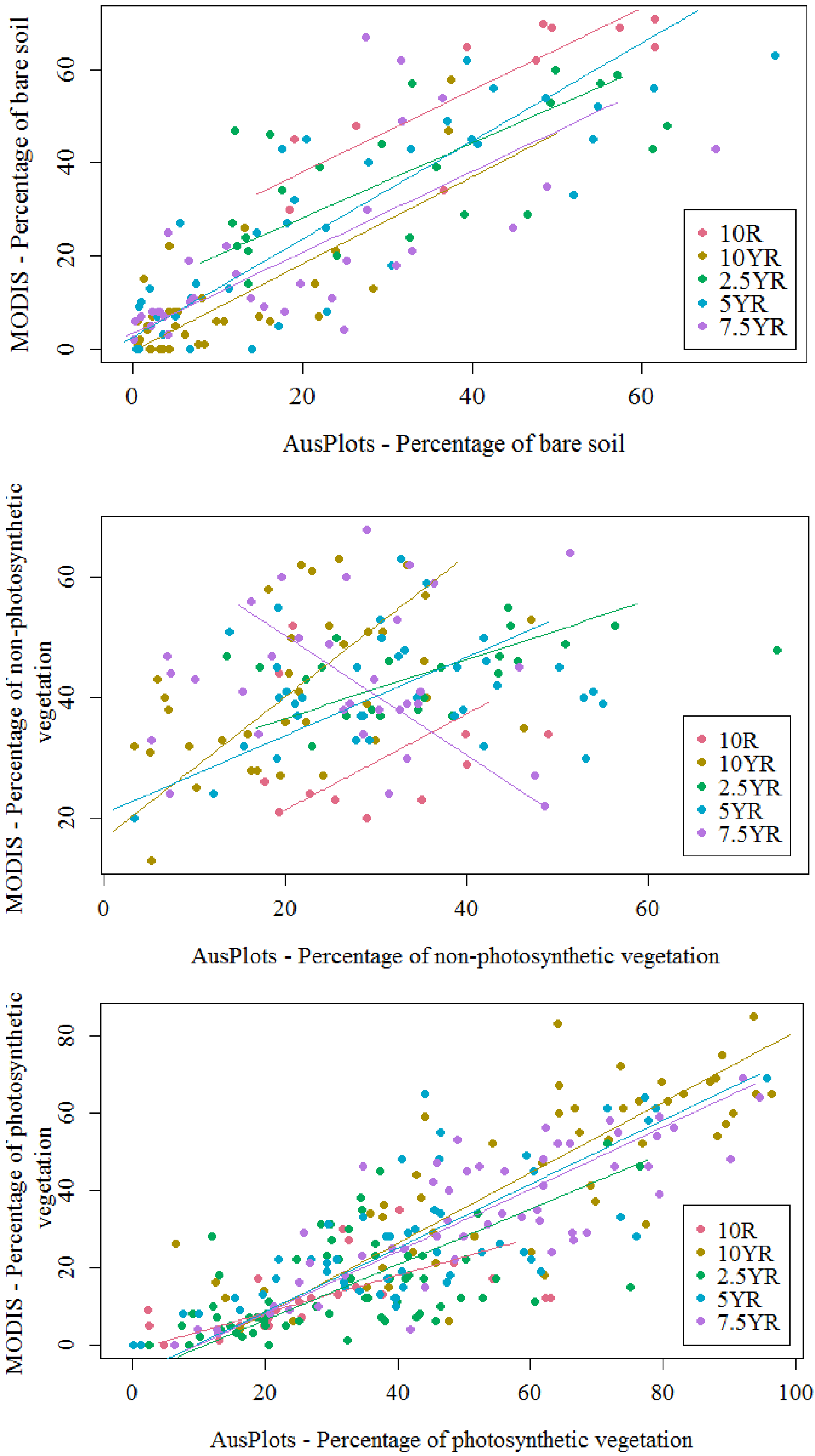

Figure 13 Lines of best fit for dry soil hues.

For BS the slope of the AusPlots-MODIS relationship does not significantly differ from 1 for any of the hue groups other than 2.5YR (slope = 0.84, CI 0.72 - 0.98 and 7.5YR (slope = 0.82, CI 0.69 – 0.97). Conversely, all NPV and PV slopes differ from 1. Overall BS is systematically overestimated by the MODIS product with the majority of the points sitting above the 1:1 line (Figure 14). NPV points typically sit higher than the 1:1 but are not distributed evenly across the line like BS and PV due to the weak relationship between MODIS and AusPlots for this class. PV also appears to contain a systematic bias where the MODIS appears to underestimate PV with the majority of points sitting below 1:1.

When examining specific hue relationships (Figures 15 - 20), there appear to be cases of substantial bias. The most extreme cases are PV for the 10R and 2.5YR hue, where the range of MODIS values (~ 0 to 30 %) is extremely compressed compared to the range of AusPlots values (~ 0 % to 80 %) with red soils having lower MODIS fractions and darker soils higher fractions. Other noteworthy cases are PV values for all other Hues (MODIS values systematically lower than AusPlots), soil for 10R (MODIS values systematically higher than AusPlots), and NPV for 2.5YR, 5YR, 7.5YR, and possibly 10YR (MODIS values systematically higher than AusPlots). For NPV, the darker soils colours are typically situated above the 1:1 line while red and light brown/yellow soils are situated in the middle or below 1:1.

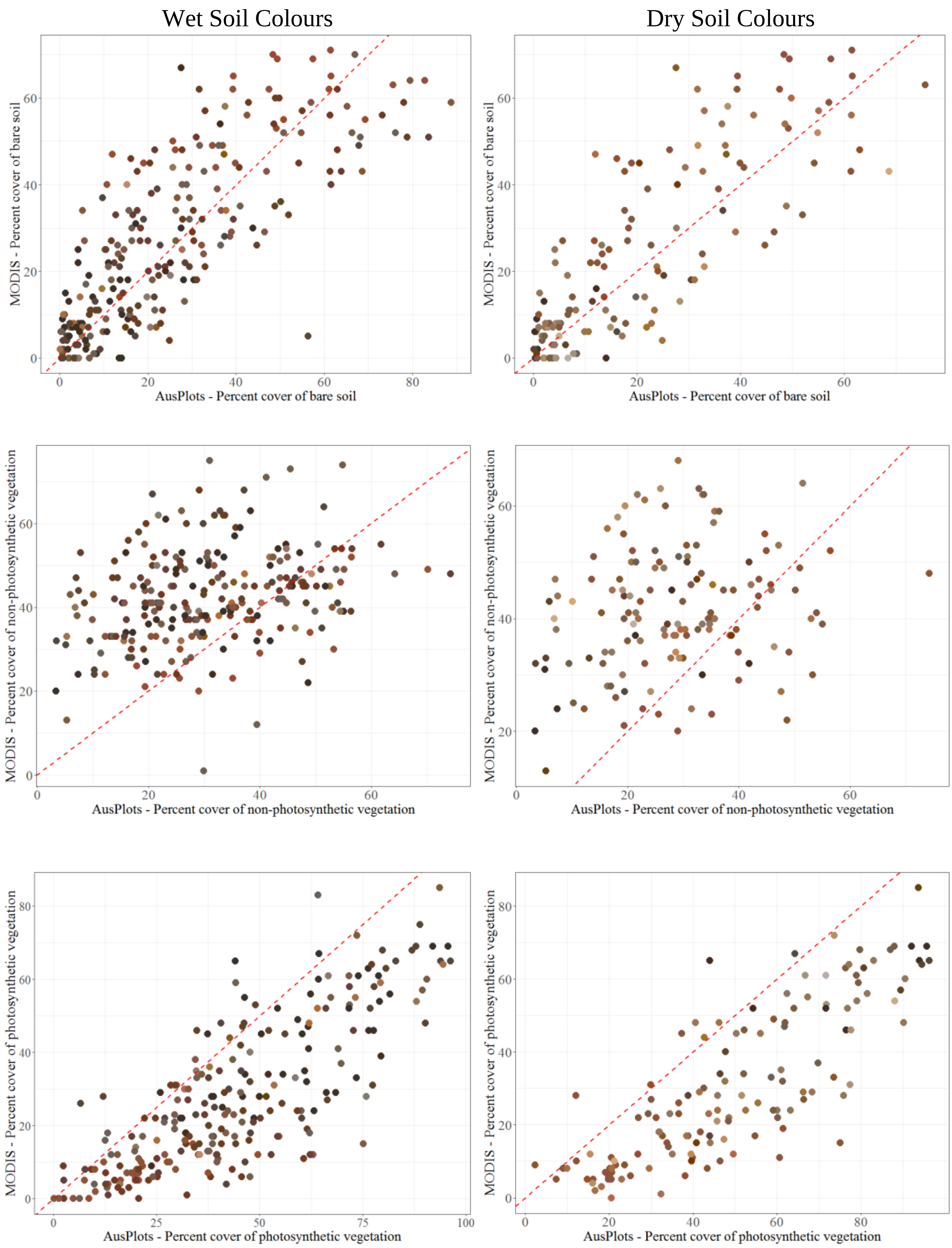

Figure 14 Comparison of MODIS and AusPlots fractional cover values for BS, NPV and PV. Red line represents the 1:1 line and the colour of each point represents the Munsell soil colour for that site. Wet soil colours are represented in the left column and dry soil colours in the right column.

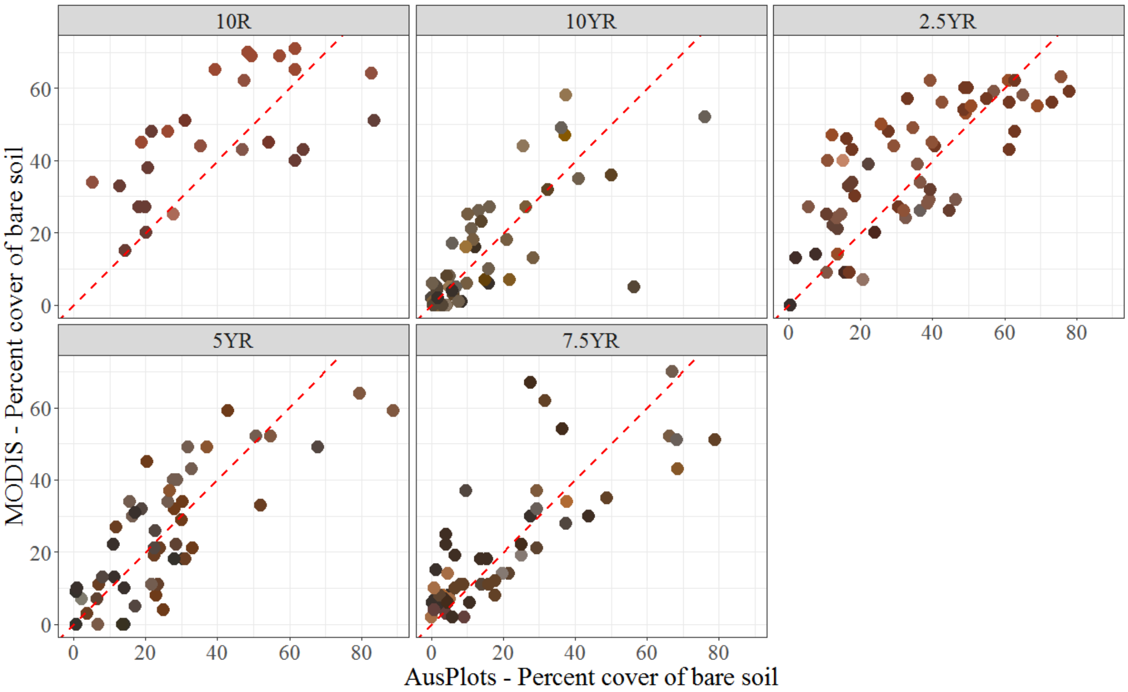

Figure 15 Comparison of bare soil fractions from MODIS and AusPlots grouped by Munsell hue (wet soil).

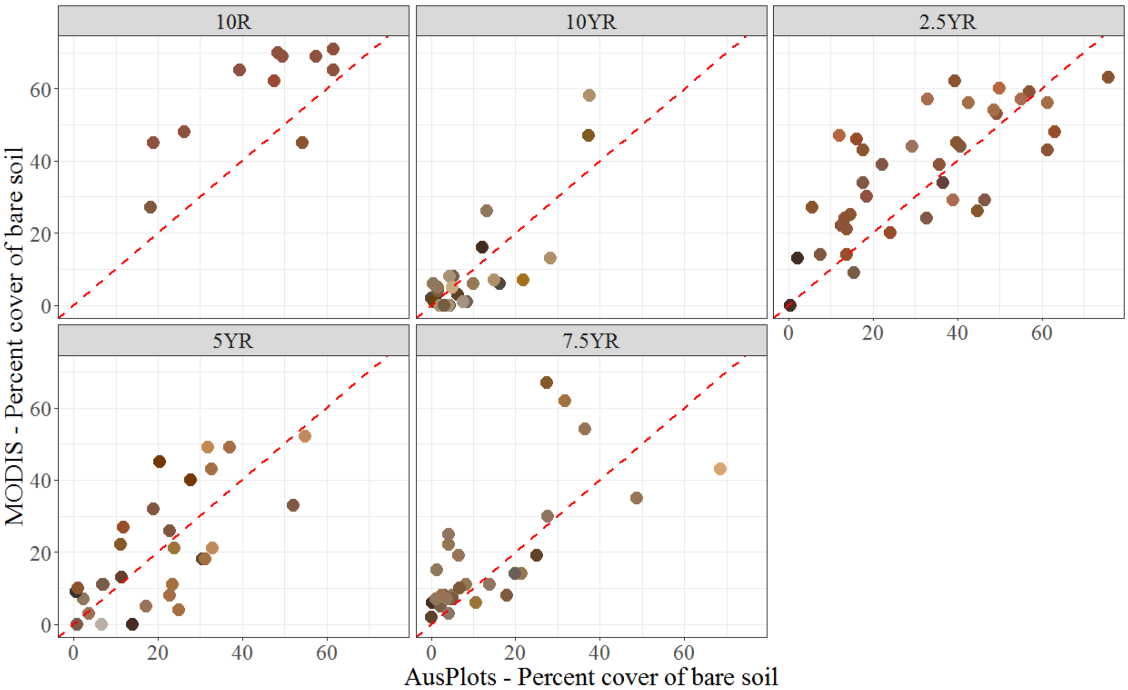

Figure 16 Comparison of bare soil fraction from MODIS and AusPlots grouped by Munsell hue (dry soil).

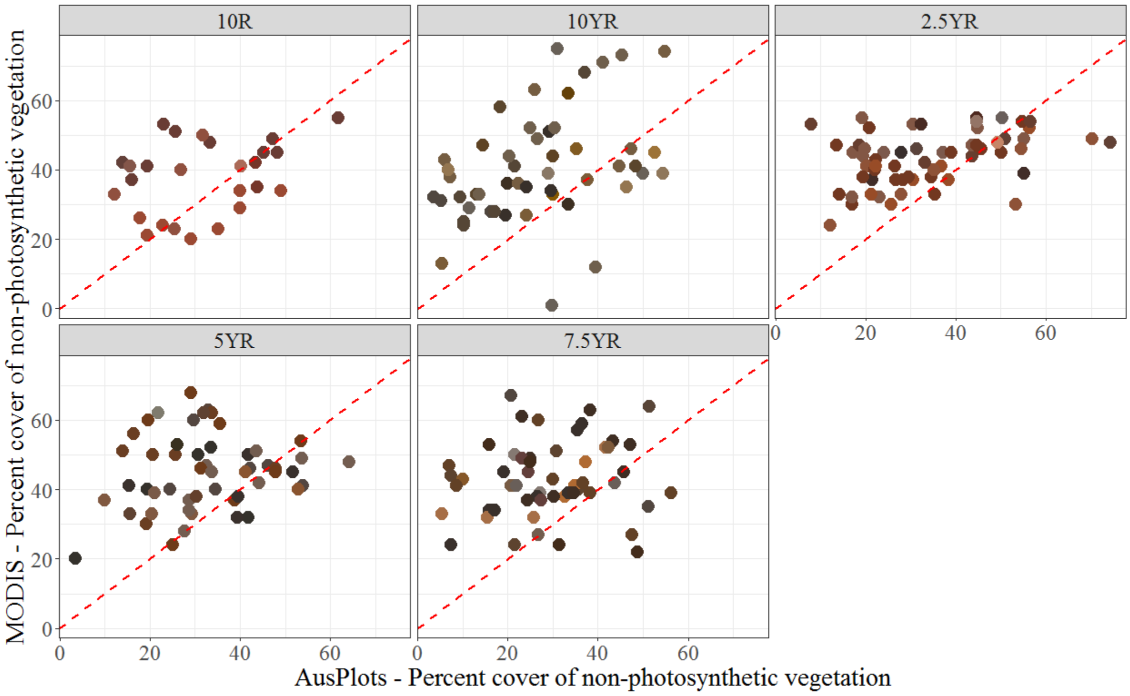

Figure 17 Comparison of non-photosynthetic vegetation fractions from MODIS and AusPlots grouped by Munsell hue (wet soil).

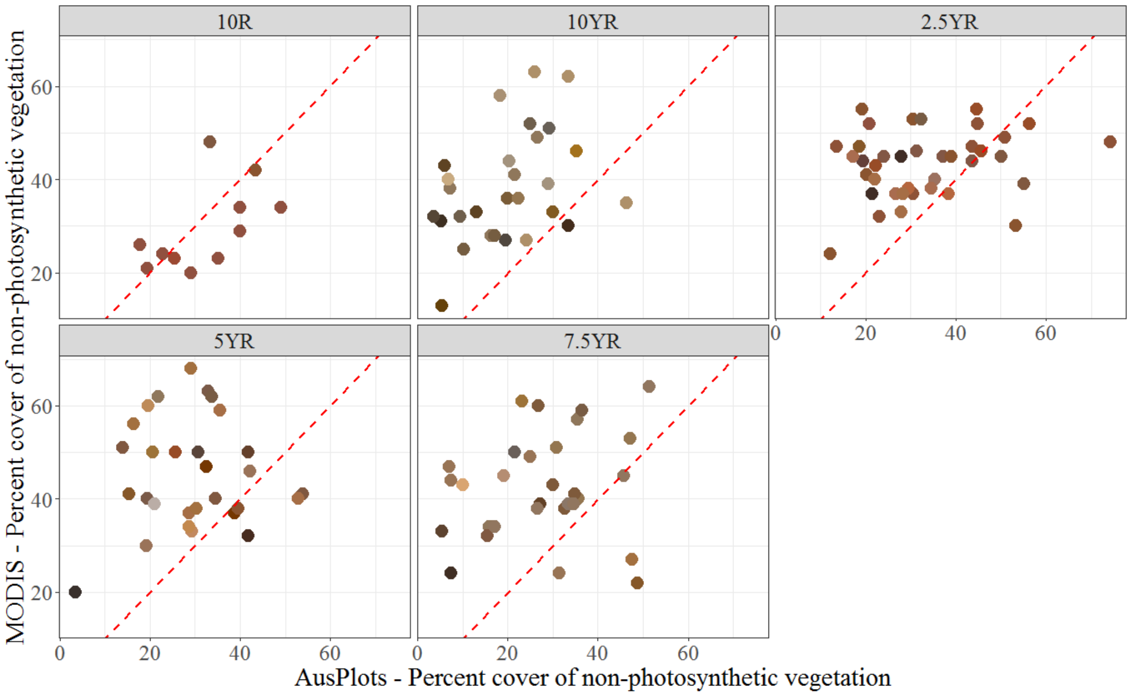

Figure 18 Comparison of non-photosynthetic vegetation fractions from MODIS and AusPlots grouped by Munsell hue (dry soil).

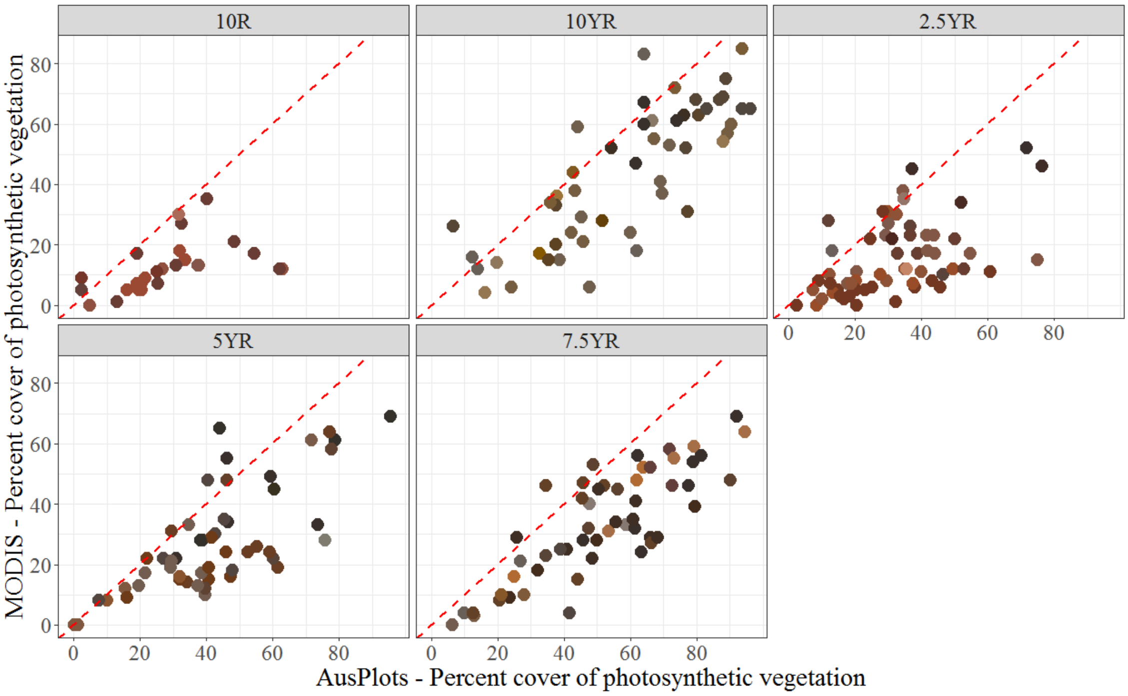

Figure 19 Comparison of photosynthetic vegetation fractions from MODIS and AusPlots grouped by Munsell hue (wet soil).

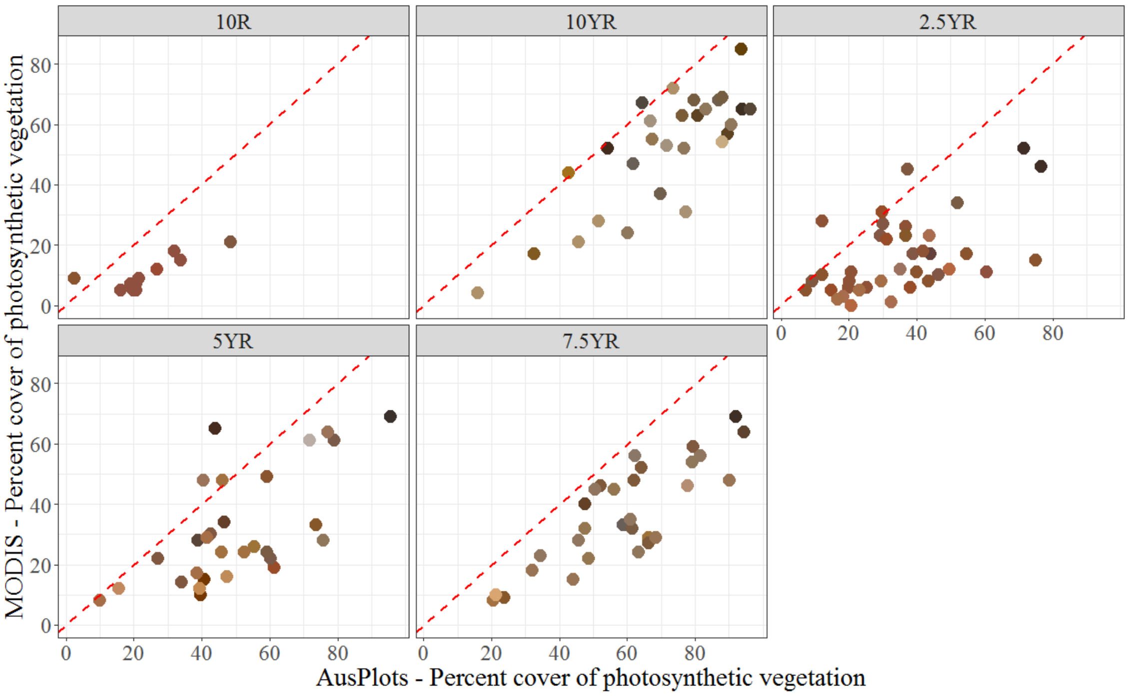

Figure 20 Comparison of photosynthetic vegetation fractions from MODIS and AusPlots grouped by Munsell hue (dry soil).

4.4 Discussion

The aim of this study was to perform a systematic evaluation of the Australian MODIS fractional cover product to determine if soil colour has any influence on the estimates of bare soil, photosynthetic and non-photosynthetic vegetation. By comparing the MODIS fractional cover product to AusPlots *in situ* measurements of fractional cover and soil colour, we have highlighted biases in the data and determined which soil colours are most affected.

Our first objective was to test the relationship between the AusPlots *in situ* fractions and the MODIS product fractions. Statistically significant relationships were observed for all three ground cover types with PV and BS showing the strongest relationships (r^2 between 0.63 and 0.68) and NPV showing a very weak but still statistically significant relationship ($r^2 = 0.05$ for dry soils; $r^2 = 0.08$ for wet soils). Thus, MODIS and AusPlots appear to be measuring the same ground cover types. However, we revealed that the MODIS product systematically underestimated PV and overestimated BS and NPV relative to the AusPlots *in situ* values and that the degree of over- or underestimation was influenced by soil colour (hue). For the BS and PV classes, our results are consistent with past studies conducted on the MODIS products that showed a strong relationship between *in situ* data and MODIS product BS, NPV and PV values (Guerschman and Hill 2018; Guerschman et al. 2012). The relationship between the MODIS product and AusPlot fractional cover values is similar to that demonstrated by Guerschman et al. (2012). They reported a high correlation between their field values and the MODIS product for PV and low correlation for NPV and BS. Examination of Figure 20 in Guerschman et al. (2012) shows that PV was underestimated by the MODIS product and BS was overestimated, consistent with our observations. This high correlation for PV is consistent with other studies and is likely due to the spectral uniqueness of photosynthetic vegetation which facilitates successful spectral unmixing

(Meyer and Okin 2015; Mishra et al. 2014). NPV and BS are more likely to be confused in the unmixing process and it is common in similar studies to see weaker relationships between image and field fractional measures for these cover types.

Our second aim was to examine the influence of soil colour on the MODIS product. Analysis of the sites grouped by soil colour (as represented by Munsell hue) revealed several colour-specific relationships. We detected a substantial influence of soil colour on the relationship between MODIS and AusPlot fractional cover. Overall, there was no relationship observed between the five wet hues analysed and the dry PV hues. This shows that a statistical difference is observed within the MODIS and AusPlot fractional cover values based on hue. An exception to this was for dry BS and NPV MODIS and AusPlot comparison where a relationship was observed between the hues. The effect of specific hues was most strong for PV where 10R and 2.5YR is underestimated and red soil colour are observed and associated with > 50% MODIS PV. The effect is also seen strongly for NPV; for dark soil colours NPV is overestimated by the MODIS product. For BS, the most observable effect is for red soils (10R) where MODIS over-estimates bare soil.

Our initial assumption was that the fractional values of the MODIS and AusPlots BS, NPV and PV should follow a 1:1 relationship and be distributed evenly either side of the line. This would suggest a 1:1 relationship between the image fractional cover values and the field values, confirming that the MODIS product was accurately representing ground cover conditions. For BS the relationships between MODIS and AusPlots fractions do not deviate from 1:1 for hues 10R, 10YR and 5YR whereas for all other hues in the PV and NPV categories they do deviate. Examining the bare soil plots shows that the majority of 10R sites sit above 1:1 and consists of sites with red soils while the majority of the 10YR sites are clustered within the 0 - 30% BS range of the plot. In the NPV plots the points are typically clustered towards the centre of the plot with the majority sitting above the 1:1 suggesting that the MODIS product is overestimating NPV.

Visual representation of soil colours for each site shows that dark soils (i.e. with a low value) within each hue sit above the 1:1 across most groups in the wet soil graphs while red soils sit near the 1:1 or just below the 1:1. For dry soil hue 7.5YR there was a negative relationship between MODIS and AusPlot variables. Lastly, considering PV again red soils sit low in the plot >30% MODIS PV and > 40 – 60% AusPlots PV especially for soil with a hue of 10R and 2.5YR. Otherwise darker soil colours typically sit higher and are more evenly distributed just below the 1:1 line.

Key strengths of the AusPlot soil colour measurements are that the sites are distributed across Australia and that the Munsell soil colour represents first-hand field observations. Five hues that represented red and red yellow soils were available for analysis: 10R, 10YR, 2.5YR, 5YR and 7.5YR. These five hues represent a majority of those outlined in the Munsell Soil Colour charts. Hues 2.5Y and 5Y were not included since there were too few sites available for analysis at the time of this study and there were no AusPlot sites that represented any of the Gley hues (Munsell Colour 1992).

A limitation of our study is that we have up-scaled field data collected over a 1 ha area and compared it to a MODIS pixel (500 m^2), such up-scaling of data is regularly used due to the intensive and time-consuming nature of collecting field survey data. In contrast, Guerschman et al. (2015) utilised an Australia-wide digital soil colour map that had a spatial resolution of 5 km and underwent significant processing in order to produced the digital Munsell maps (Viscarra Rossel et al. 2010). This processing has implications for the Munsell soil colours developed and may have affected the result of previous soil colour / soil brightness studies.

Another limitation is that the collection of soil colour information was introduced late into the AusPlots survey meaning that only 250 sites around Australia out of the approximately 733 sites available at the time of this study could be utilised. As new AusPlot sites become available or old sites that lack soil information are revisited it would be useful to revise this analysis and determine if these trends are more widespread as well as investigate the influence of currently un-sampled soil hues.

Fractional ground cover values derived from MODIS imagery are a valuable resource for scientists and land managers especially for those that require broad-scale or continent-wide estimates of ground cover. Analysing Munsell soil colour notations, AusPlot and MODIS fractional cover data has uncovered soil colour bias that has not been previously discovered in the MODIS product. Future studies should utilise this information to determine if the MODIS fractional cover algorithm can be calibrated to minimise or remove the effects of soil colours therefore producing a more reliable product for end-users.

4.5 Conclusion

The MODIS fractional cover product is an important resource in Australia for monitoring and reporting on changes to our landscape and ecosystems. It is essential to ensure that this data is a good representation of the Australian environments and where possible to improve the model through calibration and validation. Past studies used coarse resolution soil colour maps derived from transformed and interpolated soil spectra to understand the influence of soil colour on the MODIS fractional cover product. These studies reported that soil colour or soil brightness did not influence the MODIS product but there is some doubt about this conclusion. This study used AusPlots *in situ* measurements of fractional ground cover and Munsell soil colour to determine if there was an observable influence of soil colour on the MODIS product.

We found that compared to the AusPlots fractional cover values the MODIS product systematically overestimates BS and NPV and underestimates PV. Secondly, there is a significant difference between the MODIS – AusPlots fractional cover relationship for five hues recorded in the 250 sites studied across Australia, suggesting that soil colour has an observable effect on the MODIS fractional cover values. Lastly, we found that for the bare soil fraction, sites with a hue of 10R and 10YR were observably different from the other hues. In the non-photosynthetic fraction darker soil colours (low value) where associated with sites where the MODIS product overestimated non-photosynthetic vegetation. For photosynthetic vegetation, sites with a hue of 10R and 2.5YR were associated with lower photosynthetic vegetation values (>25% PV) reported by MODIS product and darker soils were associated with higher photosynthetic values (< 25% PV). While this study is limited to 250 sites across Australia these results suggest that soil colour does have an observable influence on the MODIS product and requires further exploration to determine how these soil colour effects can be mitigated in future versions of the MODIS product in order to ensure that natural resource managers, farmers and scientists have the best quality information for decision making and future research.

4.6 References

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CHAPTER FIVE

DISCUSSION AND CONCLUSIONS

Earth observation data is an essential resource for exploring our natural and built environment. Environmental concerns such as land degradation and regeneration (Eckert et al. 2015), desertification (Ajaj et al. 2017), fire severity (Loschiavo et al. 2017), vegetation dynamics (Jamali et al. 2015) and ocean productivity (Auricht et al. 2018) are a few examples of studies that can utilise earth observation data to understand, monitor, and manage these issues. This thesis has focused on fractional ground cover products developed from remotely sensed measures of the proportion of vegetation and soil cover, which can be used as indicators of landscape condition or the success of management practices. Calibration and validation are essential steps in the development of satellite-derived fractional cover products to ensure reliability and provide users with confidence in the quality of the information used for decision making and further modelling or monitoring. The overarching aim of this thesis was to investigate methods of improving fractional ground cover mapping in Australia. This aim was approached from two angles (1) studying the collection of validation data, and (2) a systematic evaluation of soil colour influence on satellite-derived fractional cover estimates for Australia.

5.1 Key Outcomes

Chapter two investigated the collection of fractional cover field measurements using hyperspectral sampling. This was the first time hyperspectral sampling was tested in Australia for the validation of fractional cover mapping, and this chapter outlines an appropriate sampling design for this survey technique. Hyperspectral reflectance measurements of ground cover were shown to produce comparable estimates of fractional cover to traditional step-point measurements but with advantages such as improved consistency and objectivity of measurements as well as logistic ease of use. Comparing both *in situ* methods with two current Australian image-derived fractional cover products produced from Landsat and MODIS imagery showed that overall both datasets were strongly correlated with the *in situ* values but that this relationship did differ between the two image products. While this study was limited in its sample size, this method shows considerable potential and should be explored further. In Australia, TERN's AusPlot facility is responsible for plot-based surveillance of ecosystems across Australia in order to monitor and contribute to our broader understanding of the Australian landscape. While hyperspectral imagery is collected at what are known as TERN supersites, these are limited to 15 sites across the country. One key reason TERN was established was to collect and manage data that could be used to calibrate and validated remotely sensed products created for landscape and ecological assessment purposes. The adoption of hyperspectral sampling in the AusPlot rangeland protocol would provide invaluable data to Earth observation scientists in Australia.

When collecting *in situ* measurements of ground cover using traditional methods such as step-point, wheel point or transect-based sampling, it is common to have multiple observers contributing to a single dataset that will be used to calibrate or validate remotely sensed products. Sampling designs are generally created to be consistent and easily repeatable, but observers still have the potential to introduce errors in particular when classifying photosynthetic and non-photosynthetic vegetation. Chapter three examined observer consistency when classifying vegetation photosynthetic status and examined the relationship between the classification of vegetation spectra and human observations. Unlike discriminating other ground cover types in the field such as soil and rock, photosynthetic and non-photosynthetic vegetation are better thought of as extremes of a continuum rather than binary categories. This makes distinguishing between the two categories difficult. We found that at the extremes (100% PV or 100% NPV) observers were consistent in their observations and strongly agreed with the spectral classification but as the leaves senesced variation between observers increased and overall we saw up to 17% variation between observers classifying photosynthetic leaves and 14% non-photosynthetic leaves. Similar to the observer agreement at the extremes of leaf photosynthetic expression there was a substantial agreement between observer decisions and spectral classification but as the leaves transitioned this relationship weakened, with little agreement for leaves close to 50%. This comparison between observers is not typically conducted in the field as field surveys are time-intensive and expensive. Implications of this study are that users have more information when deciding which field technique should be used to estimate fractional cover. For example, if the majority of vegetation in the field is expected to be close to 100% green or dry then the field observers may be satisfied with traditional observer surveys, but if the majority of vegetation is senescing, then hyperspectral sampling provides a more objective means to collect field observations. Conducting this study in a controlled scenario ensured observers were categorising the same samples, in the same locations, which in conjunction with the collection of the spectral measurements ensured observer consistency could be examined successfully. While we cannot directly apply our results to other studies, it provides a baseline understanding of how observers can react when categorising vegetation as green or dry.

The overarching aim of this thesis was to investigate methods of improving fractional ground cover mapping in Australia. Chapters two and three studied the collection of validation data while chapter four's aim was to perform a systematic evaluation of fractional ground cover estimates. The Australia MODIS fractional ground cover product provides essential data for landscape and ecological monitoring in Australia and has been revised multiple time since its initial development in 2009 to improve the accuracy of the data (Guerschman and Hill 2018; Guerschman et al. 2009; Guerschman et al. 2012). Past versions of the MODIS product were found to provide poor estimates of cover in arid regions where vegetation is sparse, and soil dominates the ground cover (Lawley et al. 2014). Regions in Australia with bright soils have also been associated with poor model performance (Guerschman et al. 2012). A recent study found that soil brightness did not affect the MODIS product but recommended that this result be examined further. Specifically, the coarse resolution of the digital soil colour maps (5 km) used was thought to influence the results (Guerschman et al. 2012; Guerschman et al. 2015). An additional concerning factor is the processing undertaken to create the maps. Over 4000 hyperspectral measurements of soil collected across Australia were processed and interpolated to create continent-wide maps. This chapter instead used direct soil colour measurements collected as a part of national AusPlots surveys. An initial assessment of MODIS fractional cover estimate found that for 250 AusPlot sites across Australia strong correlation between BS and PV MODIS and the AusPlots *in situ* measurements. While NPV displayed a weak relationship, it was still statistically significant. Using direct Munsell soil colour measurements showed that for the five soil hues present across the 250 sites are significantly different from one another and that this difference in hue across the sites is observable in MODIS and AusPlot fractional cover data. Lastly, we were able to determine which hues were associated with over or underestimation of MODIS fractional cover values such as 10R associated with the overestimation of BS and the underestimation of PV. This work has provided a greater understanding of the pattern and influences that soil colour has on the MODIS products. This knowledge should be used to guide future research efforts to calibrate the MODIS product in order to mitigate the effects of soil colour on the extraction of fractional cover values.

5.2 Significance and implications of the research

Findings from this thesis demonstrate that hyperspectral sampling is a viable method of improving the collection of fractional cover validation and calibration data. Hyperspectral transect sampling provides an objective and consistent way to collect ground cover data, and our study found that it performed well in arid rangelands. This thesis demonstrates an alternative field survey method that can be used to collect validation data which removes subjective decision making by observers and reduces problems associated with the consistency of data collection. While this data was collected specifically for fractional cover validation, these measurements have the potential to be used to validate or calibrate other remotely sensed products. For example reflectance measurements are being used to validate Australian surface reflectance products from Landsat and Sentinel imagery using a similar survey design (Malthus 2019). Efforts should be made to create a national standard for the collection of ground reflectance measure outlining a standard procedure to ensure that the data is suitable for multiple applications.

Chapter three explored the inconsistency in observer classification of photosynthetic and non-photosynthetic vegetation. Understanding these inconsistencies is critical to understand potential bias that could be introduced into a validation dataset. Observers who over- or underestimate photosynthetic or non-photosynthetic vegetation create bias in the data collected that will be used to validate an image-derived fractional cover map. The flow on effect is that the accuracy assessment will be biased and will not appropriately assess the image product. Understanding inconsistencies and bias that can be introduced into validation datasets may help explain errors that are observed when comparing field estimates to image-based estimates. Chapter three also highlighted that there is potential to improve the definition of green and dry leaves that are provided as part Muir et al. (2011) technical guide for field measurement of fractional cover. Lastly, this chapter emphasized the benefit of using hyperspectral sampling of vegetation to classify vegetation. Hyperspectral sampling provides more consistent and objective records of vegetation cover as well as providing greater information about vegetation status beyond whether the leaf is photosynthetic or not. The chapter recognises when it is appropriate to use traditional step-point or when hyperspectral sampling would be more beneficial. For example when sampling an area that is expected to contain vegetation close to 100% green or 100% dry then traditional observer-based sampling is adequate but if the majority of vegetation will be senescing then spectral sampling is a more reliable, objective sampling technique.

Chapter four outlined the observable affect soil colour has on fractional ground cover estimates derived from MODIS imagery. While past studies stated that soil colour, in general, does not influence MODIS fractional cover values, chapter four utilised direct field measurements of soil colour to demonstrate that across 250 AusPlot sites soil colour does have an observable effect on MODIS fractional cover. The chapter specifies which soils colours are associated with over- or underestimation of soil, photosynthetic and non-photosynthetic vegetation as well as other observable effects. This knowledge will have significant implications for those working to improve fractional cover mapping. Understanding the influence of soil colour and specifically what is occurring in the MODIS data is the first step in developing a way to mitigate or remove the effect of soil colour in future versions of the MODIS product. The intention being that through removing soil colour errors the MODIS product will provide an improved representation of Australian soil and vegetation exposure especially for areas containing high proportions of exposed soils.

5.3 Recommendation for future research

The following are areas of future research that have been identified as part of the work presented in the thesis.

- Development of a technical guide outlining a national approach to the collection of hyperspectral field measurements of fractional cover for the calibration and validation of remotely sensed ground cover maps.

- Trials of hyperspectral ground cover sampling in a variety of other environments across Australia to further explore the potential of this method and identify any problems that may be encountered related to specific environments (i.e. those containing < 2 m overstory vegetation).
- Refinement of the definitions used in Muir et al. (2011) technical guide to define green and dry leaves.
- Examination of the consistency of observer observations of photosynthetic and non-photosynthetic for other vegetation types.
- Expansion of research in Fisk et al. (2019) (chapter three) to include more vegetation samples in order to learn more about the decisions made by observers classifying vegetation within the 25 % -75% photosynthesis range.
- Development of calibration methods to mitigate the influence of soil colour in order to improve fractional cover values derived in future versions of the MODIS fractional cover product.
- To use direct hyperspectral measurements of soil to further analyse the effects of soil on the MODIS fractional cover product.
- To examine the classification of soil crust / cryptogram as photosynthetic or non-photosynthetic vegetation for the calibration and validation of fractional cover maps.

5.4 Conclusions

Calibration and validation is an integral part of the developed of remotely sensed products. Validation should not be an afterthought and should be considered during the development of these products where possible, and more consideration needs to made by the global remote sensing community to develop standard methods of collecting fractional ground cover data through traditional and new techniques like hyperspectral field sampling. This thesis has outlined the potential of hyperspectral field sampling showing that it is a comparable to traditional sampling methods when conducted at the same scale and provides improved objectivity, increased information and has greater potential to be used for producing and assessing other remotely sensed products. It has outlined how field observers are likely to vary based on the level of photosynthetic activity when conducting traditional and widely-used field sampling of ground cover. This information can be used to determine which method should be used field campaign in relation to the state of the vegetation (i.e. 100% photosynthetic, senescing or 100% non-photosynthetic). Lastly, the effects of soil colour were explored and soil was found to have an observable effect on the MODIS fractional cover product with specific colours associated with significant bias. This work has highlighted the need for further research to be conducted in order to minimise the influence of soil colour on the MODIS product. Overall, improving fractional ground cover mapping needs to be approached from multiple angles. The work conducted in this thesis will contribute toward the improvement fractional cover maps and the data used for validation. These improvements will help to ensure scientists are able to develop high quality datasets and that end-users such as researcher or land managers can be confident in their decisions informed from these measures.

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