Reconstructing Lake Hydrological Variability using Satellite Imagery: A case study for western Victoria, Australia

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RECONSTRUCTING LAKE HYDROLOGICAL VARIABILITY USING SATELLITE IMAGERY: A CASE STUDY FOR WESTERN VICTORIA, AUSTRALIA

ABSTRACT

Australia is well known for its climate of relatively low rainfall and high rates of evaporation and due to these sorts of conditions, lakes can be considered quite rare. However, even due to this rarity, lakes in Australia represent important landscape features that hold environmental, cultural and economic value. With forecasted increases in temperature and declines in rainfall for the future, this will have a negative impact on Australia's lakes, however, these effects are poorly understood. Therefore, there is a need for research that examines the response of lake hydrology to climate change. One approach that has proven effective, is the involvement of satellite-based observation methods. This study adopted an approach of using Landsat imagery to reconstruct the surface area of 15 lakes in western Victoria. Data were obtained from the Water Observations from Space (WOfS) algorithm accessed through the Digital Earth Australia (DEA) data platform, to infer lake surface area change from 1987 – 2020. By comparing surface area changes to annual rainfall and evaporation data, the resulting correlations give better insight in explaining if the correlations are best described by either one of these variables independently, or if lake variation is determined more so by a combination of factors. The results of this study demonstrate that each of the 15 lakes show very similar responses in annual maximum surface area variation. Despite morphological differences between the lakes, the similarity in their surface area responses implies a universal factor being strongly responsible for their hydrological variability – namely climate variability. Correlations with individual climate variables and lake surface areas are low, leading towards the idea that lake variation cannot be examined through only one independent variable, but rather a combination of factors that all have differing effects on lake fluctuation through time. Understanding which combination of factors go into determining individual lake fluctuation is crucial to understanding how lakes respond to changing climate conditions. To ensure lake survival into the warming and drying future, more focussed, process-based research into the fluxes of water into and out of these lakes is needed in order to comprehend the resilience of the lakes under future climate changes.

KEYWORDS

- Climate Change
- Lake Variability
- Landsat
- Satellite Imagery
- Surface Area Change
- Water Observations from Space (WOfS)
- western Victoria
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INTRODUCTION

Lakes are extremely vulnerable to projected climate warming and drying and due to their rarity of existence within the Australian climate, they are highly valued. Understanding how surface area has varied in the past is crucial to determining how lakes will respond to future climate changes. Since 1950, global climates have been warming significantly due to human activities (Steffen & Hughes, 2013). Looking into the future, climate conditions within Australia are expected to get warmer, accompanied with decreased rainfall (Yihdego et al., 2015; Pittock & Salinger, 1991) resulting in this critical need to understand how lakes respond to a changing climate becoming more urgent. Certain lakes have had their future levels calculated to different GCMs (Global Climate Models) through to 2100 which concludes that levels will continue to decrease into the near future (Kirono et al., 2012). With this critical need to better understand past and present lake hydrology, the current level of knowledge regarding the effects that climate warming has on lakes is substantial, however, the data required to back up this statement is lacking.

Various techniques have been used to measure and monitor lake hydrology, one being remote sensing. The implementation of satellites as a means of data collection has many benefits, a couple of which include, its accuracy and speed of collection as well as being able to access historical data, as opposed to using in-field data or dated lake bathymetry and survey information (Duan & Bastiaanssen, 2013). This study has utilised remote sensing to reconstruct lake surface area variability to emphasise the idea that the lack of knowledge regarding lake variation due to climate can be reduced through satellite observation methods as a means of data collection.

Understanding past and current lake hydrology mechanisms is crucial to improving present knowledge on the effects of climate warming as the near future approaches. The main aims for this study are to investigate lake hydrological responses to climate variability within western Victoria, between 1987 – 2020. Within this, the effect of lake morphology and surface area will be evaluated by comparing a range of different lakes within the region through the use of remote sensing.

BACKGROUND

LOCATION

The Newer Volcanics Province of western Victoria is an ideal case study for the investigation of lake responses to climate because the region has multiple lakes, representing a broad range of environmental states. The region of interest, within the Newer Volcanics Province, spans an approximate area of 3,330 km^2, (latitude: -38.05 to -38.35, longitude: 143.00 to 143.90), situated 100 km west of Geelong, Victoria (Fig. 1). The region is composed of Plio-Pleistocene basaltic lava flows that range from 10 – 130 m thick. The older flows (1 – 6 Ma) are covered in thick, clay-rich soils which can get up to 10 m in thickness. The more recent basalts (300,000 to 8,000 years old) are dominated by rocky outcrops that have little soil development and frequently form aquifers that spread around individual volcanoes (Yihdego et al., 2016). 15 lakes were selected, Lakes: Beeac, Bookar, Bullenmerri, Colac, Colongulac, Corangamite, Elingamite, Gnarpurt, Gnotuk, Keilambete, Martin, Murdeduke, Purrumbete, Rosine and Weering.

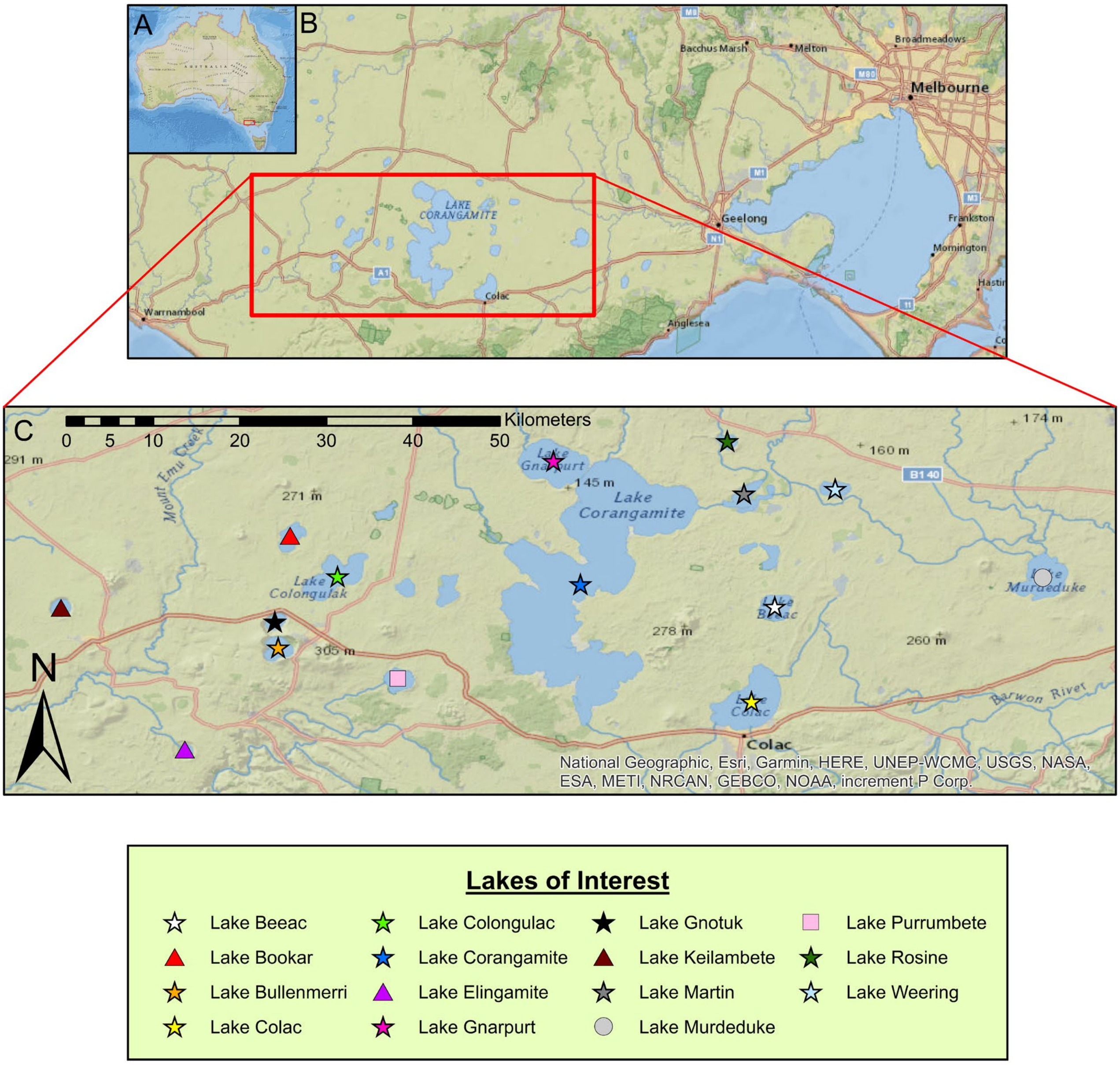

Figure 1: (a) Map of Australia with highlighted study region. (a) Highlighted study region in relation to Melbourne. (c) Enlarged study region with locations of each lake of interest. Star symbols represent lakes in the Corangamite Basin, triangle symbols represent lakes in the Hopkins River Basin, square symbols represent lakes in the Otway Coast Basin and circle symbols represent lakes in the Barwon River Basin.

LAKE INFORMATION

Most of the lakes in the study region are situated within the Corangamite Basin which consists of different sub-basins that drain into separate terminal lakes. This basin is predominantly fed by The Woady Yaloak River which drains into Lake Corangamite and Lake Martin (Leahy et al., 2010). Other lakes involved in this study are situated in adjacent basins resulting in a variety of water inputs throughout the region, one of which is the Curdies River that supplies Lake Purrumbete with runoff input. (Yihdego et al., 2016). The lakes involved in this study span many different characteristics: ranging from semi-permanent, hyper-saline lakes – Lakes Beeac and Weering. Shallow (<5 m), permanent, saline lakes – Lakes Bookar, Colongulac, Gnarpurt and Rosine, and also deep (>5 m), permanent saline lakes – Lakes Bullenmerri, Corangamite, Gnotuk, Murdeduke. The inclusion of freshwater lakes is represented by two open freshwater, shallow lakes – Lakes Colac and Martin and three open freshwater, deep lakes – Lakes Elingamite, Keilambete and Purrumbete (Leahy et al., 2010). Individually, these lakes hold varying degrees of importance. Six lakes are Ramsar listed due to their recognised importance to conserving biological diversity. Some have been used to generate palaeoclimate reconstructions: Lakes Bullenmerri, Colac, Elingamite, Gnotuk, Keilambete, and Purrumbete (Bowler, 1981; Chivas et al., 1993; Wilkins et al., 2013; Yihdego et al., 2015; Tyler et al., 2015; Tibbey et al., 2012) These lakes of interest are also a source of recreational and economic use in the forms of boating, commercial fishing and a range of entertaining activities for the Ramsar listed lakes (Kirono et al., 2012; Hale & Butcher, 2011).

LAKE RESPONSES TO CLIMATE IN WESTERN VICTORIA

There has been a number of previous published studies on these lakes in the western Victorian region, Lakes Bullenmerri, Gnotuk and Keilambete are just a few examples that represent the broad range of studies that have been completed in the past. P/E ratios have been determined for these lakes (Jones et al., 1998), along with models of their historical lake levels (Jones et al., 2001) and how climate change has impacted these lakes and their potential future risks (Kirono et al., 2012). The use of satellites for methods of data collection regarding surface area changes has also been utilised in the past to achieve similar analyses. By implementing a satellite-based data collection method in conjunction with field based measurements, limitations regarding insufficient data from field measurements are being overcome (Tweed et al., 2009). Field based methods involve the use of *in-situ* gauging stations installed near water sources (Duan & Bastiaanssen, 2013) and one of its biggest limitations is being able to only record data in the present day, and because of this there is a lacking in historical data associated with field based measurements. As technology continues to improve, studying lake fluctuation will not require in-field measurements as a means of data collection as remote sensing is proving promising (Smith, 1997; Douglas et al., 2007; Leblanc et al., 2006).

SATELLITE REMOTE SENSING

Satellite imagery as the method for data collection, in particular, the Landsat series satellites use, ‘thematic water surface extraction algorithms’ which are categorised into satellite spectral bands and different kinds of water indices (Rundquist et al., 1987; Gao, 1996; McFeeters, 1996). Another benefit associated with satellite imagery is its uses of multispectral wavelengths. Landsat multispectral imagery comprises different wavelength ‘bands’ that can be displayed in multiple combinations to enhance particular features (Mueller et al., 2016). Water can be identified from Landsat data using the Modified Normalised Difference Water Index (MNDWI). Water is detected using the green band (band 2) and the short-wave infrared band (band 5) (Xia et al., 2019). This MNDWI index is the most up to date and effective water detection index available. It has been improved from the NDWI (Normalised Difference Water Index) by replacing the near infrared (NIR) band with the short-wave infrared (SWIR) band due to the SWIR bands increased effectiveness at reflecting more subtle characteristics of water (Xu, 2006).

(Tweed et al., 2009) discusses the limitations of solely using ground-based methods and how the implementations of Landsat remote sensing data can overcome spatial and temporal limitations associated with *in-situ* monitoring. The use of satellite imagery is not exclusive to Australia and there have been developments in remote sensing to improve global land coverage images which includes the potential to monitor changes in lakes and wetlands (Crétaux et al., 2016). Currently there is a database, the Global Water Bodies database (GLOWABO), that has utilised satellite imagery to collect geographic and morphometric data for ~117 million lakes across Earth (Verpoorter et al., 2014). Satellite-based methods are capable of providing information about surface water in locations that are remote, inaccessible, or dangerous to approach (Frazier & Page, 2000). By providing data on water sources that fit this description, safety is ensured, time spent collecting data is reduced and the costs of collecting data is minimised too. Overall, satellites are able to cover large surface areas with a fine spatial resolution all within particular time periods (Leblanc et al., 2006; Pan et al., 2009; French et al., 2006).

Estimates of the area of inundated land surface (i.e. lake area) were obtained using the WOfS algorithm for data dating back to the 1980's for each lake of interest. Water Observations from Space (WOfS) is an algorithm that displays information of the behaviour of surface water across Australia through time and provides an understanding of surface water persistence and recurrence (Mueller et al., 2016). WOfS is accessible through the DEA (Digital Earth Australia) data platform within Geoscience Australia, which uses a water classification for every image produced from the Landsat satellites. Landsat 8, along with Landsat Thematic Mapper (TM) and enhanced Thematic Mapper (ETM+), provides data over the whole of Australia in the form of a consistent surface reflectance product that enables spatio-temporal analysis of freshwater optics to support monitoring and water management strategies (Lymburner et al., 2016). This classification is able to map the locations of waterbodies across Australia with a 30 m pixel resolution and at time intervals of 16 days (E. Krause et al., 2021).

Using WOfS, the combinations of bands can be visualised in 'true colour' and 'false colour' images. The 'false colour' image visualisation is the result of utilising only the near infrared, red and green bands with the exclusion of the blue band to produce an image (Patra et al., 2006). With the absence of the blue band the colouring of the final product highlights water features exceptionally well, even during times of influential cloud cover. This is depicted well when comparing Lake Corangamite and Lake Martin under a 'true colour' style (Fig. 2a) compared to the same image, using the 'false colour' style (Fig. 2b) which highlights water features to appear dark blue as opposed to the surrounding land which is represented in a lighter green colour. Another style is MNDWI (Fig. 2c), which visually depicts the occurrence of inundation through a colour gradient and showcases the effectiveness of the cloud exclusion algorithm, Fmask, leaving individual clouded sections unrecorded.

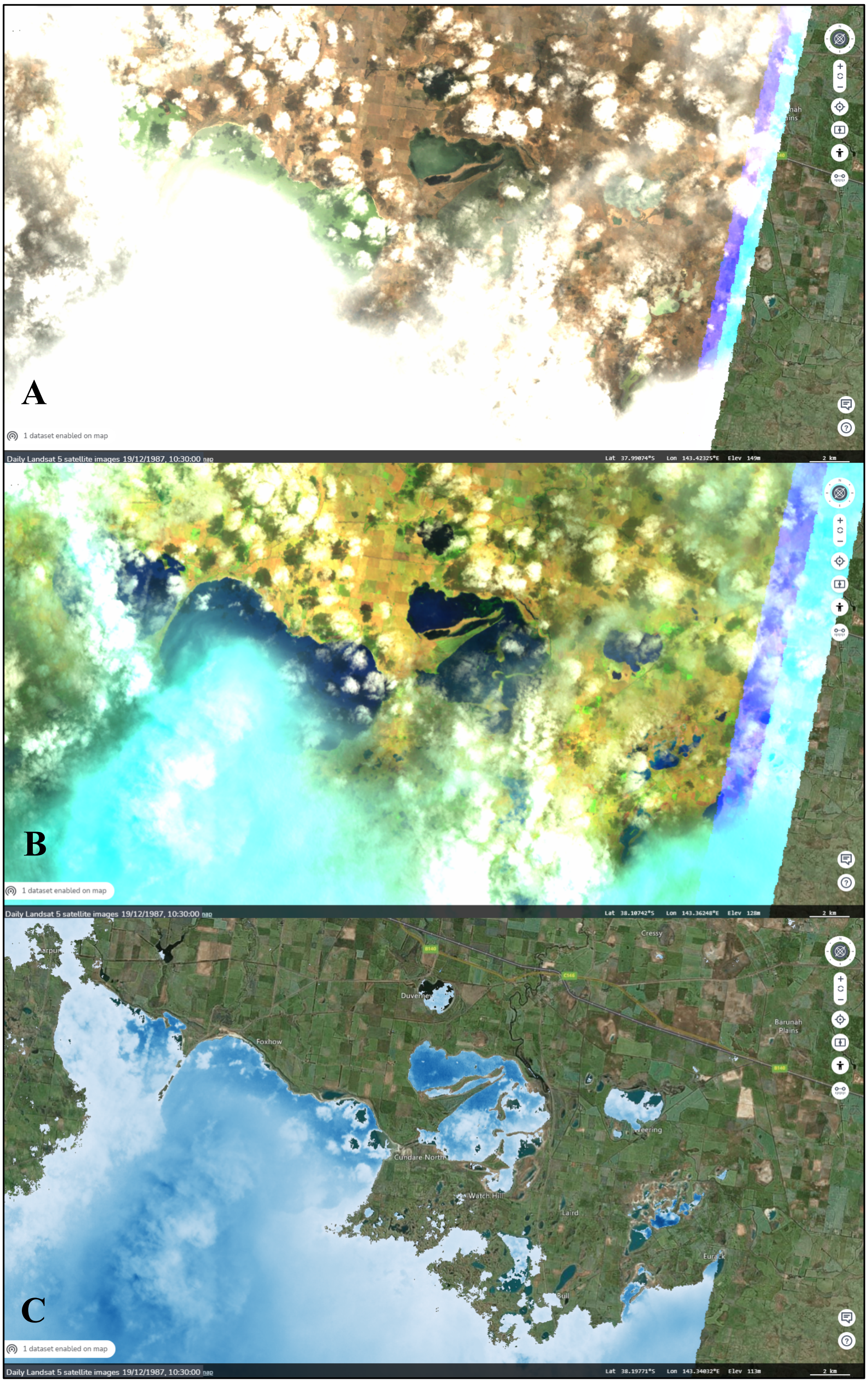

Figure 2: Satellite imagery of Lake Corangamite (left) and Lake Martin (right). Styles available in WOfS for satellite imagery visualisation, (a) 'true colour', (b) 'false colour' and (c) MNDWI.

LIMITATIONS OF USING REMOTE SENSING DATA

With the important benefits satellite sensing represents, it also has some limitations. The quality and use of information from satellite imagery can be subject to different factors that can lead to poor image and information quality including: cloud interference, misidentification between water and vegetation, instrument/hardware failure and others like topographic shading and poor geo-locations (Mueller et al., 2016). Cloud coverage has the ability to significantly decrease image information (Huang et al., 2018) and their influence is fuelled by their temporal and spatial occurrence along with their varying degree of effect on satellite data. Clouds can cause different types of effects, the clouds themselves cause a brightening effect and their shadows cause a darkening effect, both of which create issues (Zhu & Woodcock, 2012). The type of cloud causing the interference also has an effect. This is particularly the case for thin and semitransparent clouds, as their reflectance value is that of both clouds and the surface underneath (Gao & Kaufman, 1995; Gao et al., 1998; Gao et al., 2002), rendering them harder to identify. Thick opaque clouds are easier to identify due to their high reflectance in visible spectral bands. Cloud influence is common in satellite imaging and there are multiple algorithms for detecting them, Fmask is one that has proven to be an effective cloud detection method. Fmask is used to automatically scan satellite images for clouds for easier water detection information and has an accuracy recognition for clouds equal to 96.4% (Zhu & Woodcock, 2012). Overhanging vegetation is another issue that can lead to mixed vegetation-water signals when within close proximity to waterbodies and interfere with water detection (Santoro et al., 2015). However, this issue can start to be resolved with information on the terrain the water body is situated in (Huang et al., 2018). Ultimately, areas in which clouds, trees and floating vegetation do not obscure the water surface, satellite imagery is able to provide definitional details of the inundated areas of interest (Smith, 1997). But for locations that do contain these sometimes-unavoidable influential factors, there are ways to identify them. Another issue involves the satellite itself, specifically the Landsat 7's Scan Line Corrector (SLC) mechanism. The SLC which usually consists of two mirrors that oscillate in synchronisation with the scan mirror to compensate for the satellites motion during cross-track scanning, which kept the forward and reverse ground imaging sweeps of the detector's fields of view parallel (Markham et al., 2004). The failure caused the SLC to become stuck in one position resulting in gaps and overlaps between successive scans (Fig. 3). The resulting images with this failure resulted in gaps in the data which gave the satellite images the appearance as being viewed through "venetian blinds" (Mueller et al., 2016). Despite the potential errors associated with misidentification, Landsat is a strong satellite-based method of data collection and has been proven to be very successful in mapping waterbodies (Nguyen et al., 2019).

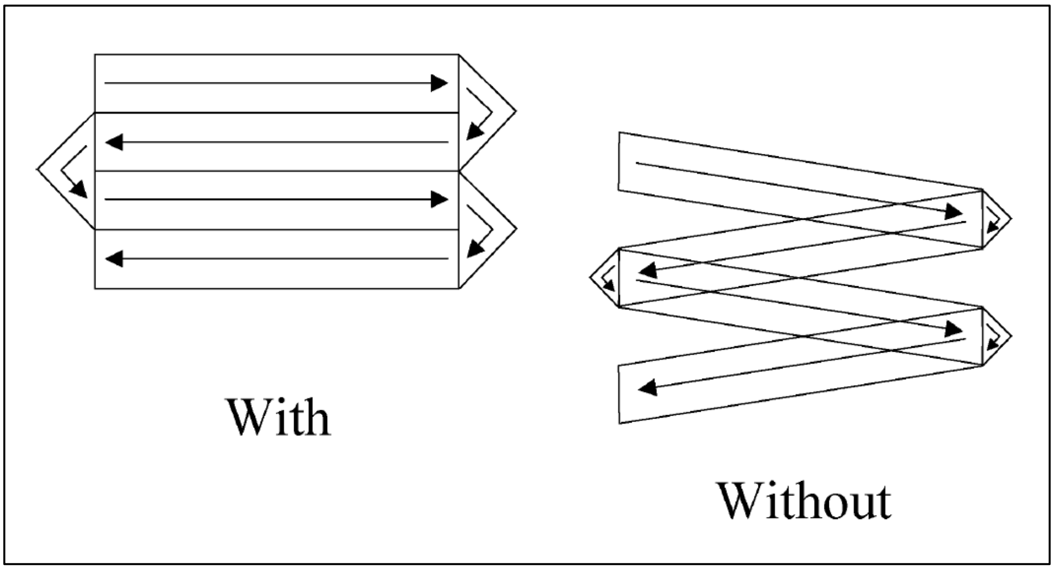

Figure 3: Data coverage through Landsat 7 Satellite with and without the Scan Line Corrector. (Markham et al., 2004).

METHODS

Using the DEA data platform, individual data sets for each lake of interest were downloaded and included data from 1987 – 2020. The WOfS algorithm was utilised to collect data that represented each lakes change in surface area through time in the form of the number of pixels that were considered ‘wet’, ‘dry’ or ‘invalid’. The identification of pixels that were considered ‘wet’ was completed with the use of the MNDWI index. Individual ‘wet pixel’ data sets were converted into surface area data sets with the equation:

$$Surface\ Area\ (km^2) = wet\ pixel\ count\ \times 0.000625$$

Through WOfS detection ability, its algorithm was used to detect cloud cover and return data as invalid data when clouds were covering the lakes. Several careful steps were implemented to avoid inaccurate representations of lake variation being constructed. The invalid data were filtered out of each dataset and in order to account for occasional partial coverage on some observation days due to cloud cover, the datasets were binned into annual groups and only the maximum surface area value for each year was used for reconstruction. Some lakes had entire years with invalid data points which resulted in those years being excluded due to filtering out the invalid data. The final step involved a quality control check which was performed by identifying potential anomalies within each individual lake surface area change representation and then inspecting the original satellite images to determine if more data points were necessary to be excluded to improve the final data representation. The final representations for each lake depicted surface area variation over 33 years from 1987 – 2020.

Climate data were obtained via the Scientific Information for Land Owners (SILO) database. SILO is a climate reanalysis product that has information dating from 1889 to present, which interpolates between the Bureau of Meteorology weather station data to estimate conditions at a 5 km x 5 km resolution. To account for potential differences in climates between sites, climate data for each individual lake was extracted from the SILO database. Climate variables of interest included daily rainfall (mm) and evaporation (class A pan; (mm)). A third variable, effective moisture (precipitation:evapotranspiration) (Luoto et al., 2010), was calculated using the rainfall and evaporation data. Due to some missing years in the surface area data caused by the excluded invalid data, the climate data was also summarised into annual maximum values for each climate variable.

The relationships between lake area variability and the three climate variables were examined using linear regression for each individual site. Differences in regression slope and goodness of fit (R^2) were used as indicative measures to assess the sensitivity and importance of each variable against lake surface area change. Principal Component Analysis (PCA) were conducted to assess the occurrence of common patterns of lake area variability between the 15 lakes. PCA was performed on the annual maximum lake surface area estimates using the package 'vegan' (Dixon, 2003) in R (Team, 2013). Three lakes had missing lake surface area estimates for a single year up to three years in total. In these instances, linear interpolation was used to infer a lake area value to fill the missing data and ensure a complete series for inclusion in the PCA analysis.

RESULTS

15 lakes in the western region of Victoria were studied, generating reconstructions of surface area variation over 33 years from 1987 – 2020 (Fig. 4).

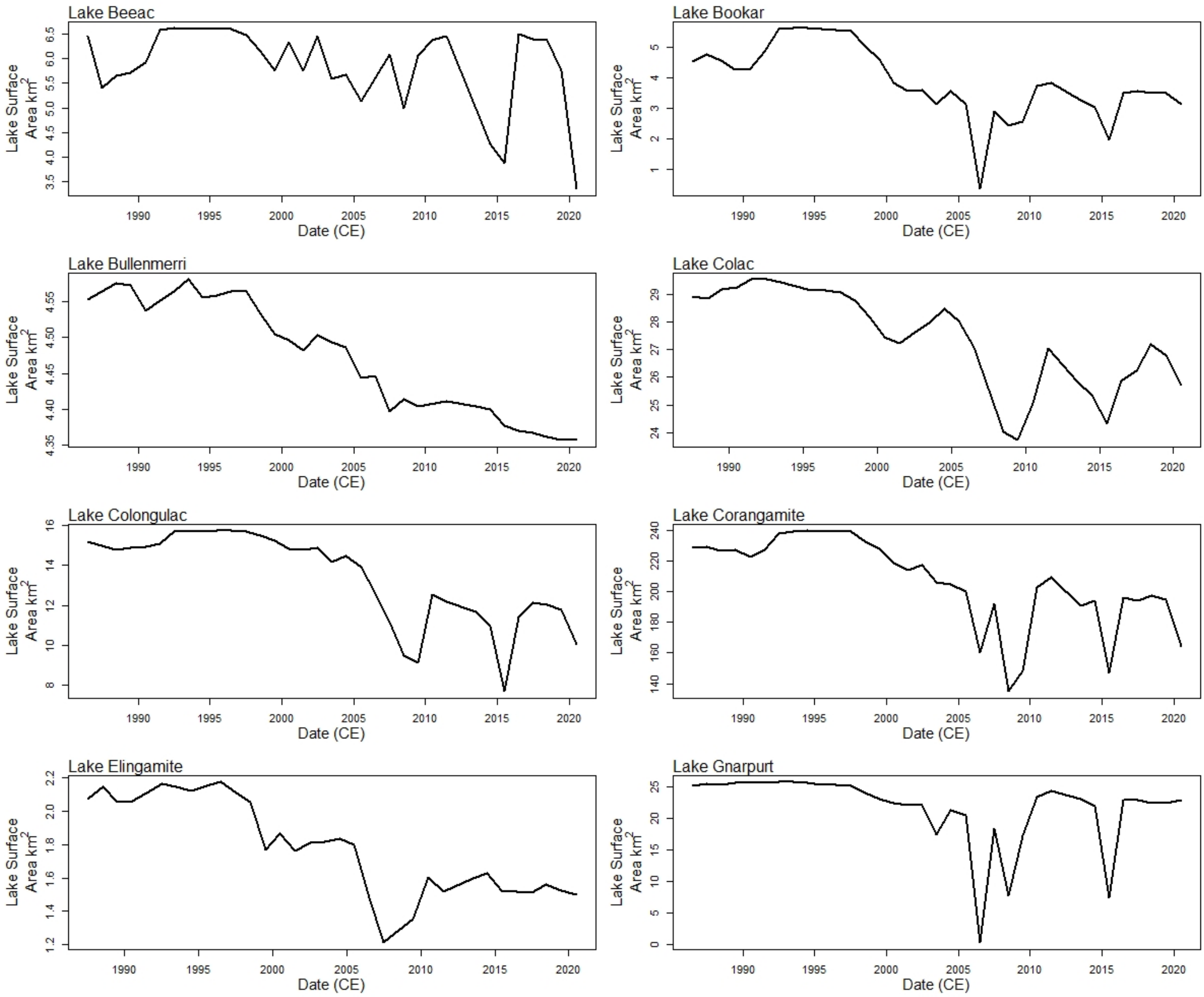

Figure 4: Annual maximum lake surface area derived from WOfS, 1987-2020.

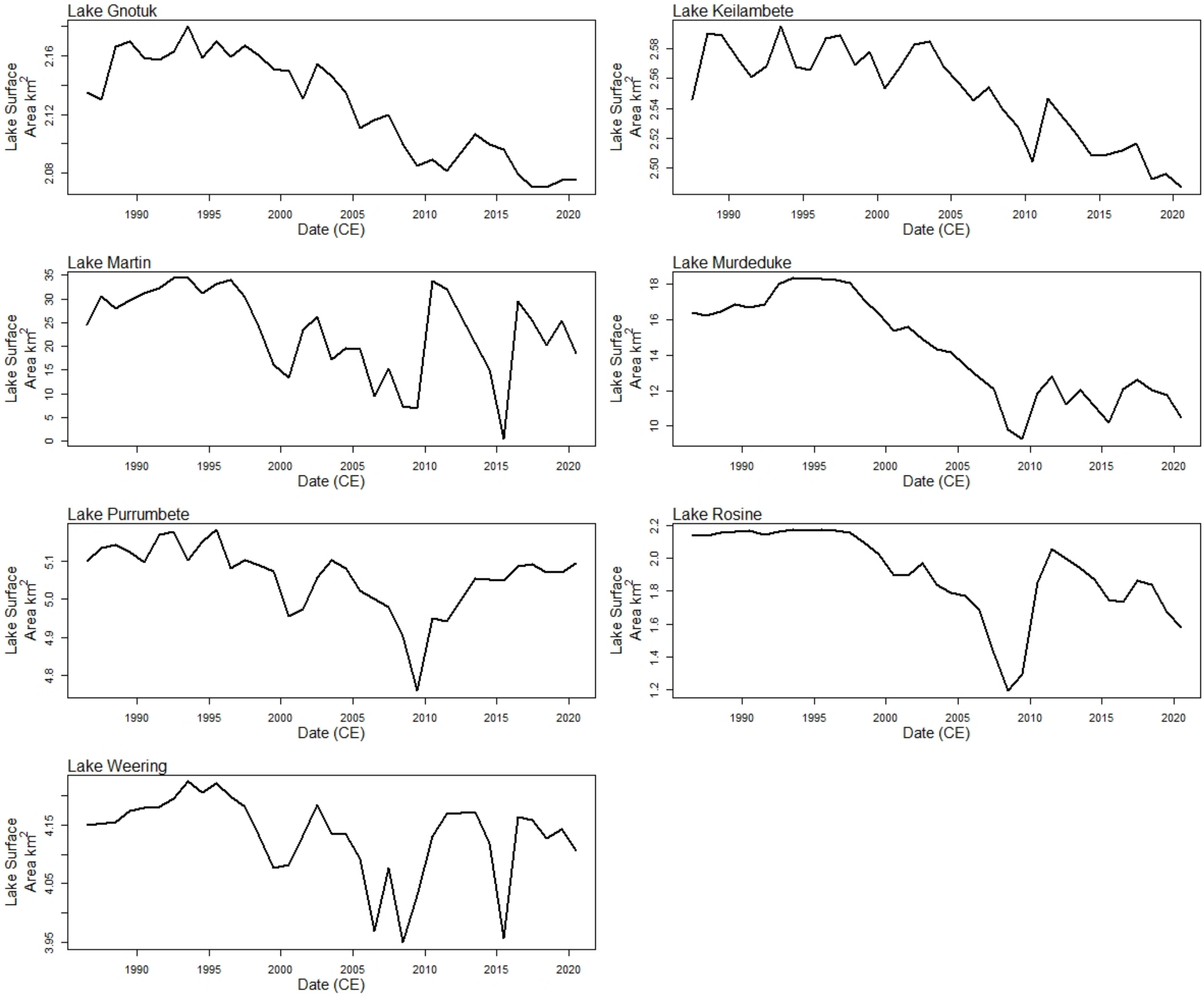

Figure 4 (Continued): Annual maximum lake surface area derived from WOfS, 1987-2020.

Over the study period, all lakes exhibited clear variability in annual maximum surface area, ranging from 1.2 km^2 – 2.2 km^2 at Lake Rosine, through to 140 km^2 – 230 km^2 at Lake Corangamite. All lakes exhibited maximum surface area values between 1990 and 1995, with minimum surface area values between 2005 and 2010 for Lakes Bookar, Colac, Corangamite, Elingamite, Gnarpurt, Murdeduke, Purrumbete, Rosine and Weering and minimum surface areas values between 2015 to 2020 for Lakes Beeac, Bullenmerri, Colongulac, Gnotuk, Keilambete and Martin. Strong surface area declines are shown by Lakes Gnarpurt and Martin in which their surface areas hit 0 km^2 and dried up between 2006 – 2007 and 2015 – 2016 respectively. Another dominant characteristic in some annual maximum surface area trends was a decline during 2015. Lakes Beeac, Colongulac, Corangamite, Gnarpurt, Martin and Weering exhibit this decline followed by a recovery. Some lakes show slight evidence of being influenced in 2015, namely Lakes Bookar, Colac and Murdeduke. As for Lakes Bullenmerri, Elingamite, Gnotuk, Keilambete, Purrumbete and Rosine, they show no evidence of decline in 2015. Of the 15 lakes, only Lakes Gnarpurt, Purrumbete and Weering show evidence of a maximum surface area towards the end of the study period in 2020 that is similar to maximum surface area values observed in 1987. Using the last 6 years of data, from 2015 to 2020, Lakes Beeac, Bookar, Colac, Colongulac, Corangamite, Keilambete, Martin, Murdeduke, Rosine and Weering depict some level of decrease. Whereas, Lakes Bullenmerri, Elingamite, Gnarpurt and Gnotuk give no indication of an increasing or decreasing maximum surface area into the near future.

The individual climate variable data sets collected from SILO have been plotted on an identical time series as the annual maximum surface area changes, in order to display responses in surface area fluctuation as a response to the individual climate variables (Figs. 5a, 5b & 5c).

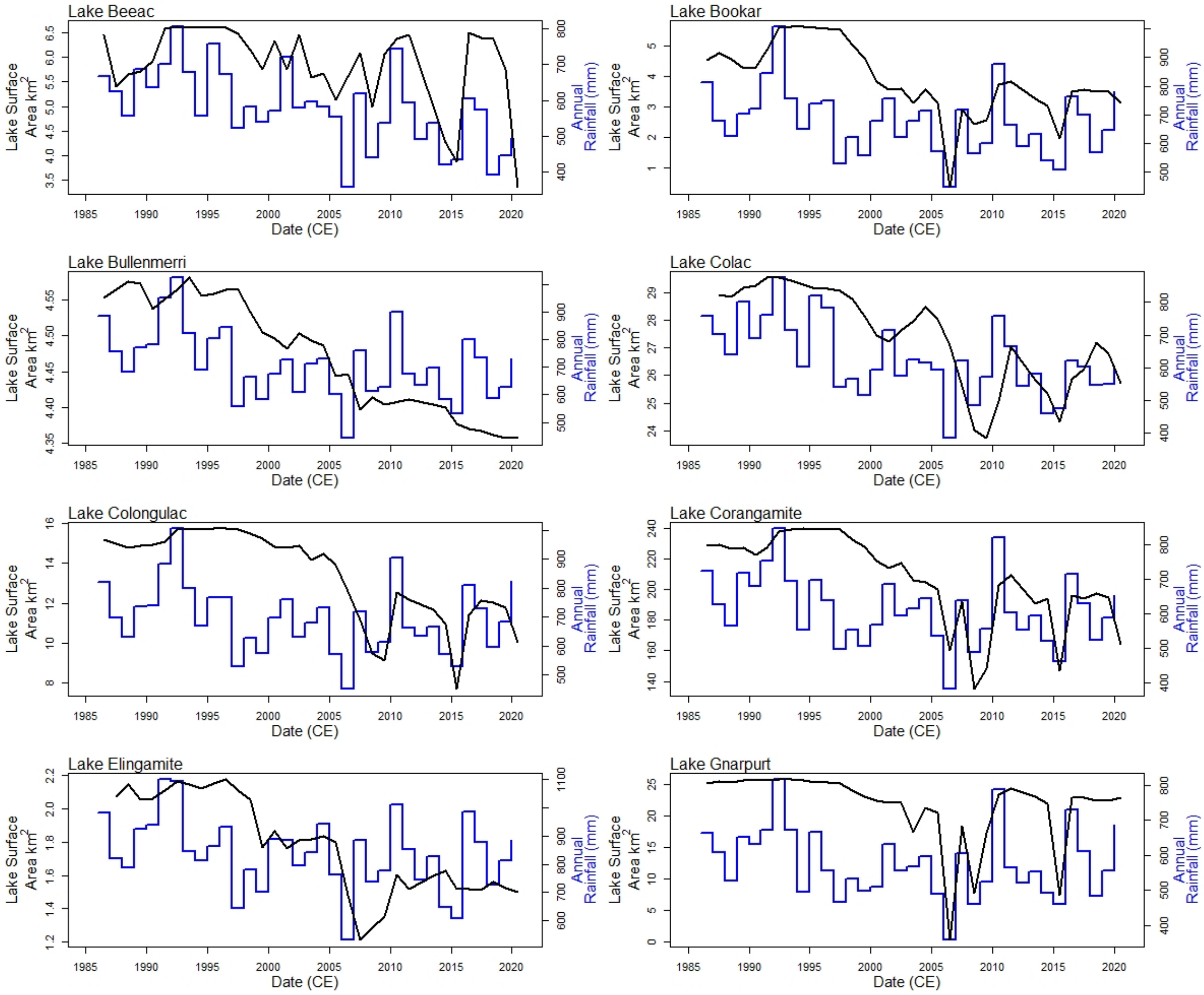

Figure 5a: Annual maximum lake surface area derived from WOfS, 1987-2020, along with their associated rainfall climate variable.

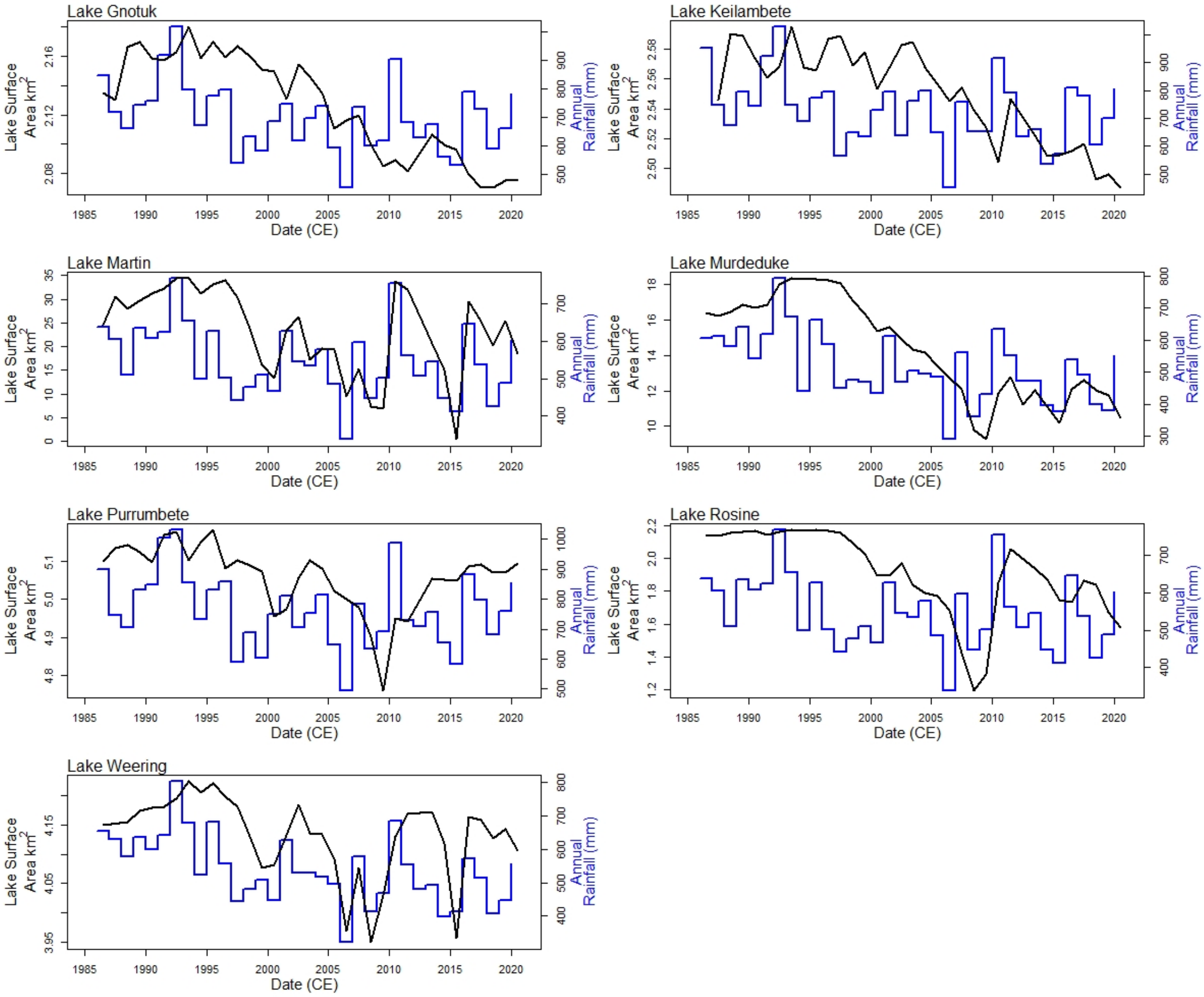

Figure 5a (Continued): Annual maximum lake surface area derived from WOfS, 1987-2020, along with their associated rainfall climate variable.

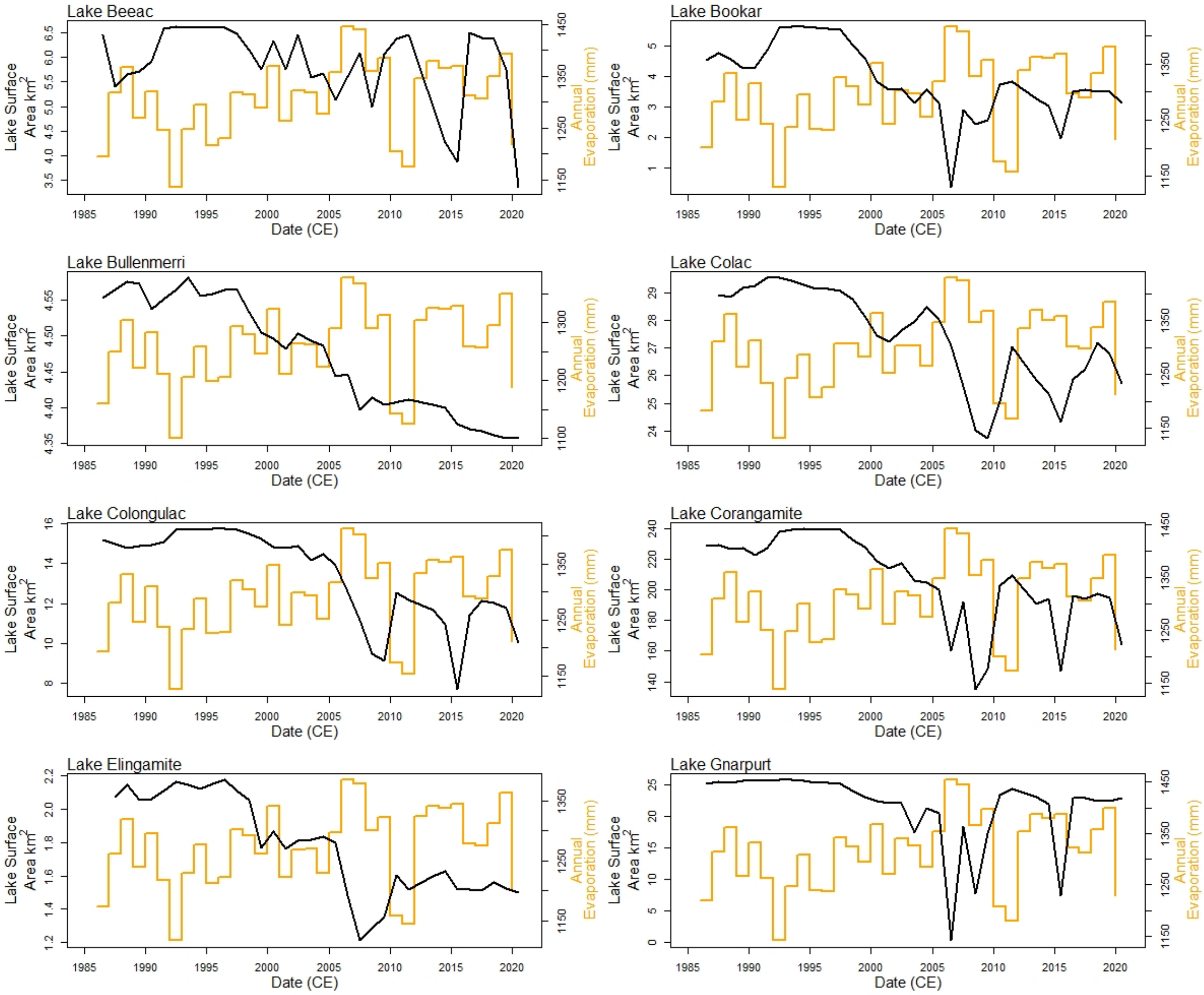

Figure 5b: Annual maximum lake surface area derived from WOfS, 1987-2020, along with their associated evaporation climate variable.

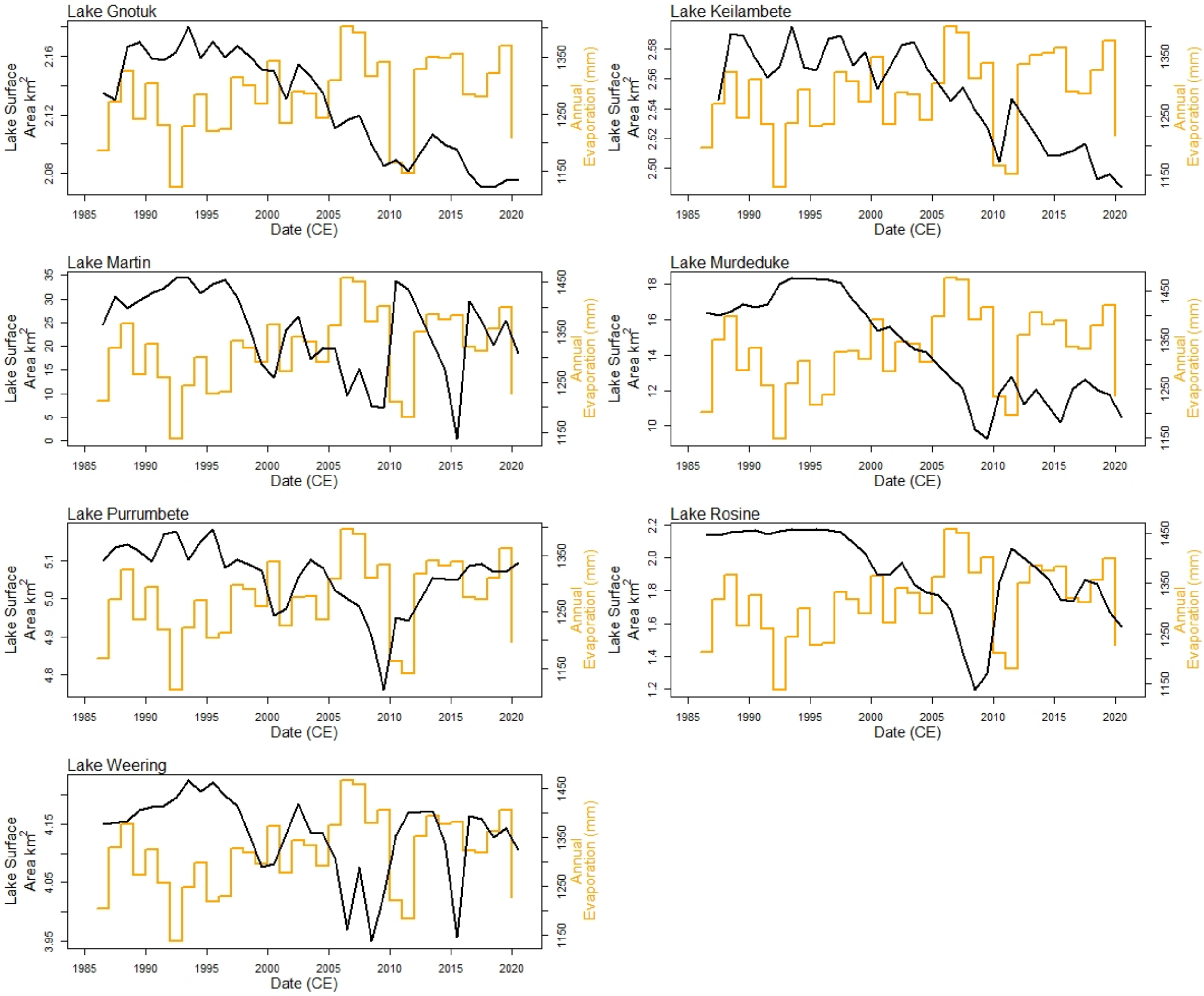

Figure 5b (Continued): Annual maximum lake surface area derived from WOfS, 1987-2020, along with their associated evaporation climate variable.

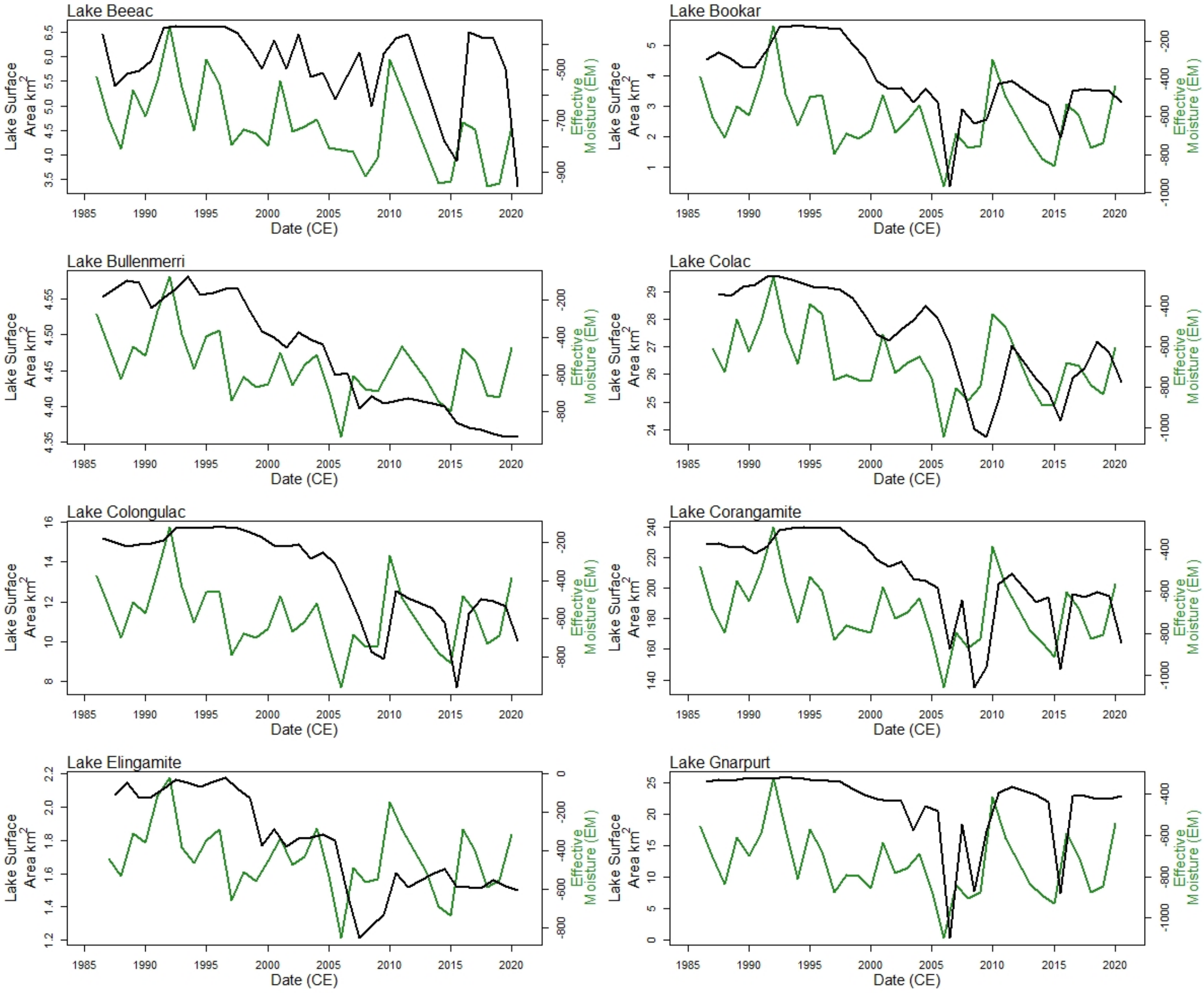

Figure 5c: Annual maximum lake surface area derived from WOfS, 1987-2020, along with their associated effective moisture climate variable.

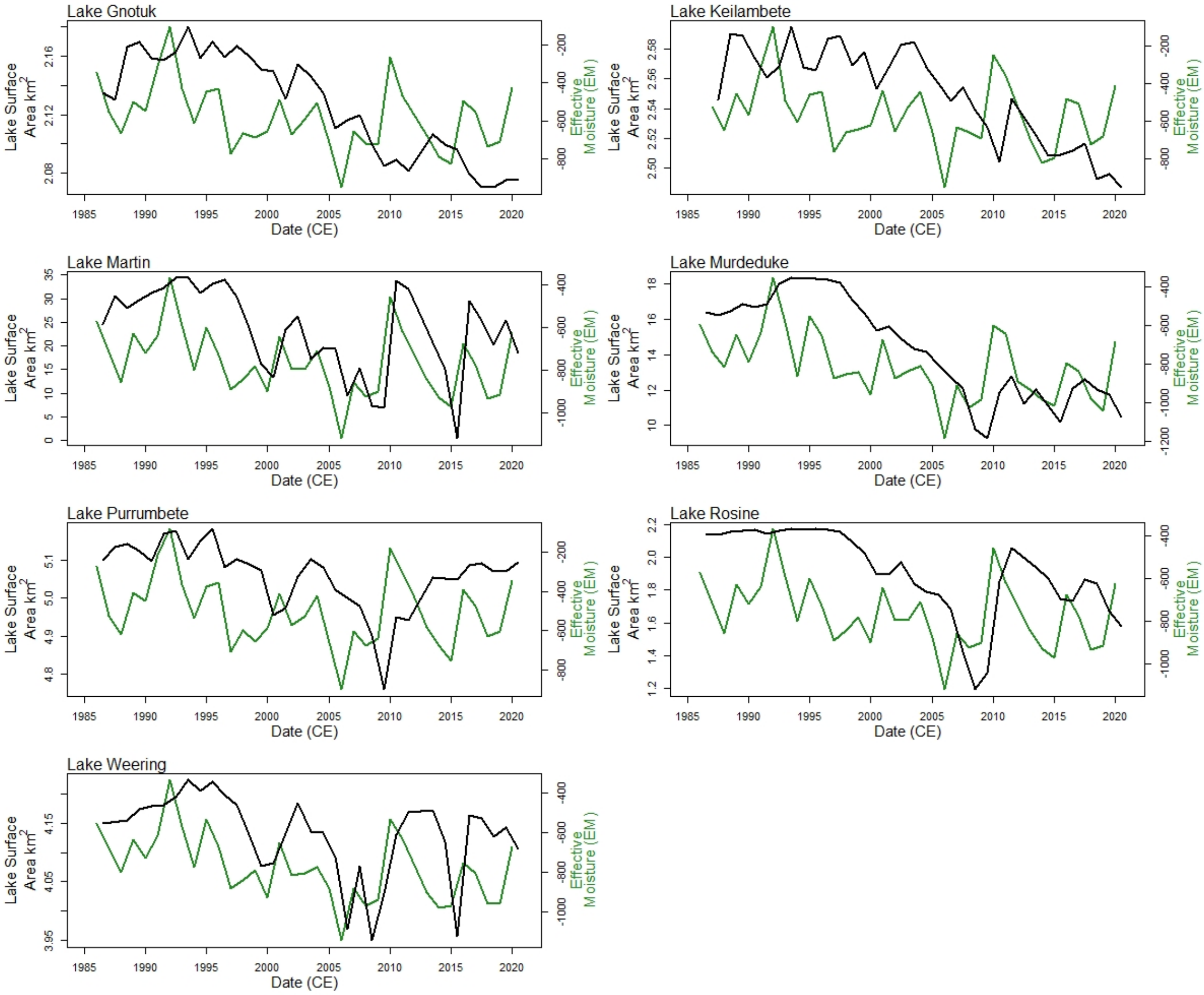

Figure 5c (Continued): Annual maximum lake surface area derived from WOfS, 1987-2020, along with their associated effective moisture climate variable.

A declining annual rainfall trend was dominant from 1995 – 2009 for most lakes (Fig. 5a). Between 2010 – 2011, an increase in annual rainfall occurred, after which the rainfall trends decline again through to 2020. Lakes Bullenmerri, Gnotuk and Keilambete demonstrate a declining annual maximum surface area trend from 2010 onwards, despite annual rainfall trends that were relatively consistent through the same time period. Annual maximum surface area compared with annual evaporation data, (Fig. 5b), depicts that all lakes had higher annual evaporation amounts leading into 2020 compared to their 1987 amounts. Evaporation rates at each of the lakes increased from

1995 – 2009 before they decreased in 2010. There is a clear pattern between the annual maximum rainfall and evaporation amounts, which is that all lakes exhibited higher rainfall amounts towards the start of the study period compared to the end. Whilst evaporation depicted the opposite and that towards the start of the study period, the lakes had lower evaporation amounts compared to the end of the study period. The comparison between annual maximum surface area and effective moisture, (Fig. 5c), shows that Lakes Colongulac, Gnarpurt and Rosine have a stable maximum surface area trend between 1987 – 1997 despite a fluctuating effective moisture value through the same time period. A similar depiction from 1993 – 1997 is visible in Lakes Bookar, Corangamite and Murdeduke that also mimic little change in surface area variability compared to the effective moisture amounts within the same time period.

As expected, each lake of interest had varying linear regressions between annual maximum surface area and the different climate variables, (Figs. 6a, 6b & 6c).

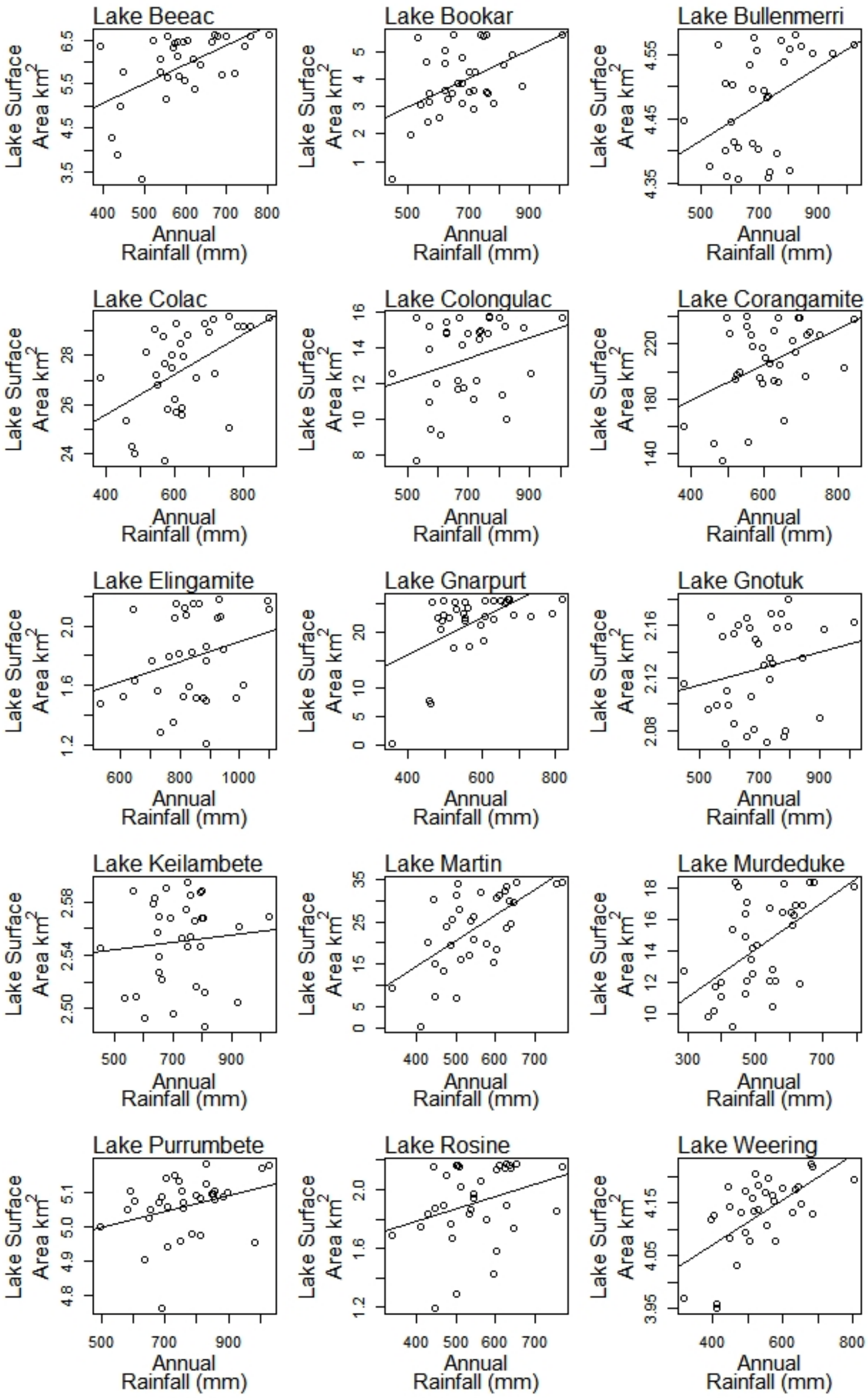

Figure 6a: Linear regressions between annual maximum surface area and annual rainfall for each lake of interest.

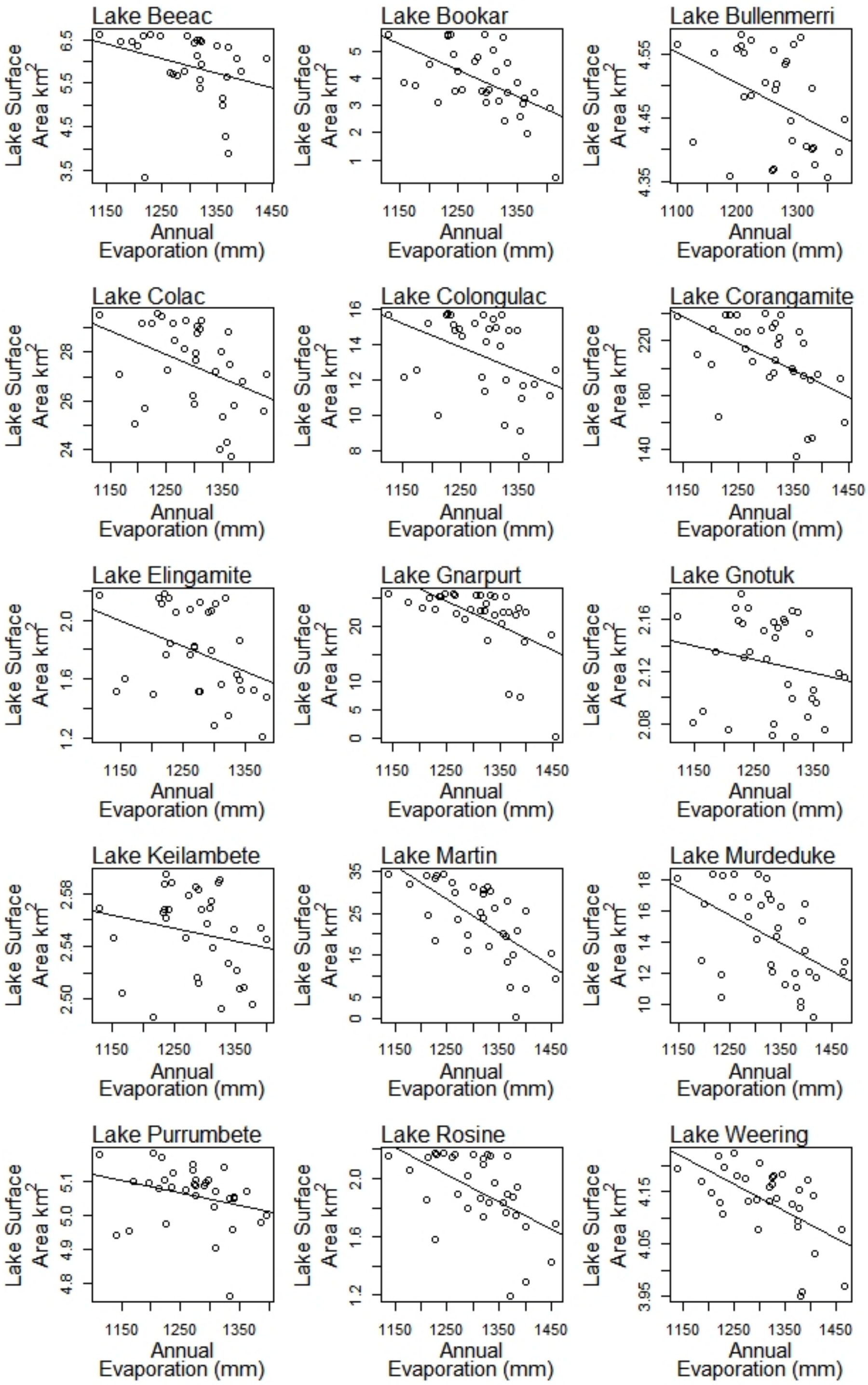

Figure 6b: Linear regressions between annual maximum surface area and annual evaporation for each lake of interest.

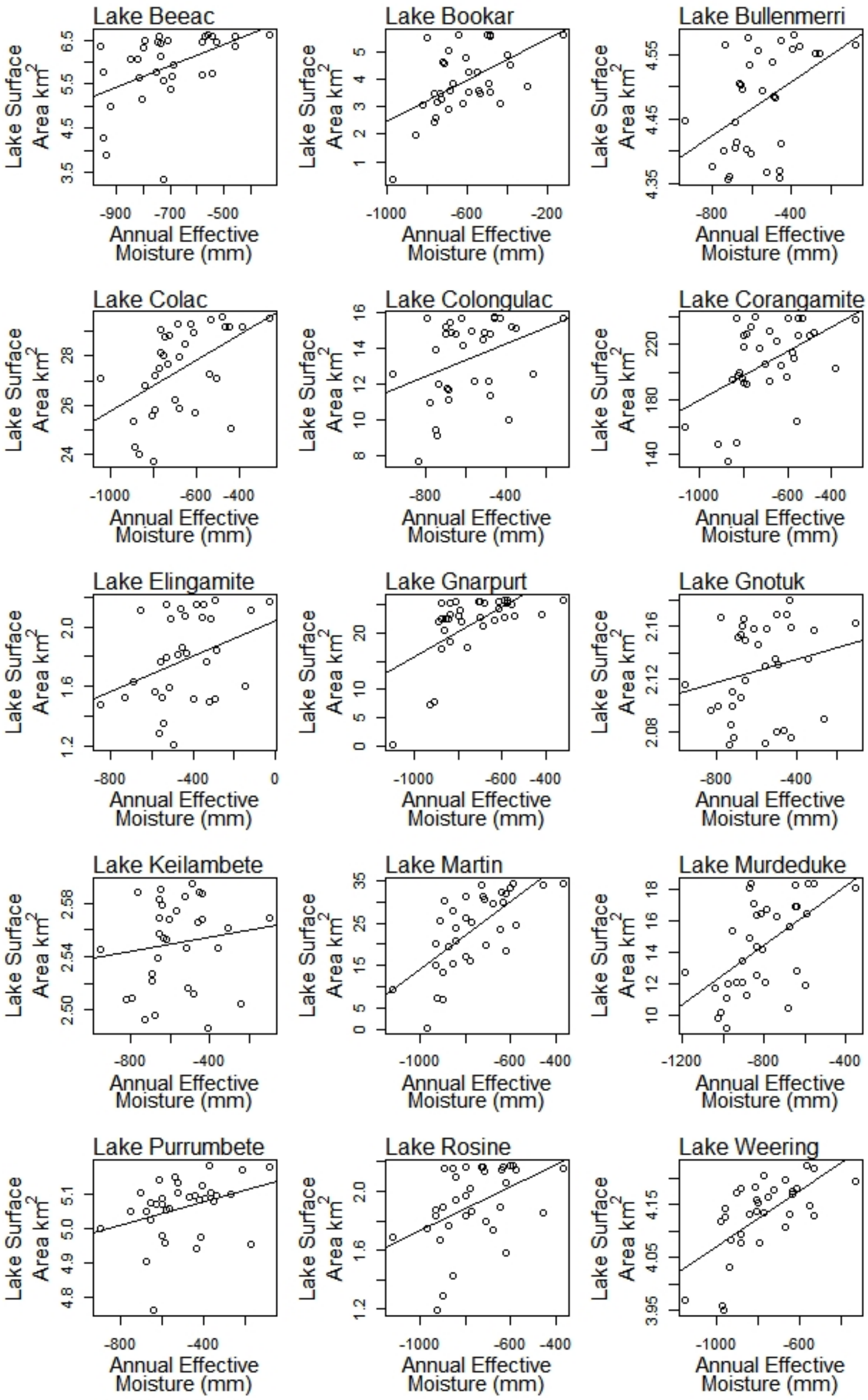

Figure 6c: Linear regressions between annual maximum surface area and annual effective moisture for each lake of interest.

All lakes exhibited a positive linear regression with annual maximum surface area compared with annual rainfall and annual effective moisture respectively, (Figs. 6a & 6c). A negative linear regression is depicted in all lakes when comparing annual maximum surface area and annual evaporation, (Fig. 6b). With different degrees of regression between each lake, collectively, they all represent similar positive and negative trends associated with climate variables.

Based off the linear regression models, correlation coefficients were determined between annual maximum surface area and the climate variables for each lake (Fig. 7). The R^2 values between annual maximum surface area and annual rainfall range from a maximum of 0.39 for Lakes Martin and Weering to a minimum of 0.01 for Lake Keilambete. For annual maximum surface area and annual evaporation, R^2 values range from a maximum of 0.44 for Lake Martin to a minimum of 0.04 for Lake Gnotuk and Keilambete. Lastly, annual maximum surface area and annual effective moisture R^2 values range from a maximum of 0.48 for Lake Martin to a minimum of 0.02 for Lake Keilambete. Lake Martin represents the highest R^2 values for each climate variable and Lake Keilambete represents the lowest R^2 value for each climate variable. The correlations between annual maximum surface areas and each climate variable for all 15 lakes are all less than 0.5. Of the three climate variables, effective moisture produced regression models with the highest R^2 values for eight lakes: Lakes Bullenmerri, Corangamite, Gnarpurt, Gnotuk, Martin, Murdeduke, Purrumbete and Weering. The evaporation climate variable represented stronger R^2 values with annual maximum surface area for five lakes: Lakes Bookar, Colongulac, Elingamite, Keilambete and Rosine. Lastly, the correlation with rainfall and annual maximum surface area represented stronger R^2 values for lakes Beeac and Colac. Lakes Bullenmerri, Corangamite, Gnarpurt, Gnotuk, Purrumbete and Weering all had R^2 values that were pretty similar across each of the three climate variables and these six individual lakes also all had slightly higher effective moisture R^2 values.

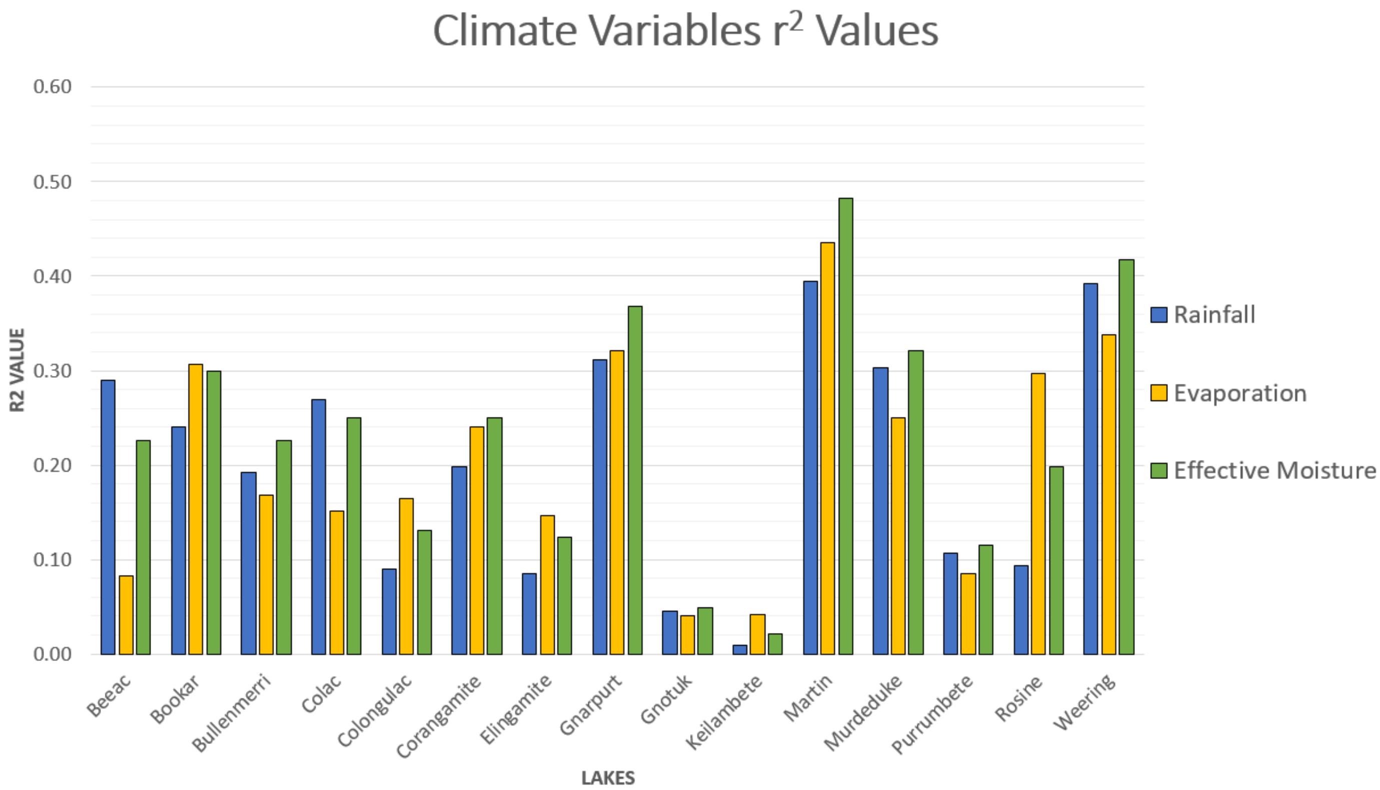

Figure 7: R2 values between annual maximum surface area and individual climate variables for each lake of interest.

The slope coefficient of the climate-lake surface area regressions varies between sites and between climate variables (Table 1). 11 of the 15 sites have a rainfall slope correlation value of less than 0.01, 12 lakes have effective moisture slope correlation values less than 0.01 and 8 lakes display an evaporation slope correlation value more than -0.01. Lake Corangamite has the highest rainfall and effective moisture slope values along with the lowest evaporation slope value of all the lakes.

Lake	Rainfall Slope Value	Evaporation Slope Value	Effective Moisture Slope Value
Beeac	0.00435	-0.00332	0.00247
Bookar	0.00510	-0.00958	0.00378
Bullenmerri	0.00028	-0.00049	0.00021
Colac	0.00823	-0.00960	0.00517
Colongulac	0.00569	-0.01317	0.00463
Corangamite	0.12820	-0.19470	0.08959
Elingamite	0.00068	-0.00173	0.00059
Gnarpurt	0.03268	-0.04472	0.02200
Gnotuk	0.00006	-0.00010	0.00004
Keilambete	0.00003	-0.00010	0.00003
Martin	0.05993	-0.07884	0.03982
Murdeduke	0.01483	-0.01800	0.00934
Purrumbete	0.00023	-0.00037	0.00017
Rosine	0.00084	-0.00188	0.00074
Weering	0.00043	-0.00052	0.00027

Table 1: Regression slope coefficient values between annual maximum surface area and annual rainfall, annual evaporation and annual effective moisture amounts for each lake of interest from 1987 – 2020.

Principal Component Analysis (PCA) analysis of the lake area estimates identified a single component that describes 71% of the variance. A table containing the Eigenvalues, proportion explained and cumulative proportion values can be found in the Appendix. The importance of a single principal component that indicates all other principal components do not pass the broken stick significance test (Fig. 8a). All sites cluster around positive PC1 values, with Lakes Colac and Rosine closest to the centre and Lakes Keilambete and Gnarpurt furthest from the centre (Fig. 8b). Combining each of the lakes PCA results to depict an average and then comparing this average against each individual lake, (Fig. 8c), shows that PC1 compares well with variability at each site as evident by the similarity between both lines.

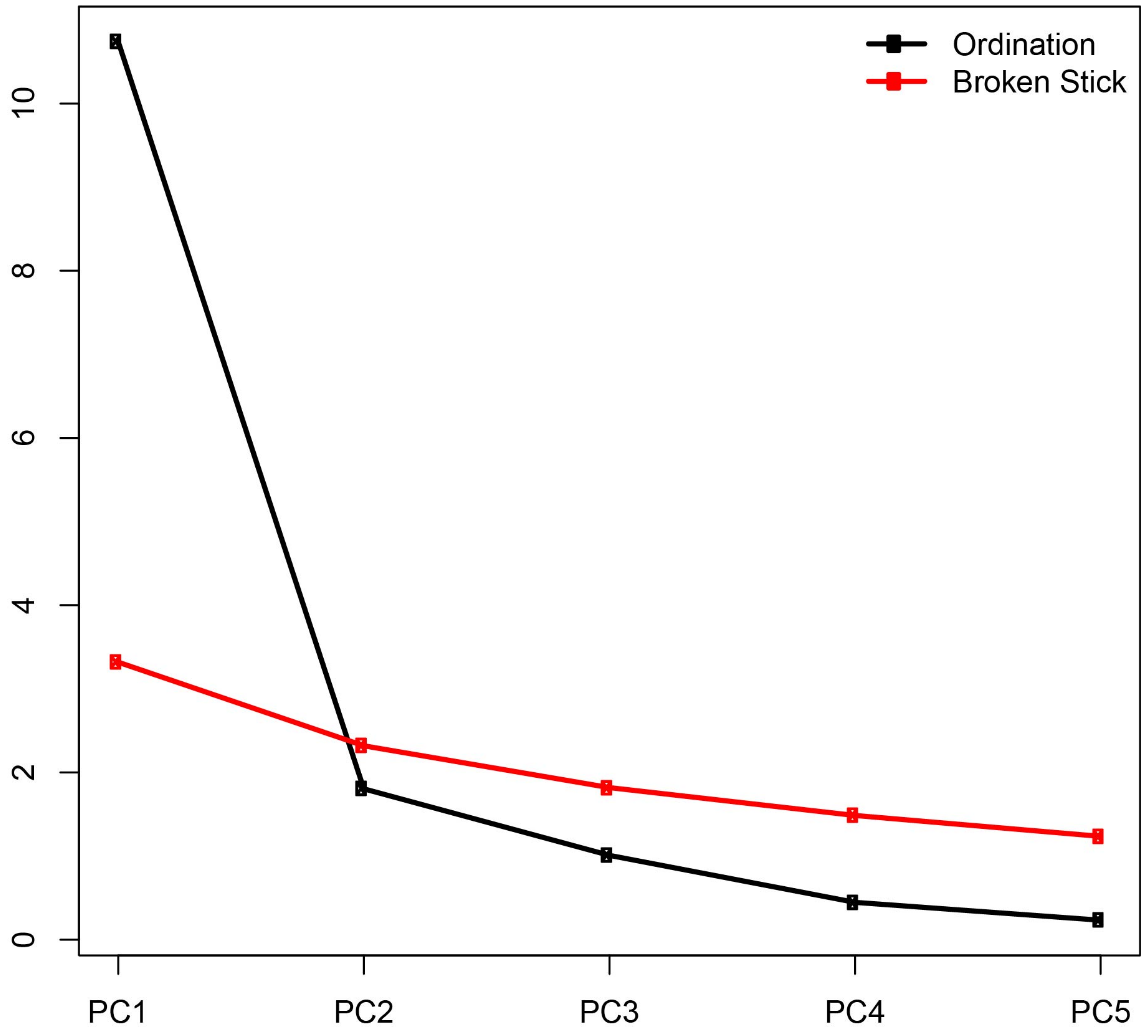

Figure 8a: Screeplot highlighting the dominance of influence by PCA1 compared to the other PCAs for the lakes of interest. Black Ordination line indicates the combined 15 lakes PCA data. Red Broken Stick line indicates randomly generated data to act as a comparison.

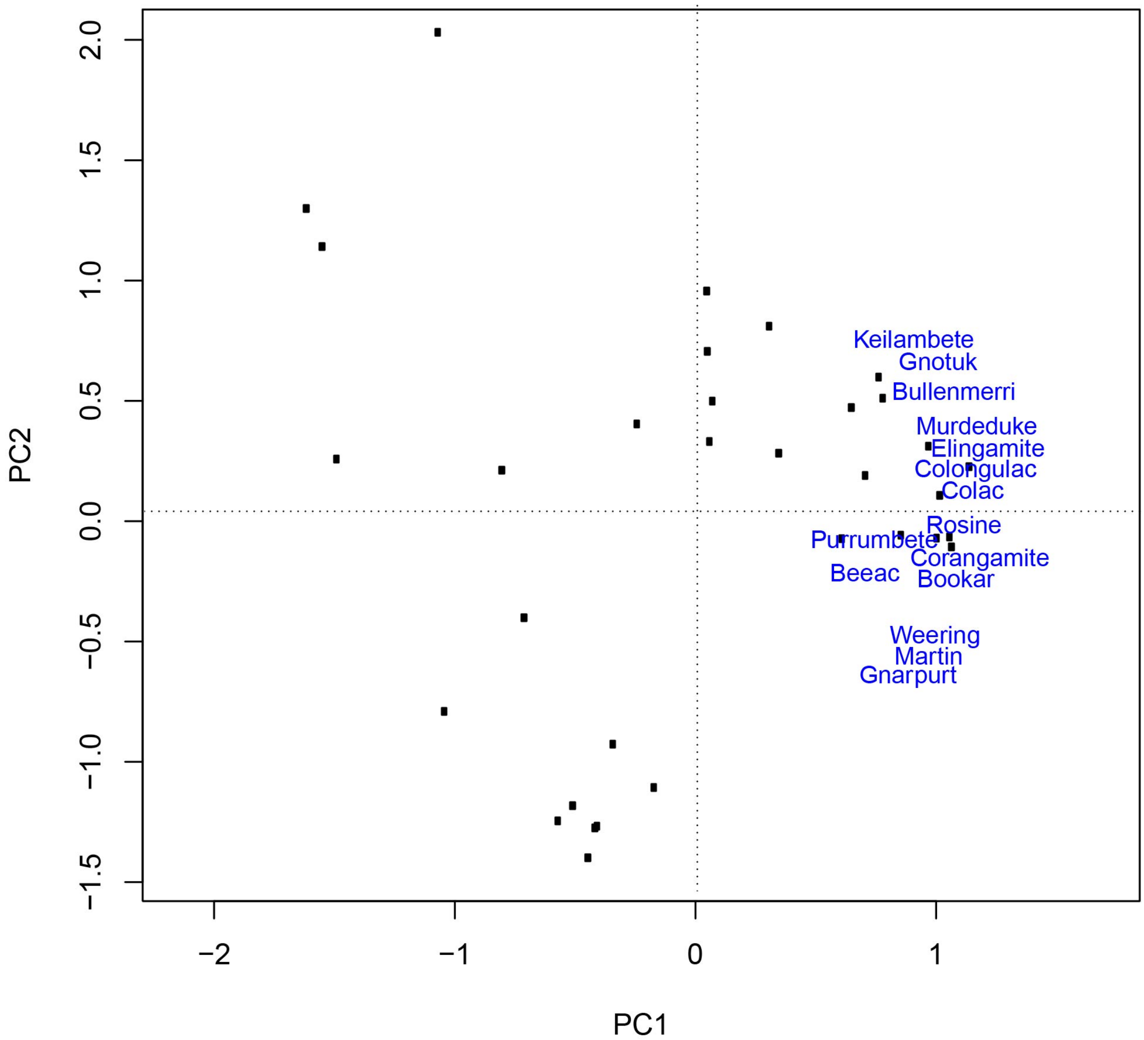

Figure 8b: PCA1 versus PCA2 biplot showing the locations of each lake of interest in comparison to each other, as well as compared to each year within the study period. Site scores are indicated by name as test. Sample scores (years) are indicated by squares.

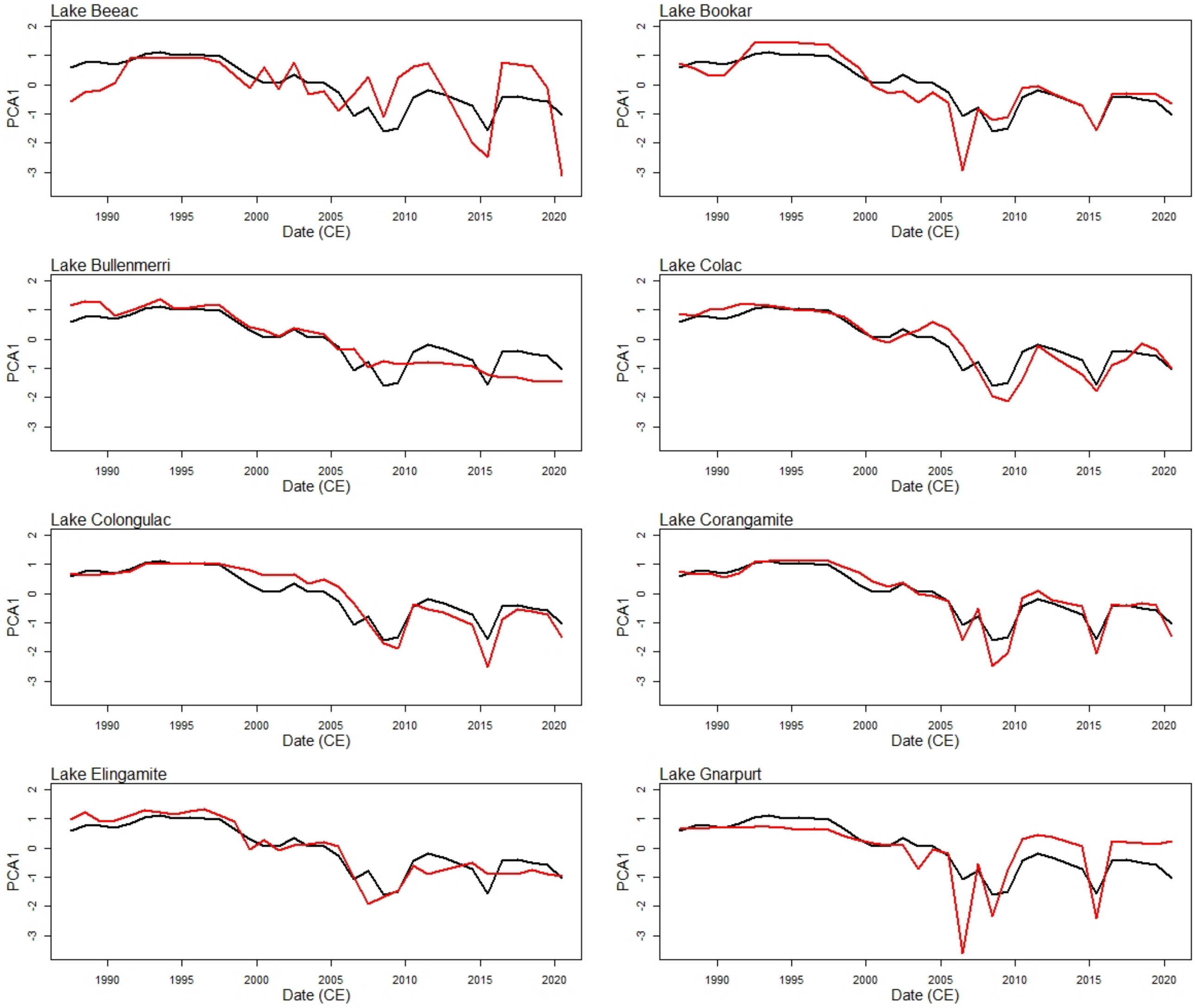

Figure 8c: Combined PCA results of each lake of interest indicated by the black line. Individual PCA results of each lake of interest indicated by the red line.

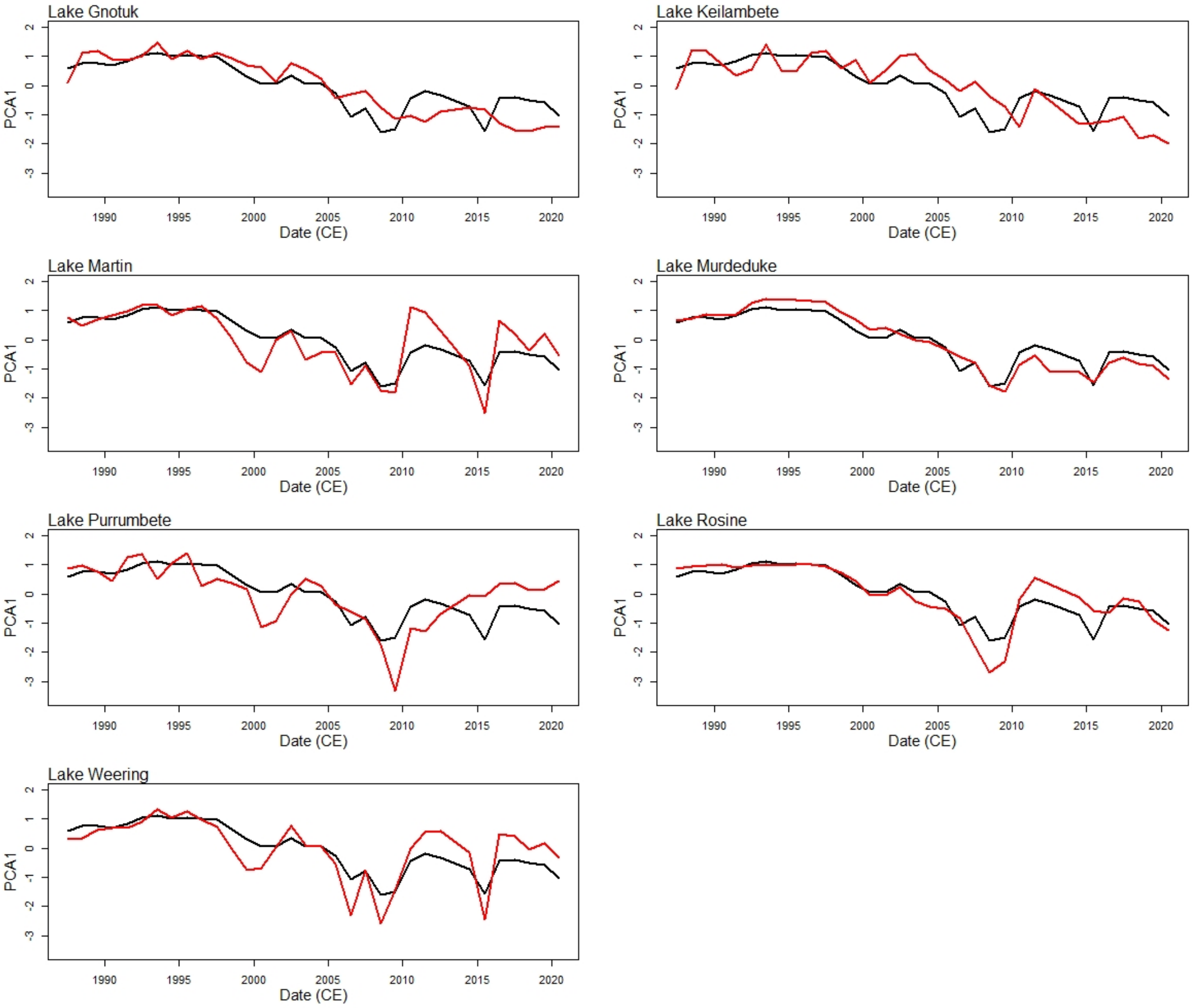

Figure 8c (Continued) – Combined PCA results of each lake of interest indicated by the black line. Individual PCA results of each lake of interest indicated by the red line.

DISCUSSION

The broad aim of this study was to examine the effect that climate has had on lake variability across multiple sites. By using satellite remote sensing to create reconstructions of surface area fluctuations, the effectiveness of utilising satellites in this field of study has been explored. Through the analysis of 15 different lakes located in the western Victorian region, all lakes show evidence of lake variation and surface area decline through time giving evidence of a climate-based cause for their depletion due to the similar trends shown for each lake. This conclusion is based off observing similar responses in annual maximum surface area variation in every lake (Fig. 4) along with PCA statistics (Figs. 8a, 8b & 8c) showing adherence towards a single principal component for all 15 lakes.

SIMILARITES AND DIFFERENCES IN LAKE VARIABILITY IN WESTERN VICTORIA AND WHY?

The dominant pattern shown in each lake is a general decline in annual maximum surface area from 1987 – 2020. Within this study period, there are two events that are of particular interest – the Millennium Drought (1997 – 2009) and the subsequent La Niña event in 2010 – 2011 (Heberger, 2012). During the Millennium Drought, the study region, like most of Australia, experienced prolonged periods of higher-than-average temperatures along with lower-than-average rainfall. This twelve year-long drought period resulted in lake area decline at all sites, alongside a decrease in rainfall and increase in evaporation (Figs. 5a & 5b). The occurrence of the La Niña event in 2010 – 2011 also coincides well with the annual maximum surface area trends. Each of the lakes of interest, except for Lakes Bullenmerri and Gnotuk, display visual indication of an increase in annual maximum surface area in 2010. Similarly, to the Millennium

Drought, the La Niña event, can also be used to explain the increasing trends in lake surface area variability between 2010 – 2011, as a result of an increase in rainfall and a decrease in evaporation (Figs. 5a & 5b). These case studies are good examples at explaining the hypothesis regarding the wide-spread effect climate is having, as effects of both events are visible across multiple lake locations, all during the same time periods. Lakes Bullenmerri and Gnotuk show the least amount of increase during 2010, along with this, they also show the least erratic change in annual maximum surface area values through the study period. Lake Bullenmerri has a change from 4.55 km^2 in 1987 to 4.35 km^2 in 2020 and Lake Gnotuk displays a change from 2.14 km^2 in 1987 to 2.08 km^2 in 2020, both display a slow, consistent rate of decline through the study period. An example of why they both collectively show this type of decline is due to their situation to each other. Both lakes are located closely together and when Lake Bullenmerri floods, Lake Gnotuk receives the excess water (Leahy et al., 2010). The stable, consistent rate of depletion can also be attributed to their structures. (Timms, 1976) images profiles of both these lakes in which depicts a cup-like structure (Fig. 9). Lakes with this sort of structure are less effected by varying evaporation amounts because their depletion rate does not change since the lakes surface area remains the same throughout depletion.

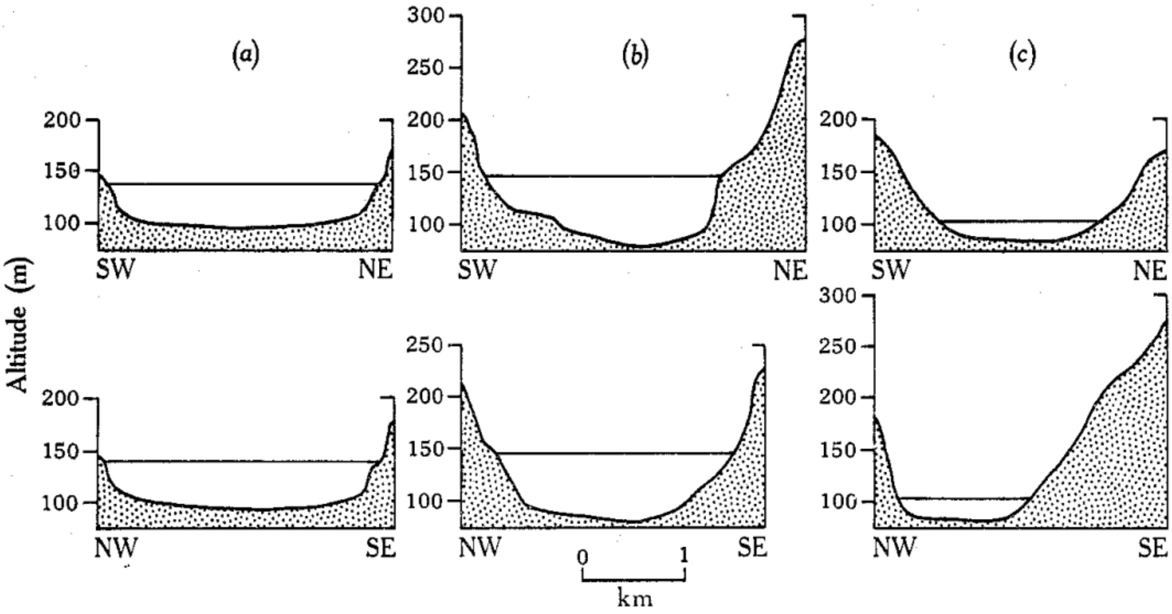

Figure 9: Profiles of Lake Purrumbete (a), Bullenmerri (b) and Gnotuk (c). (Timms, 1976).

DRIVERS OF LAKE LEVEL CHANGE IN WESTERN VICTORIA

Increases and decreases visible in surface area trends for most lakes follow periods of more of less annual rainfall (Fig. 5a). However, this is not always the case as Lakes Bullenmerri, Gnotuk and Keilambete display a declining annual maximum surface area trend from 2010 onwards, despite annual rainfall trends that are relatively consistent through the same period of time. This anomaly represented by these three lakes give evidence of the complexity of lake hydrology and that even though rainfall is a dominant input source into lakes, it is not the sole factor that controls lake level fluctuation. Analysis between annual maximum surface area and each climate variable was completed for individual lakes and Lake Corangamite represented the highest regression slope values for each climate variable and the reason for this could be due to its size in comparison to the other lakes in this study. Lake Corangamite has a historical lake surface area value of ~240 km^2, which is a massive difference as the second largest lake is Lake Martin that has historical lake surface area value of ~35 km^2. Being the largest lake in this study in terms of its surface area size, it also has a large catchment area and receives input from a number of streams (Timms, 2004), which can give further reason for its high regression slope value. However, this factor cannot be the sole determinant as a lake's depth, structure and other factors are also crucial to understanding what makes a lake sensitive to rainfall.

Annual maximum surface area variation is also influenced by evaporation amounts, Lakes Bullenmerri, Colac, Colongulac, Corangamite, Elingamite, Gnotuk, Keilambete and Murdeduke in particular, show obvious indication of the effects that evaporation has on surface area through time. This is shown through the consistent depletion of surface area as the evaporation amounts per year remain high or increase. All 15 lakes show evidence of having increased evaporation amounts compared to their earlier observations in the study period. This is concurrent with the idea that climate conditions are warming, as higher amounts of evaporation are being caused from increased temperatures. The negative correlation between annual maximum surface area and evaporation that is evident across all of the 15 lakes is further evidence that lakes are vulnerable to climate change, not just individually, but collectively as a water source. The effective moisture variable of the three different climate variables has the highest R^2 value for most of the 15 lakes when correlated with annual maximum surface area (Fig. 7). Ultimately, as effective moisture is a product of both rainfall and evaporation, as expected, it is exhibiting higher levels of correlation. Each of the individual lakes annual maximum surface area correlations with the different climate variables never reach over 0.5 (Fig. 7). Basic lake hydrology involves water input minus water output to calculate the change in volume. These factors within the calculation are best represented by rainfall and evaporation, leading to the product of effective moisture. After observing each of the individual annual maximum surface area correlations with individual climate variables (rainfall or evaporation), as expected, the correlations are of lower value, due to only part of the calculation being relied upon for results. Even with using effective moisture amounts as another variable, its correlation values are still low, this can stem from the idea that there are other factors involved in determining lake hydrology along with the concept of water in versus water out.

Other factors that increase the complexity behind studying lake variability through time involve factors that affect evaporation which can include water colour, salinity, individual lake morphometries (depth, perimeter, basin structure), interaction and input from groundwater sources and external factors predominantly including agricultural practises. The 15 different lakes within this study encompass a broad range of morphometry factors: for size differences, Lake Corangamite is the largest, representing a size of 234 km^2 all the way to as low as 2 km in diameter for lakes Keilambete and Elingamite. Another broad range is the salinity content, ranging from hyper-saline lakes, Lake Beeac and Weering, through to multiple freshwater lakes, Lakes Colac and Martin. By including multiple sites in this study that represent different ranges in sizes and salinity, the effects of these individual factors can be depicted and used for explanation regarding the lakes surface area variation through time. The structure of the lakes themselves are also another factor that can help explain some differences in lake variation. When regarding the structure of lakes, the need to understand the associated bathymetry information is critical. Of the 15 lakes in this study, only four have bathymetry depictions, Lakes Bullenmerri, Gnotuk, Keilambete, Purrumbete (Jones et al., 2001; Yihdego et al., 2015; Timms, 2009; Wilkins et al., 2013). Bathymetry constructions of Lakes Bullenmerri and Purrumbete by (Timms, 2009), involves captions that indicate that these lakes have shoreline development and volume development values that are consistent with a more circular, cup-like structure, as opposed to a conical structure. This statement coincides with the annual maximum surface area trends for each lake as, Lake Bullenmerri has a change of 4.55 km^2 to 4.35 km^2 and Lake Purrumbete has a change from 5.1 km^2 to 4.8 km^2. This slow, consistent declining trend exhibited by both lakes coincides with the shape of their basin structures. (Jones et al., 2001) and (Wilkins et al., 2013) images Lakes Keilambete and Gnotuk respectively, there is no information about their shoreline or volume development values, but both lakes are quite circular and their contour lines are very similar to Lake Purrumbete which indicate that its structure is more cup-like than conical. Similarly, Lakes Keilambete and Gnotuk also have very little change in surface area through the study period. Reconstructions for Lake Keilambete involves a change from 2.58 km^2 to 2.50 km^2 and Lake Gnotuk from 2.18 km^2 to 2.08 km^2. This slow rate of decline in surface area through the same period of time is displayed in each of these four lakes, which all collectively have similarly shaped basins. A lakes depth will also have some level of influence on its variability through time, this is best evident through Lakes Martin and Keilambete. Lake Martin is a shallow lake (5 m) with the highest correlation values of all the lakes of interest, whereas Keilambete is a deep lake (40 m) and has the lowest correlation values within this study. With increasing depth, climate variables have a lesser effect on a lakes surface area, for example, Lake Keilambete will require more rainfall than a shallower lake in order to increase its surface area size. On the other hand, Lake Martin will have its surface area value increase at a faster rate due to its smaller capacity which results in it being more vulnerable to climate variables like rainfall and evaporation. Groundwater influence within the study region also has a differing level of impact for each individual lake. Lake Purrumbete has proven to be affected greatly by a groundwater source. A combination of its significant depth and its highly permeable basalts along its shoreline results in a greater interaction with groundwater than a lake which does not exhibit these characteristics (Yihdego et al., 2016). Lake Purrumbete does show evidence of impact by the Millennium Drought and the subsequent La Niña event, but its overall annual maximum surface area change through the study period is relatively low. Its surface area ranges from 5.1 km^2 to 4.8 km^2 within the study period and given its regular access to groundwater, this lake will show resilience in times of lower rainfall and higher temperatures. (Tweed et al., 2009) depicts lakes within the surrounding area of Lake Corangamite to have a groundwater elevation ranging from 115 m to 140 m in 2006 (Fig. 10). The level of groundwater input into Lakes Colac and Corangamite is also included, from 1992 – 2006, Lake Corangamite had a groundwater input range from 0% to 49% (mean of 7%) and Lake Colac had a groundwater input range of 0% to 47% (mean of 20%) (Tweed et al., 2009). Previous work within the same study region on groundwater sources in the area concludes that the lakes in the western Victorian region have different interactions with groundwater. Most lakes within this region operate either as groundwater “throughflow” systems, or as terminal basins (Hale & Butcher, 2011). However, labelling a lake as “through flow” has not been consistent in published studies. (Barton et al., 2008) states that Lakes Corangamite is a through flow system, (Coram, 1996) says that Lakes Murdeduke along with Bookar, Colongulac and Gnarpurt were throughflow systems and (Tweed et al., 2009), concludes that it is not possible to accurately determine if Lake Corangamite is either a “through flow” or a terminal system. With different input percentages for individual lakes, and the difference in flow-type that groundwater interacts with each lake, both give evidence of the different amount of influence that groundwater has on each individual lake.

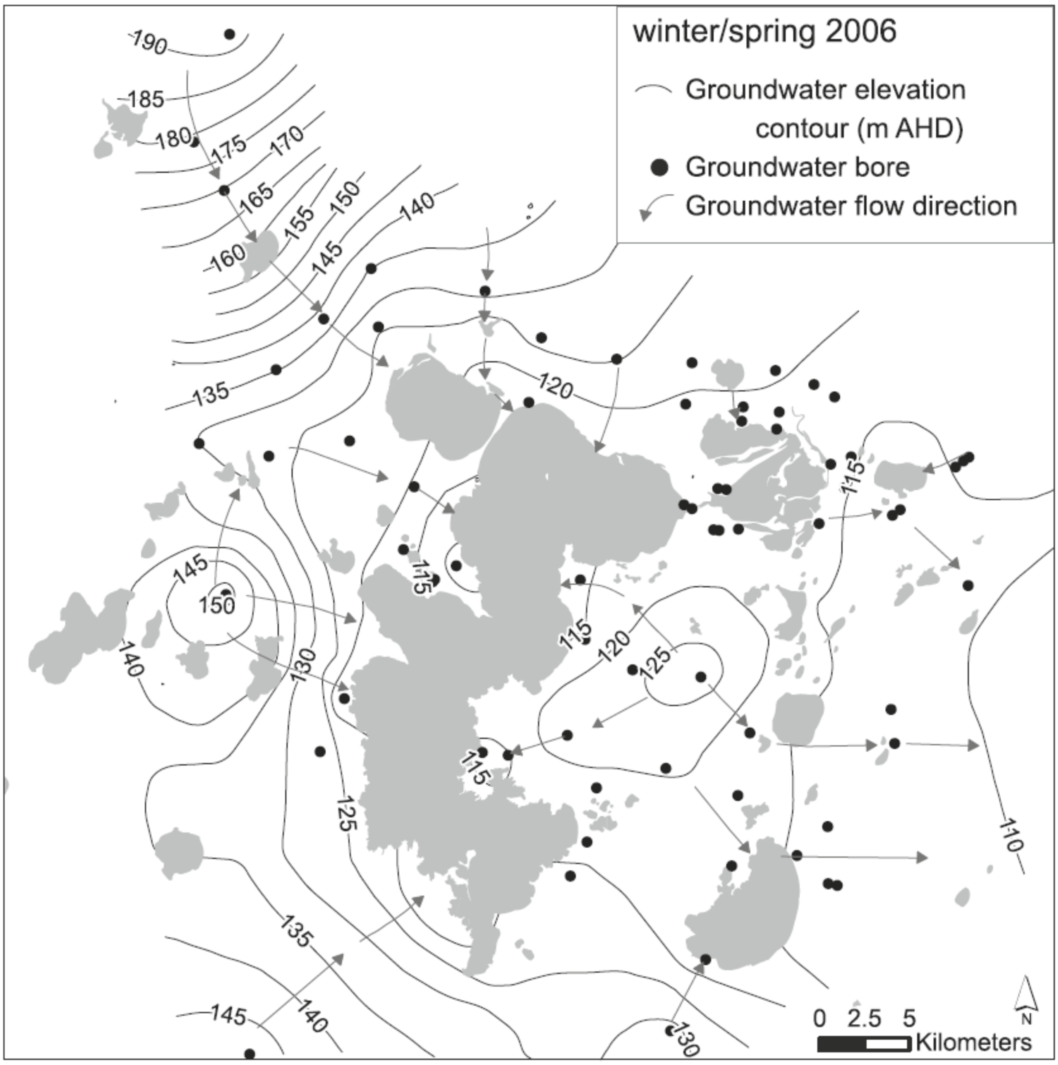

Figure 10: Contoured water table data for winter/spring 2006 and groundwater flow directions. (Tweed et al., 2009).

Another external cause to lake variation and depletion through time can be accounted by agricultural practises. Of the 15 lakes within this study, majority of which are included within the Corangamite Basin region, in which land-use consists mostly of dryland grazing (Jones et al., 1998) and is dedicated to agriculture – 73% for grazing and 10% for crops (Tweed et al., 2009). Considering most of the lakes of interest are within this region, their input towards agricultural necessities will have some level of impact on their surface area variation. With climate conditions projected to warm into the future, the amount of water needed for agriculture will increase and if the agricultural industry extracts water from lakes through pumping lake water out, redirecting runoff or by pumping out ground water, all of these will further impact lake levels within the western Victorian region. Other farming practises that impact lake level variation include clearing native vegetation, irrigation and pumping from bores (De Deckker & Williams, 1988). Abstraction as a term for total water removed from lakes can also have influence over lake variation. However, this can include two different types, for Lake Purrumbete, there is licensed abstraction and unlicensed abstraction. Each year, abstraction can occur for irrigation to the limit of 510×10^3 m^3/year; as for unlicensed, there is no limit for stock and domestic abstraction (Yihdego et al., 2016). With this knowledge, assumptions can be made for the general water depletion of Lake Purrumbete, however, this amount is not reliable as the unlicensed abstraction is unknown and without proper licensing and recording, this value will be difficult to determine. All of these examples can be used as external factors that can help to explain lake variation through time that is not caused by climate influence.

IMPLICATIONS FOR THE FUTURE OF THE LAKES IN THE REGION?

The most important implication concluded from this study is that the lakes are all clearly sensitive to climate and are all subject to a common declining trend as a result of a drying climate. With this conclusive evidence, based off of a group of lakes representing different characteristics and varying degrees of influence from external factors, this information can assist us in predicting the future trajectory of the lakes. All the lakes exhibit clear indication of a decline that is evident when comparing surface area levels towards the start of the study period in 1987 compared to the end of the study period in 2020. Other implications lead on from this overarching issue, mostly involving lake resilience into the future. With groundwater interaction increasing during times of less rainfall, and with a warming future approaching, groundwater will be more influential in the water budget of the lakes. With the level of importance these lakes represent, predictions of their resilience into the future are critical to determine if management can be done in the present to ensure their survival. Lakes Bullenmerri, Gnotuk and Keilambete have had their lake levels modelled through to 2100 based on different climate scenarios from 14 GCMs (Global Climate Models). The results suggest that all three will experience lake level declines into the future, with Lake Bullenmerri experiencing the most depletion (Kirono et al., 2012). These results are in agreeance with the data presented in this study as Lakes Bullenmerri, Gnotuk and Keilambete are all declining and Lake Bullenmerri has exhibited the highest range in surface area change of the three lakes mentioned from the start of this study in 1987 through to the end in 2020.

REVIEW OF ADVANTAGES/DISADVANTAGES OF REMOTE SENSING FOR LAKE VARIABILITY

Remote sensing as a method for measuring lake variability is a big step forward from ways of dated *in-situ* methods. Satellite-based methods have the ability to image and monitor continent-wide surface water dynamics and is also able to archive data to a multi-decadal scale (E. Krause et al., 2021). The continued use of satellite imaging for data collection will involve the SLC-Off issue that is apparent in Landsat 7 satellite images. This issue affected this study as it reduced confidence when creating accurate time-series reconstructions of surface area for each lake. This issue can have detrimental effects as the missing data from this SLC-Off issue left substantial areas of the lakes unrecorded, this is especially true when monitoring smaller lakes since their surface area is already small, the loss of surface area data due to a satellite failure, can result in unreliable reconstructions. Other forms of data collection, like examining aerial photography to determine surface areas changes, should be considered to determine the level of impact this SLC-Off issue is having on certain time periods. With the limitations and encountered issues considered, the movement from *in-situ* collected data to remotely sensed data provides an effective way of obtaining the spatial distribution of surface water across large areas (Huang et al., 2018).

FUTURE RESEARCH

Understanding lake variability as a response to climate and other factors is a very broad concept, in which there are a number of different ways in which future research can be best utilised for this area of study. One crucial idea involves increasing the amount of bathymetric data and hypsographic models that are available. As mentioned previously, of the 15 lakes analysed in this study, only four lakes have available bathymetric data.

This type of data is extremely important and can be used for calculations regarding individual lake surface area, length and depth, shoreline development and volume development (Timms, 2009). Considering the value of bathymetric data and the importance of these lakes, an increase in this data will greatly benefit lake management and future studies.

Another direction for future research includes the continued use and improvement of remote satellite sensing to collect data. This form of data collection is highlighted through the use of the WOfS algorithm; however, it does pose some limitations regarding the DEA Waterbodies outline. Two issues that have arisen, involve mapping multiple different waterbodies that are closely situated together into a singular waterbody or being unable to map complex waterbody perimeters into one waterbody resulting in multiple small waterbodies (Krause et al., 2021). Future work into improvements and higher resolution quality imaging will lead to better capturing the perimeters of water bodies.

Agricultural practises like abstraction, act as an external influence to lake fluctuation. Depending on the reason for the abstraction, there is no limit on the amount of water that can be taken, nor need to be recorded. With climate conditions becoming warmer, the demand for abstraction will increase which will cause lakes to deplete at a faster rate. Future work should include starting to record the total amount of abstraction from lakes to give some indication if excessive amounts of water are being withdrawn from lakes within certain time frames. Having this sort of information on public record will give lake management authorities better insight into how much water is being used for agricultural purposes and if they need to take further action to stop or slow lake fluctuation.

CONCLUSIONS

The goal for this study was to understand lake variability and how climate can affect its fluctuation. By analysing 15 different lakes that encompass dissimilar features (morphometries, depths, salinities, etc.), this study suggests that climate plays a substantial role in lake variation through time. All lakes within this study display a general decline in their annual maximum surface area trends throughout the study period, and they also exhibit increases and decreases that coincide with the Millennium Drought from 1997 – 2009 and the subsequent La Niña event in 2010 – 2011. These key pieces of information that every lake is displaying gives evidence that helps to explain the increasing level of impact that the warming climate is having on these lakes in western Victoria. This analysis on lake variation was completed through the use of remote sensing, and with only some limitations, this method has proven accurate in displaying the changes these lakes are undergoing. Lake hydrology calculations are best suited for this type of study and by analysing individual values associated with this type of calculation, rainfall and evaporation amounts, the level of influence these variables have on lake variation was determined. The results of a third variable, effective moisture, represented the best correlation for most lakes of interest. To better understand lake mechanics, a combination of variables and factors need to be considered when studying lake variation. Through the analysis of important climate variables and other external factors that have significant impact of lake variation, the evidence of surface areas depletion in multiple lakes is obvious, suggesting that lake fluctuation will increase into the future.

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APPENDIX

Table with the correlation R^2 values for each lake of interest and their changing surface area values from 1987 to 2020 with each climate variable. Bold text indicating the highest value of the three climate variables.

Lake	Rainfall	Evaporation	Effective Moisture
Beeac	**0.29**	0.08	0.23
Bookar	0.24	**0.31**	0.30
Bullenmerri	0.19	0.17	**0.23**
Colac	**0.27**	0.15	0.25
Colongulac	0.09	**0.16**	0.13
Corangamite	0.20	0.24	**0.25**
Elingamite	0.09	**0.15**	0.12
Gnarpurt	0.31	0.32	**0.37**
Gnotuk	0.05	0.04	**0.05**
Keilambete	0.01	**0.04**	0.02
Martin	0.39	0.44	**0.48**
Murdeduke	0.30	0.25	**0.32**
Purrumbete	0.11	0.09	**0.12**
Rosine	0.09	**0.30**	0.20
Weering	0.39	0.34	**0.42**

Calculated eigenvalues, proportion explained and cumulative proportion values for the lakes of interest that further highlight the dominance of influence by PCA1 compared to the other PCAs to the lakes of interest.

	PC1	PC2	PC3	PC4	PC5
Eigenvalue	10.740	1.8036	1.00780	0.44570	0.23207
Proportion Explained	0.716	0.1202	0.06719	0.02971	0.01547
Cumulative Proportion	0.716	0.8363	0.90345	0.93317	0.94864