Evaluating the climatic impacts on dryland crop growth using multi-source datasets across Australia

A Dissertation Presented

by

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in partial fulfillment of the requirements for the degree of

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Certificate of Original Authorship

I, Jianxiu Shen, certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of requirements for a degree except as fully acknowledged within the text.

I also certify that the thesis has been written by me. Any help that I have received in my research work and the preparation of the thesis itself has been acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

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Publications arising from this thesis

Journal papers directly included in this thesis

Shen, J., Huete, A., Tran, N.N., Devadas, R., Ma, X., Eamus, D. & Yu, Q. 2018, 'Diverse sensitivity of winter crops over the growing season to climate and land surface temperature across the rainfed cropland-belt of eastern Australia', *Agriculture, Ecosystems & Environment*, vol. 254, pp. 99-110. (Chapter 4)

Shen, J., Huete, A., Tran, N.N., Ma, X., Joiner, J., Beringer, J., Eamus, D. & Yu, Q. 2019, 'Dynamics of light-use efficiency using satellite solar-induced chlorophyll fluorescence and the enhanced vegetation index across Australian rainfed croplands'. (Under review) (Chapter 5)

Shen, J., Huete, A. & Yu, Q. 2019, 'Dryland climate-crop growth relationship: a Review' (Under review) (Chapter 2)

Parts of the journal paper arising from this thesis

Azmi, M., Shen, J., Mohan, C., Dijk, A. 2019, 'Spatiotemporal prediction of rainfed grain annual yield across Australia based on soil moisture and gross primary production estimates'. (Under Review) (Chapter 3)

Peer-reviewed conference proceedings

1. Shen, J., Huete, A., Tran, N.N., Ma, X. & Yu, Q. 2017, 'Detecting the response of seasonal light-use efficiency to canopy temperature by using satellite solar-induced chlorophyll fluorescence and enhanced vegetation index across Australian rainfed croplands', *American Geophysical Union Fall Meeting (AGU)*, New Orleans, Louisiana, U.S.A, 11-15 December.

2. Shen, J., Huete, A., Ngoc, T.N., Devadas, R. & Yu, Q. 2016, 'Incorporating remote sensing methods into crop-climate relationships across the rain-fed cropland belt in NSW, Australia', *The Australian energy and water exchange research initiative National workshop*, Canberra, Australia, 14-15 December.

3. Shen, J., Tran, N.N., Devadas, R., Huete, A., Zhang, H. & Yu, Q. 2016, 'Climate impacts on wheat phenology and production using muti-source data in NSW, Australia', *Geoscience and Remote Sensing (IGARSS), IEEE International Symposium*, Beijing, China, pp. 6296-99. 10-15 July.

Contents

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Abstract

The rainfed cropland belt in Australia is of great importance to the world grain market but has the highest climate variability of all such regions globally. This thesis aims to quantify the spatial temporal climatic impacts on crop productivity, crop phenology and cropland photosynthesis activities across the Australian rainfed cropland belts using multiple source of observed datasets.

The literature review on climate-crop growth relationship called for a future agenda on integrated climate driving factor employment, crop phenology and photosynthesis response focus, multiple source of datasets engagement, and bottom-up approaches for agricultural adaptation. Consistent findings from the three empirical studies in this thesis, which focused on different broad angles of the crop response, indicate that: (1) August and September are the optimum trigger months to spatially predict agricultural annual yield across the rainfed cropland belts in Australia; (2) two critical 8-day periods, beginning on day of the year (DoY) 257 (in September) and 289 (in October), were identified as the key 'windows' of crop growth variation that arose from the variability in climate and land surface temperature. (3) there was a seasonal hysteresis of crop photosynthesis activities in response to surface temperature change throughout the winter crop growing season in Australia. The optimum surface temperature range for satellite observed photosynthesis activity were identified as16.6-17.6 °C during August.

This thesis systematically assessed the climatic impacts on crop growth across the Australian rainfed cropland belts. Practically, it provides new opportunities for large-scale cropland heat and water stress detection and can serve as an early warning system

for agricultural adaptation in broad-acre rainfed cropping practices. Theoretically, it offers a fresh understanding for analyses of the climate-crop growth relationship across diverse spatial-temporal scales.

Key words

Climate change and variability, crop growth, rainfed croplands, multi-source datasets, remote sensing, Australia

Chapter 1. Introduction

1.1 Background

1.1.1 Global climate change and variability

Future climate scenarios where local temperatures increase by 2℃ or more above late-20th-century values will, according to the Intergovernmental Panel on Climate Change (IPCC), negatively impact wheat growth in tropical and temperate regions (Field et al. 2014). Increases in global temperature, water shortage, as well as extreme weather events (heatwave, drought, flood), combined with increasing food demand, would pose great risks to all aspects of food security globally and regionally (Calzadilla et al. 2013; Godfray et al. 2010; Lobell et al. 2011).

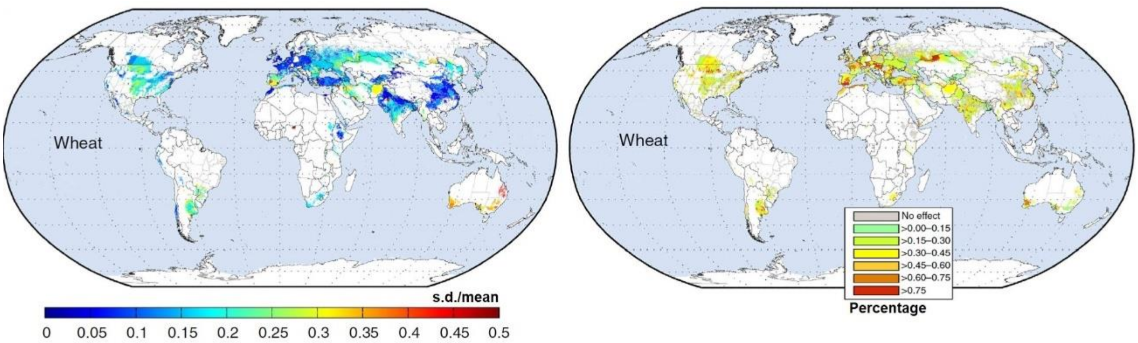

Figure 1.1 Global year-to-year wheat yield variability over the last three decades (1979-2008) (left) and total wheat yield variability explained due to climate variability (right)
* Figure cited from (Ray et al. 2015).

Ray et al. (2015) have mapped the global year to year wheat yield variability over the last three decades. They used the ratio of standard error to thirty-year mean to represent crop yield variability and collected data from ~13,500 political units. From figure 1.1 we can find that, climate variability accounts for roughly a third (~32-39%) of the observed wheat yield variability globally. Regionally, Australia cropland belts have the greatest variability over the last 3 decades and its wheat yield variability can be explained by climate around 43%. Particularly, the percentage was greater than 60% in parts of western Australia.

1.1.2 Climate trends and variability in Australia

According to the Commonwealth Scientific and Industrial Research Organisation (CSIRO) and Bureau of Meteorology in Australia (Figure 1.2), there has been a warming trend across most parts of Australia in annual mean surface air temperature of 0.16 °C per decade since 1970, and rainfall shows considerable variability toward drier conditions from year-to-year (Pearce et al. 2007).

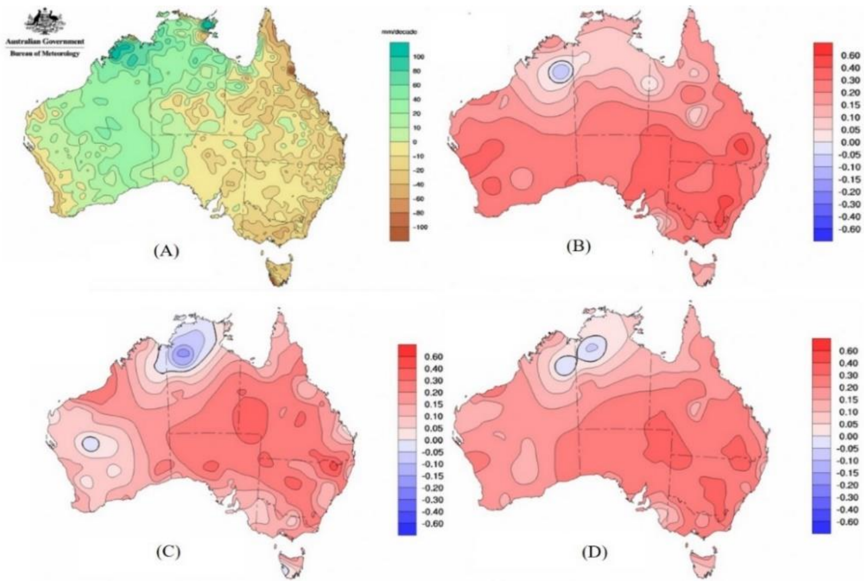

Figure 1.2 Trends in total rainfall (A, mm/10yr), maximum temperature (B, ℃/10yr), minimum temperature (C, ℃/10yr), and mean temperature (D, ℃/10yr) from 1970 to 2017 in Australia
* Source: Bureau of Meteorology in Australia: http://www.bom.gov.au/climate/change/

Meanwhile, climate in Australia is well known to be influenced by multiple climate components (Stokes & Howden 2010), which include the El Niño-Southern Oscillation, the Southern Annular Mode, the Indian Ocean Dipole, the Inter-decadal Pacific Oscillation, the Madden-Julian Oscillation, and seasonal synoptic circulations and frontal systems.

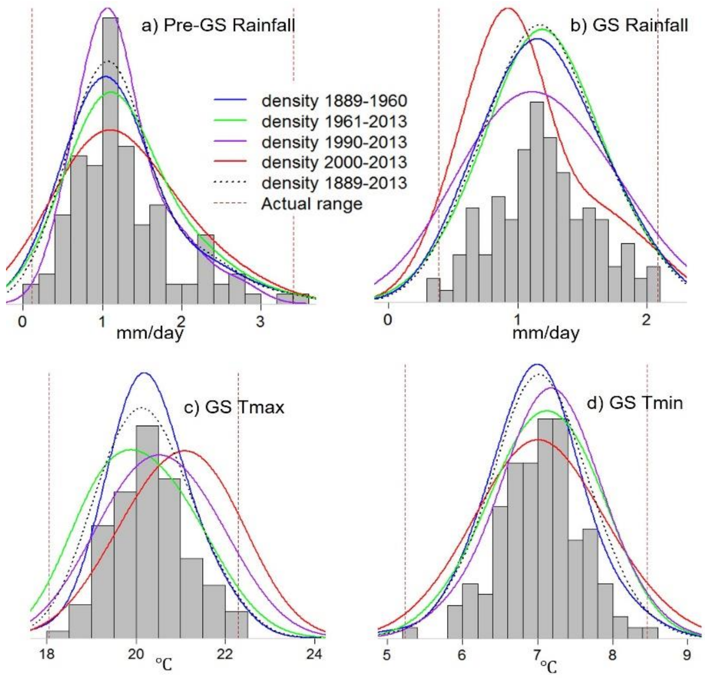

Figure 1.3 Normal Density curves of the historical climate conditions across Australian cropland. a) Pre-growing season rainfall, b) growing season rainfall, c) growing season maximum temperature, d) growing season minimum temperature
* Data collected from Australian Scientific Information for Land Owners (SILO) patched point dataset (http://www.bom.gov.au/silo/); Growing season (GS) was defined as 1st May to 30th November; Tmax is daily maximum temperature; Tmin is daily minimum temperature; Purple vertical dash lines in the left and right in each panel were the minimum and maximum actual observations respectively. Y-axis: Density distribution.

The red curves in each panel in Figure 1.3 are the climatic conditions during the current decade from year 2000 to 2013. We can see that, the average growing season rainfall has been decreasing and maximum temperature has increased. Meanwhile, the minimum temperature and the average pre-growing season slightly decreased by less than 1℃and

0.2 mm, respectively. These indicated that Australian cropland is getting drier and hotter, and the extreme weather events are becoming more frequent in last century.

In the dryland dominated Australian farming systems, the wheat crops are sown based on defined sowing rains (20 mm over a 10-day period) over a “sowing window” from the start of May to the end of July (Keating et al. 2002). Therefore, both long-term climatic conditions and year-to-year climate variability in Australia would definitely threaten its rain-fed arable land planting system (Anwar et al. 2007; Hochman et al. 2012).

1.1.3 Agricultural land use in Australia

In Australia, the 2012-13 (http://www.daff.gov.au/abares) area of land that can be used for agriculture was 397 million hectares, which covers approximately 52% of Australia's total land. But only less than 10% of the area is crop planted area (31.6 million hectares), which has also declined over the past decade (http://www.abs.gov.au/). Australia has a first world economy, but a third world export profile, with 20% of its export value derived from agriculture (Hamblin 2009; Lawrence et al. 2013). This means its farming system needs to provide enough food to feed a population of 22 million domestically, and also another 40 million people abroad (Lawrence et al. 2013). In the following 40 years, the population in Australia is expected to double (Lawrence et al. 2013; Millar & Roots 2012), while the projected growth in the world will reach 9 billion from the current 7 billion (Godfray et al. 2010), which would directly bring serious pressure to Australia’s food security. Meanwhile Australia’s dominant rain-fed farm production levels are low by world standards because of the low and erratic nature of the rainfall and the infertile, acid, alkaline or salty soils (Hamblin 2009). During 2001-2011, Australia suffered a “big dry”

(2001-2009) that was followed by a “big wet” (2010-2011) hydro climatic events, which greatly influenced Australia’s crop system (Steffen et al. 2013).

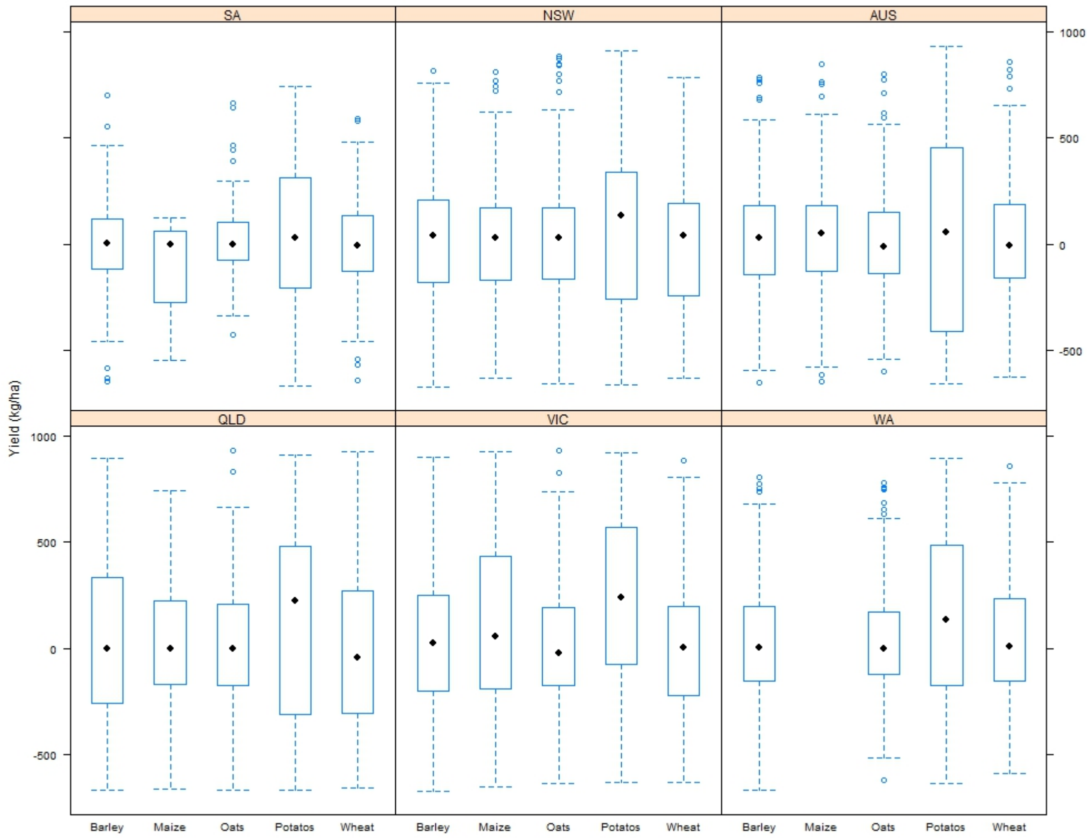

Figure 1.4 Boxplots of de-trended crop yield (kg/ha; Wheat, Potatoes, Oats, Maize, and Barley) from 1877 to 2011.
* Data comes from Australia Bureau of Statistics (ABS, www.abs.gov.au/); The de-trending method of first-difference is used to remove the possible confounding effects of non-climatic factors; Yield (Kg/ha) is expressed as the quotient of production (Kg) divided by planting area (ha); Black dots inside boxes indicates the mean value, box-boundaries are the 25 and 75 percentiles, whiskers are the 10 and 90 percentiles and blue circles indicate each outlier.

In the State of NSW,Australia, total annual wheat production varied between 2,477-10,700 kt over the past decade (2003-2014), and the harvested area ranged between 2,995-4,322 kha. Most importantly, yield per hectare varied more than five-fold, between 0.62-2.80 t/ha (www.abares.gov.au). Historically, Figure 1.4 shows the variability extents of time-series de-trended crop yield. The longer the box length, the more the yield fluctuates.

Statistical de-trended yields at all five crop planting States vary greatly among years. The extent (10 to 90 percentiles) of fluctuations reached to [+1000, -800] kg/ha.

As the climate is changing and will unavoidably change in the long run (http://www.ipcc.ch/), it is indispensable to ensure a steady growth of food production in Australia, especially for the fundamental crop outputs (Tester & Langridge 2010). A comprehensive understanding of arable land under climate change constraints is critically needed, other than only considering intensification and economic concentration (Sandhu et al. 2008). It would help us to timely identify those changes, be prepared for uncertainty, and promote adaptation strategies (Lobell et al. 2008; Stokes & Howden 2010).

1.2 Incorporating multi-source datasets in climate-crop relationship analysis

To monitor world-wide croplands in a changing climate, efforts have been made in aspects of crop simulation models (Asseng et al. 2011; Calzadilla et al. 2013), climate projection models (Liu & Zuo 2012; Turner et al. 2011; Yu et al. 2008), and remote sensing detection methods (Cong et al. 2013; Ma et al. 2014; Sakamoto et al. 2005), trying to identify specific crop growth mechanisms (Chen et al. 2010), environmental determining factors to crop yield (Asseng et al. 2011; Brown 2014; Chen et al. 2013; Yu et al. 2014), critical dates of plant life cycle (Sakamoto et al. 2005), and land allocation (Bindi & Olesen 2011; Yan et al. 2013) using either historic statistical data (Yu et al. 2001; Yu et al. 2014) or spatial distribution data (Sakamoto et al. 2005). However, each research only focused on a single method or model to conduct limited features of arable land planting system. Moreover, simulation modelling requires large workload to upscale from species level to ecosystem level or regional level. For instance, statistical crop yield data do not contain information of spatial distributive variation, and also crop growth conditions. Remotely-sensed data are able to overcome these limitations. However, they cannot achieve long term observation since most sensors emerged only from late 20 century. Estimating the climate-crop growth relationship by using a single understudied source or method would result in large potential uncertainties (Cong et al. 2013). Thus, evaluating and integrating multiple sources of datasets and methods are necessary.

Adopting novel methods by incorporating multi-source observation data will better illustrate the relationships between climate factors and crop growth measurements spatially and temporally. Take the State of New South Wales (NSW) in Australia as an example, Hutchinson et al. (2005) has divided the NSW wheat belt into 5 main agro-climatic zones (E4, E3, E2, D5, and E6). Several spatial temporal datasets were evaluated to demonstrate the advantage of incorporating multi-source data in climate-crop relationship analysis.

The weather stations dataset for each of the agro-climatic zones were collected from SILO (PPD, www.longpaddock.qld.gov.au) patched point. Each of the weather stations has a century of daily records in maximum temperature, minimum temperature, rainfall, and solar radiation. This study calculated average daily values for these five stations to represent the historical climatic patterns across NSW wheat belt. Each of the weather station data were used to characterize the climate patterns for the corresponding agro-climatic zones. The wheat growing season (GS) was then distinguished as May to November in each year, and pre-growing season (pre-GS) as January to April. As for *in-situ* data, 370 wheat trial observation records were collected, which include sowing date, harvest date and actual yield from 2005 to 2013. This ground truth data for wheat phenology and productivity came from the National Variety Trials (http://www.grdc.com.au/), Grains Research and Development Corporation (GRDC) in

Australia. MOD13A1 EVI with 16 days temporal resolution and 500 meters spatial resolution from year 2000 to 2013 were collected. Time-series profiles of EVI and integrated EVI (iEVI) for each pixel were then extracted. iEVI is an index to represent crop productivity in most cases (Broich et al. 2015).

1.2.1 Weather patterns derived from SILO and sowing and harvesting windows from NVT

By comparing rainfall distribution patterns throughout year 2005 and 2006 across the NSW wheat belt (Figure 1.5), we can see that total rainfall in year 2006 (218 mm) was half of the amount in 2005 (436 mm) and there were nearly 40 continuing days without rainfall around October in 2006. Based on the study of (Zhang et al. 2016), year 2006 can be taken as a drought year, compare to the normal year 2005. During the growing season, rainfall in 2006 (128 mm) was significantly lower than in 2005 (352 mm), but in the pre-growing season, the rainfall conditions in the 2 years were very similar (61 mm in year 2005 and 80 mm in year 2006). This explained why planting areas (Table 1.1) in years 2005 and 2006 were nearly the same, but the annual production in these 2 years has nearly 3-fold differences.

The horizontal black dash lines in Figure 1.5 are the minimum (2 ℃) and maximum (34 ℃) temperature thresholds that wheat growth can tolerate. If daily minimum temperature is lower than 2 ℃, wheat crop would suffer from freeze damage, and limits crop growth. If daily maximum temperature is higher than 34 ℃, heat stress would affect crop grain filling (Anwar et al. 2007; Asseng et al. 2011), and reduce yields and total production.

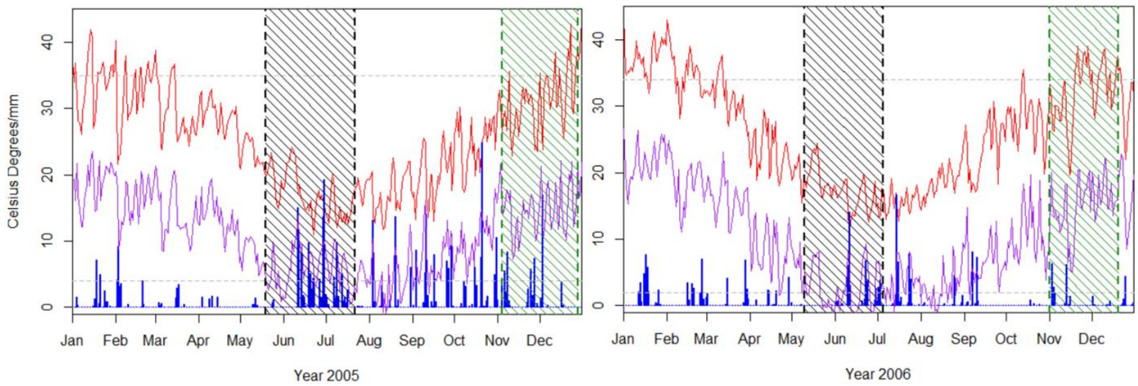

Figure 1.5 Comparison of weather conditions and sowing and harvest windows across NSW wheat belt in year 2005 and 2006.
* Blue vertical lines stand for daily rainfall; Red line is time series maximum temperature; Purple line is minimum temperature; The horizontal black dash lines are the minimum (2℃) and maximum (34℃) temperature thresholds that wheat growth can tolerate; Black and green shadowed areas are sowing window and harvest window which are extracted from observed trial sites data in years 2005 and 2006.

Figure 1.5 shows the number of extreme days (hot and cold) in 2006 were greater than in 2005, with 74 and 34 days respectively. This correspond to narrower and earlier sowing and harvest windows in 2006 compared with year 2005. In 2005, the sowing window and harvesting window began on 19-May and 4-November, each with lengths of 64 days and 54 days, respectively, while in 2006, the beginning dates were 10-May and 1-November, with respective sowing and harvesting window lengths of 56 days and 49 days.

Table 1.1 NSW wheat planting area, yield and Sowing and Harvest windows in selected years

Year	Area	Production	Yield	Sowing Date Range			Harvest Date Range			LGS Range		
	Hectares	Tonnes	Kg/m2	Min	Max	Range	Min	Max	Range	Min	Max	Range
2002	2,994,800	2,494,900	0.08	--	--	--	--	--	--	--	--	--
2005	3,554,100	8,049,700	0.23	19-May	22-Jul	64 days	4-Nov	28-Dec	54 days	134 days	205 days	71 days
2006	3,595,800	2,576,700	0.07	10-May	05-Jul	56 days	1-Nov	20-Dec	49 days	141 days	204 days	63 days
2010	3,814,700	10,488,400	0.27	28-Apr	11-Jun	44 days	6-Nov	8-Jan+	63 days	169 days	220 days	51 days

* In this table, -- means "not available"; + means "plus next year"; Range is calculated by Max value minus Min value for each attribute (Sowing date, harvest date and length of growing season).

1.2.2 EVI time series profile of wheat phenology at different agro-climate zones

Figure 1.6 shows the weather and smoothed EVI time series profiles, as a surrogate for wheat growing conditions, in the normal year 2005 and the drought year 2006 over 4 different agro-climatic zones. As region E6 has a semi-arid climate that is too dry to support wheat growth, the approach was conducted to the other 4 agro-climatic zones.

Figure 1.6 clearly shows the corresponding wheat growth conditions followed by different weather patterns among the 4 agro-climatic zones. The amount of rainfall during the wheat GS in year 2006 is around one third of that in year 2005, in all the NSW agro-climatic zones. Meanwhile, in the GS in drought year 2006, the average maximum temperature is higher than in year 2005, and the average minimum temperature is lower than in the year before. However, in zone E4, total rainfall in pre-GS 2006 is much higher than that in year 2005.

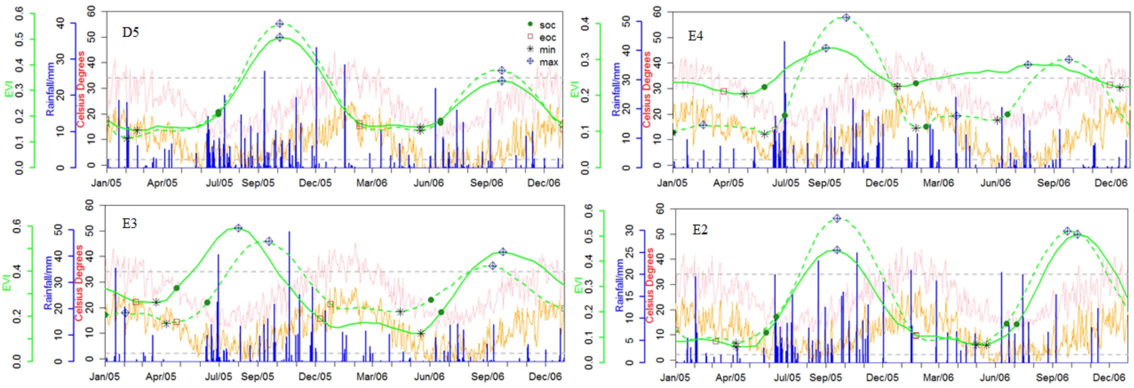

Figure 1.6 Wheat phenological smoothed EVI profile over different Agro-climate zones (E4, E3, E2, and D5).
* Pink and orange solid lines, and vertical blue line are time-series maximum and minimum temperature and rainfall, respectively; Horizontal grey dash lines are maximum and minimum temperatures that wheat growth could tolerate; Green solid line is time series EVI profile for the trial point located in a specific agro-climatic zone and with actual observation for year 2006; Green dash line is the time series EVI profile for the trial point with actual measurements for year 2005; 'soc' is start of growth cycle; 'eoc' is

end of growth cycle; ‘min’ is the minimum point of smoothed time-series EVI; ‘max’ is the maximum point of the smoothed time-series EVI.

Located in southwestern part of the NSW wheat belt, zone E2 was the region in which wheat growth was least affected by climate variabilities, with wheat EVI profiles similar in both years and its peak point EVI values are higher than all the peak values in the other regions. From the amplitude of EVI curves, drought has clearly affected wheat above-ground biomass in regions E4, E3 and D5. In the normal year 2005, the average EVI peak values at zones E4, E3 and D5 were 0.375, 0.563 and 0.535, while they were 0.293, 0.455 and 0.359, respectively in the drought year 2006.

1.2.3 Spatial temporal relationship between climate factors and crop growth

Figure 1.7 shows the crop-climate information derived from all the 3 datasets in 2005-2014. We can see that higher growing season-iEVI occurs with higher rainfall and lower number of hot days during growing season across study area (year 2010 and 2005). The average length of growing season was the longest in the “wet” year 2010, which was 200 days. We can also find from Figure 1.7 that Sowing and Harvest windows are adjustable with the corresponding climate condition each year, and the average dates have an early trend over the years from 2001 to 2013.

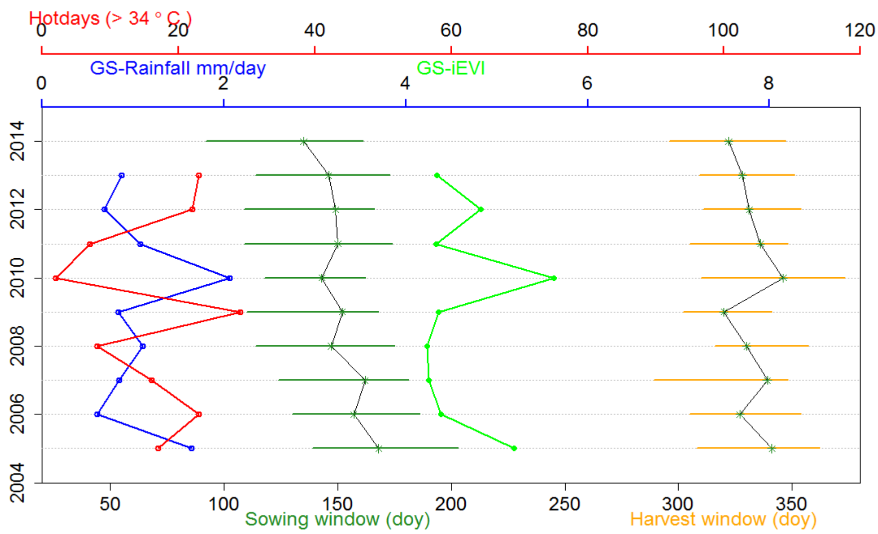

Figure 1.7 Rainfall, hot days, growing season iEVI and sowing and harvest windows of crops across NSW wheat belt in 2005-2014.
* GS is growing season; Hot days were counted as the days in which the maximum temperature higher than 34 ℃ during crop growing season; iEVI were calculated as the total EVI during crop growing season.

Therefore, it is concluded that incorporating multi-source observation datasets would better illustrate the relationships between climate factors and crop growth spatially and temporally. Thus, with the use of diverse temporal-spatial resolution datasets emerging in recent years (Thenkabail et al. 2012), this thesis proposes empirical methods using multi-source data to detect the response of rainfed cropland production, phenology and photosynthesis activity to climate variability in Australia.

1.3 Significance

Crop planted in rainfed cropland is influenced by climate variability during the whole life span. Reasons are: (1) Rain-fed agriculture mostly rely on rainfall for water supply, and it occupies more than 90% of Australia's total cultivated land (Hamblin 2009), which makes crop productivity highly sensitive to climate changes (Anwar et al. 2007; Cornish

1950). (2) Phenology is defined as the study of periodic life cycle events of living things and how those are influenced by environmental factors (such as climate, hydrology and soil) (Zhu & Wan 1973). Climate variability is the major driving factor influencing crop phenology, and even the whole arable land planting system. (3) Gross primary production (GPP) is mainly determined by the amount of photosynthetically active radiation absorbed by vegetation (Gitelson et al. 2015). Crop photosynthesis activity is highly sensitive to environmental change, such as the variability of vapour pressure deficit, and drought stress (Dong et al. 2015).

Therefore, estimating the climatic impacts on crop productivity, crop phenology and crop photosynthesis activity across the rainfed cropland belt of Australia using multi-source datasets, would practically release the timely information needed for the design and implementation of relevant adaptation strategies to climate variability in different geographical scenarios. And theoretically, the efforts will help to reduce yield gap between attainable yield and potential yield in broad-acre rain-fed cropping system both in Australia and worldwide and enhance the knowledge of researchers and industries on climate-crop growth relationship. At the same time, this thesis will help to improve the capability of policy makers and farmers to prepare for uncertainty, design farm management, and take in time agricultural adaptation strategies in the changing climate. The data and utilities will be fundamental for crop yield forecasts and can serve as an early warning system for regions suffering from crop loss and food shortages.

1.4 Structure of this thesis

The thesis including publications is structured into six chapters. Three chapters from this thesis have been under review or published in leading agricultural multi-disciplinary journals. These three journal articles have placed in the thesis as stand-alone chapters contributing to the overall aim of this thesis to evaluate the climatic impacts on crop growth across the rain-fed croplands in Australia.

Chapter 2 is a literature review paper by understanding the current status of dryland climate-crop growth relationship (CCR) by surveying 44 journals articles. Four broad research angles of state-of-art CCR research have been identified: (1) climate change and variability, (2) crop response, (3) CCR approaches, and (4) agricultural adaptation. Focusing on the broad angle of crop response, *the responses of crop productivity, crop phenology and crop photosynthesis activities* have been subsequently addressed in Chapter 3, Chapter 4 and Chapter 5. This chapter highlights the thesis foundation.

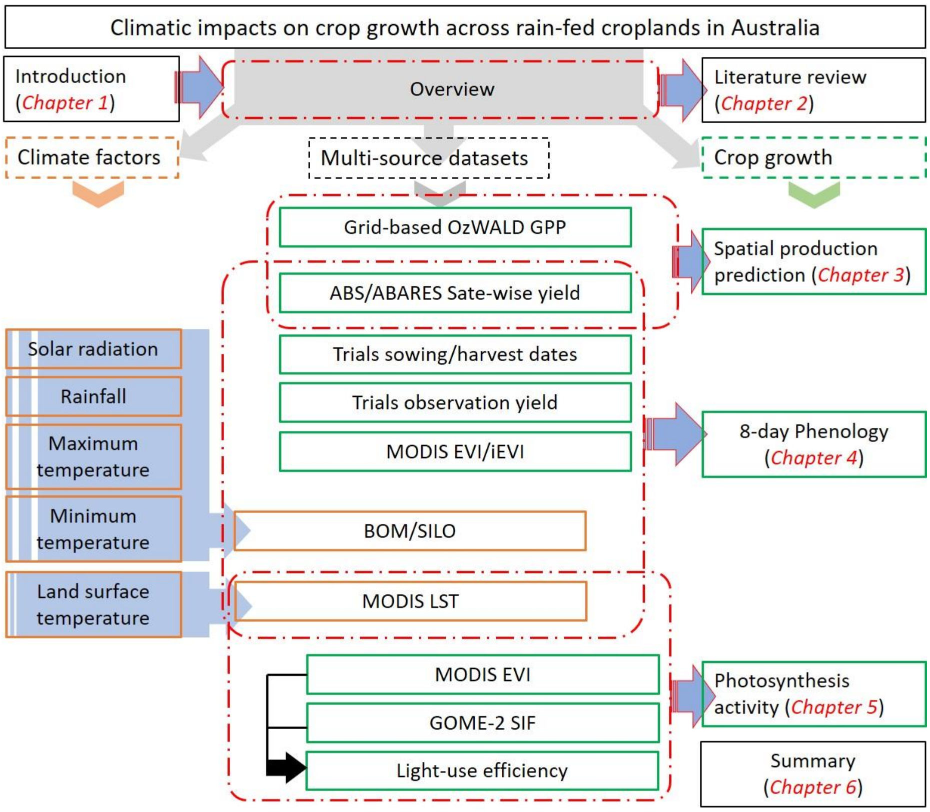

Figure 1.8 Outline of the thesis.
* Abbreviations: 'OzWALD'-Australian Water and Landscape Dynamics group, Australian National University (http://www.wenfo.org/wald/); 'ABS'- Australia Bureau

of Statistics (www.abs.gov.au/); 'ABARES'- Australian Bureau of Agricultural and Resource Economics and Sciences, Australian department of Agriculture and Water Resources. (www.abares.gov.au/); 'MODIS EVI'- Moderate Resolution Imaging Spectroradiometer, Enhanced Vegetation Index; 'iEVI'- intergrated Enhanced Vegetation Index; 'BOM'- Australian Bureau of Meteorology (www.bom.gov.au/); 'SILO'- Australian Scientific Information for Land Owners patched point dataset (http://www.bom.gov.au/silo/); 'LST'- Land Surface Temperature; 'GOME-2 SIF'- the Global Ozone Monitoring Experiment-2 sensed Solar-Induced chlorophyll Fluorescence.

Chapter 3 is an attempt to spatiotemporally predict the rainfed agricultural annual yields using satellite-based gross primary production (GPP) for Australia. This chapter investigated the relative advantages of regression in prediction. The dataset from Australian Bureau of Statistics (ABS) (annual data; 2000-14; State scale) are considered as representative of actual agricultural yields across Australian cropping belt. Monthly GPP data from 2000-14 with the spatial resolution of 0.05° was applied for my analysis. The optimum predicting months of GPP were specified in this Chapter. The results showed that it is possible to spatially predict agricultural annual yield.

Chapter 4 is an empirical study to quantify the contributions of climate and Land Surface Temperature (LST) variations to the variability of crop growth (Phenology) by using remote sensing methods, which has been published in Agriculture, Ecosystems & Environment. Different from previous studies, the data was analysed at an 8-day time-step to provide a more accurate evaluation through the rainfed cropland of Eastern Australia. The study identified two critical 8-day periods as the key 'windows' of crop growth variation that arose from the variability in climate and LST. The results show that the impacts of heat variation outweighed rainfall variation across rainfed crops.

Chapter 5 is the third empirical study to explore the potential to directly monitor cropland photosynthesis activity from space. Satellite based solar-induced chlorophyll fluorescence (SIF) and Enhanced vegetation index (EVI) provide direct measurement of vegetation photosynthesis activity and greenness, respectively. The link between SIF with crop photosynthesis is instantaneous, but satellite SIF signal often contains information of canopy structure, total canopy chlorophyll content, and canopy greenness level. The concept of light-use efficiency (LUE) constructed in this study has removed the relatively constant greenness level within a certain time. This study further demonstrated the spatial pattern and temporal dynamics of satellite-based vegetation measurements both among the cropland growing season months and within each of the months at diverse land surface temperature (LST) levels. The results of this study tend to have significant implications for large-scale cropland water and heat stress detection and monitoring, and also for remotely analyse the photosynthesis activities from canopy to leaf level.

Chapter 6 is the final chapter of this thesis. It synthesizes previous chapters in articulating the contributions of this thesis to the field of dryland crop stress detection. It concludes with the imitation of this thesis and recommendation for future research.

References

Anwar, M.R., O'Leary, G., McNeil, D., Hossain, H. & Nelson, R. 2007, 'Climate change impact on rainfed wheat in south-eastern Australia', *Field Crops Res.*, vol. 104, no. 1–3, pp. 139-47.

Asseng, S., Foster, I.A.N. & Turner, N.C. 2011, 'The impact of temperature variability on wheat yields', *Global Change Biol.*, vol. 17, no. 2, pp. 997-1012.

Bindi, M. & Olesen, J. 2011, 'The responses of agriculture in Europe to climate change', *Regional Environmental Change*, vol. 11, no. 1, pp. 151-8.

Broich, M., Huete, A., Paget, M., Ma, X., Tulbure, M., Coupe, N.R., Evans, B., Beringer, J., Devadas, R. & Davies, K. 2015, 'A spatially explicit land surface phenology data product for science, monitoring and natural resources management applications', *Environ. Model. Softw.*, vol. 64, pp. 191-204.

Brown, A. 2014, 'Agriculture: Crop-yield drivers', *Nature Clim. Change*, vol. 4, no. 12, pp. 1050-.

Calzadilla, A., Rehdanz, K., Betts, R., Falloon, P., Wiltshire, A. & Tol, R.J. 2013, 'Climate change impacts on global agriculture', *Clim. Change*, vol. 120, no. 1-2, pp. 357-74.

Chen, C., Baethgen, W.E. & Robertson, A. 2013, 'Contributions of individual variation in temperature, solar radiation and precipitation to crop yield in the North China Plain, 1961–2003', *Clim. Change*, vol. 116, no. 3-4, pp. 767-88.

Chen, C., Wang, E. & Yu, Q. 2010, 'Modeling wheat and maize productivity as affected by climate variation and irrigation supply in North China Plain', *Agron. J.*, vol. 102, no. 3, pp. 1037-49.

Cong, N., Wang, T., Nan, H., Ma, Y., Wang, X., Myneni, R.B. & Piao, S. 2013, 'Changes in satellite-derived spring vegetation green-up date and its linkage to climate in China from 1982 to 2010: a multimethod analysis', *Global Change Biol.*, vol. 19, no. 3, pp. 881-91.

Cornish, E.A. 1950, 'The influence of rainfall on the yield of wheat in South Australia', *Australian Journal of Biological Sciences*, vol. 3, no. 2, pp. 178-218.

Dong, J., Xiao, X., Wagle, P., Zhang, G., Zhou, Y., Jin, C., Torn, M.S., Meyers, T.P., Suyker, A.E., Wang, J., Yan, H., Biradar, C. & Moore, B. 2015, 'Comparison of four EVI-based models for estimating gross primary production of maize and soybean croplands and tallgrass prairie under severe drought', *Remote Sens. Environ.*, vol. 162, pp. 154-68.

Field, C.B., Barros, V.R., Mach, K. & Mastrandrea, M. 2014, 'Climate change 2014: impacts, adaptation, and vulnerability', *Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*.

Gitelson, A.A., Peng, Y., Arkebauer, T.J. & Suyker, A.E. 2015, 'Productivity, absorbed photosynthetically active radiation, and light use efficiency in crops: Implications for remote sensing of crop primary production', *Journal of Plant Physiology*, vol. 177, no. Supplement C, pp. 100-9.

Godfray, H.C.J., Beddington, J.R., Crute, I.R., Haddad, L., Lawrence, D., Muir, J.F., Pretty, J., Robinson, S., Thomas, S.M. & Toulmin, C. 2010, 'Food security: the challenge of feeding 9 billion people', *Science*, vol. 327, no. 5967, pp. 812-8.

Hamblin, A. 2009, 'Policy directions for agricultural land use in Australia and other post-industrial economies', *Land Use Policy*, vol. 26, no. 4, pp. 1195-204.

Hochman, Z., Gobbett, D., Holzworth, D., McClelland, T., van Rees, H., Marinoni, O., Garcia, J.N. & Horan, H. 2012, 'Quantifying yield gaps in rainfed cropping systems: A case study of wheat in Australia', *Field Crops Res.*, vol. 136, no. 0, pp. 85-96.

Hutchinson, M.F., McIntyre, S., Hobbs, R.J., Stein, J.L., Garnett, S. & Kinloch, J. 2005, 'Integrating a global agro-climatic classification with bioregional boundaries in Australia', *Global Ecology and Biogeography*, vol. 14, no. 3, pp. 197-212.

Keating, B.A., Gaydon, D., Huth, N.I., Probert, M.E., Verburg, K., Smith, C.J. & Bond, W. 2002, 'Use of modelling to explore the water balance of dryland farming systems in the Murray-Darling Basin, Australia', *Eur. J. Agron.*, vol. 18, no. 1–2, pp. 159-69.

Lawrence, G., Richards, C. & Lyons, K. 2013, 'Food security in Australia in an era of neoliberalism, productivism and climate change', *J. Rural. Stud.*, vol. 29, no. 0, pp. 30-9.

Liu, D. & Zuo, H. 2012, 'Statistical downscaling of daily climate variables for climate change impact assessment over New South Wales, Australia', *Clim. Change*, vol. 115, no. 3-4, pp. 629-66.

Lobell, D.B., Burke, M.B., Tebaldi, C., Mastrandrea, M.D., Falcon, W.P. & Naylor, R.L. 2008, 'Prioritizing climate change adaptation needs for food security in 2030', *Science*, vol. 319, no. 5863, pp. 607-10.

Lobell, D.B., Schlenker, W. & Costa-Roberts, J. 2011, 'Climate trends and global crop production since 1980', *Science*, vol. 333, no. 6042, pp. 616-20.

Ma, X., Huete, A., Yu, Q., Restrepo-Coupe, N., Beringer, J., Hutley, L.B., Kanniah, K.D., Cleverly, J. & Eamus, D. 2014, 'Parameterization of an ecosystem light-use-efficiency model for predicting savanna GPP using MODIS EVI', *Remote Sens. Environ.*, vol. 154, pp. 253-71.

Millar, J. & Roots, J. 2012, 'Changes in Australian agriculture and land use: implications for future food security', *International journal of agricultural sustainability*, vol. 10, no. 1, pp. 25-39.

Pearce, K., Holper, P.N., Hopkins, M., Bouma, W.J., Whetton, P., Hennessy, K.J. & Power, S.B. 2007, *Climate Change in Australia: technical report 2007*, CSIRO Marine and Atmospheric Research.

Ray, D.K., Gerber, J.S., MacDonald, G.K. & West, P.C. 2015, 'Climate variation explains a third of global crop yield variability', *Nat. Commun.*, vol. 6.

Sakamoto, T., Yokozawa, M., Toritani, H., Shibayama, M., Ishitsuka, N. & Ohno, H. 2005, 'A crop phenology detection method using time-series MODIS data', *Remote Sens. Environ.*, vol. 96, no. 3–4, pp. 366-74.

Sandhu, H.S., Wratten, S.D., Cullen, R. & Case, B. 2008, 'The future of farming: the value of ecosystem services in conventional and organic arable land. An experimental approach', *Ecological Economics*, vol. 64, no. 4, pp. 835-48.

Steffen, W.L., Hughes, L., Karoly, D.J. & Commission, C. 2013, *The critical decade: extreme weather*, Climate Commission Secretariat, Department of Industry, Innovation, Climate Change, Science, Research and Tertiary Education.

Stokes, C. & Howden, M. 2010, *Adapting agriculture to climate change: preparing Australian agriculture, forestry and fisheries for the future*, CSIRO PUBLISHING.

Tester, M. & Langridge, P. 2010, 'Breeding technologies to increase crop production in a changing world', *Science*, vol. 327, no. 5967, pp. 818-22.

Thenkabail, P.S., Lyon, J.G. & Huete, A. 2012, *Hyperspectral remote sensing of vegetation*, CRC Press Boca Raton, FL.

Turner, N.C., Molyneux, N., Yang, S., Xiong, Y.-C. & Siddique, K.H. 2011, 'Climate change in south-west Australia and north-west China: challenges and opportunities for crop production', *Crop and Pasture Science*, vol. 62, no. 6, pp. 445-56.

Yan, D., Schneider, U.A., Schmid, E., Huang, H.Q., Pan, L. & Dilly, O. 2013, 'Interactions between land use change, regional development, and climate change in the Poyang Lake district from 1985 to 2035', *Agricultural Systems*, vol. 119, pp. 10-21.

Yu, Q., Hengsdijk, H. & Liu, J.D. 2001, 'Application of a progressive-difference method to identify climatic factors causing variation in the rice yield in the Yangtze Delta, China', *Int. J. Biometeorol.*, vol. 45, no. 2, pp. 53-8.

Yu, Q., Li, L., Luo, Q., Eamus, D., Xu, S., Chen, C., Wang, E., Liu, J. & Nielsen, D.C. 2014, 'Year patterns of climate impact on wheat yields', *Int. J. Clim.*, vol. 34, no. 2, pp. 518-28.

Yu, Q., Wang, E. & Smith, C.J. 2008, 'A modelling investigation into the economic and environmental values of ‘perfect’climate forecasts for wheat production under contrasting rainfall conditions', *Int. J. Clim.*, vol. 28, no. 2, pp. 255-66.

Zhang, B., Feng, G., Read, J.J., Kong, X., Ouyang, Y., Adeli, A. & Jenkins, J.N. 2016, 'Simulating soybean productivity under rainfed conditions for major soil types using APEX model in East Central Mississippi', *Agric. Water Manage.*, vol. 177, pp. 379-91.

Zhu, K. & Wan, M. 1973, *Phenology*, Beijing: Science Press, 1-131.

Chapter 2. Dryland climate-crop growth relationship: a Review

Highlights

• A content analysis approach was employed in the literature review.

• Four broad research angles of the CCR research were investigated.

• Agenda for future research were discussed.

Abstract

To deal with the increasing challenges of climate change and climate variability, the complex climate-crop relationship (CCR) need to be better understood. This study provides a systematic, holistic and objective review of the dryland climate-crop relationship (CCR) academic literature by combining Leximancer, a content analysis tool, to conventional bibliographic analysis. Forty-four publications on climatic impacts on croplands from 2009 to 2018 (inclusive) have been identified. The findings revealed four broad areas of foci with CCR research: (1) climate change and variability, (2) crop response, (3) CCR approaches, and (4) agricultural adaptation. The specific agro-climatic change variables, crop growth measurements and models employed in current CCR research were identified by manually bibliographic analysis. This study calls for a future agenda on integrated climate driving factor employment, crop phenology and photosynthesis response focus, multiple source of datasets engagement, bottom-up approaches for agricultural adaptation.

Key Words

Climate-crop growth relationship, content analysis, Leximancer, modelling

2.1 Introduction

With the rapid growth of industrialization and population, the concentration of greenhouse gases (carbon dioxide, methane and nitrous oxide) is now unprecedentedly higher than it has been for the last 8 billion years (Pachauri et al. 2014). Increasing emission of greenhouse gases has caused and will continue causing further warming and long-lasting changes on the Earth's climate system, including intense heat waves, extreme precipitation events, and rising global mean sea level (Pachauri et al. 2014; Smith et al. 2007). In recent decades, the observed climatic impacts on all nature and human systems (rangeland vegetation, cropland system, water availability, human health, etc.) are strong and comprehensive (Asseng et al. 2011; Calzadilla et al. 2013; Ray et al. 2015). These indicate that the biodiversity, ecosystem services and economic development are highly sensitive to the changing climate. Across a wide range of regions, many studies (Calzadilla et al. 2013; Pachauri et al. 2014; Ray et al. 2015; Tripathi et al. 2016) showed the negative impacts of climate change and variability on nature and human systems, especially cropland system, have been more common than positive impacts.

The productivity of cropland system, as the foundation to human welfare, essentially and ultimately depends on climate (Navin et al. 2002), due to the limitations in accumulated temperature, precipitation (and soil moisture), solar radiation during the limited length of crop growing seasons. In dryland agricultural sector, climate is the most important factor that determines the efficiency of crop productivity (Yuan et al. 2017). Ray et al. (2015) revealed that climate variability contributes to 32-39% of the variability in global observed crop yield and they illustrated the spatial pattern of crop yield sensitivity to climate variability (temperature, precipitation and their interaction, respectively). At a regional level, croplands in the Southern provinces of Canada, north-western and north-central states of the United States, northern Europe, southern former Soviet Union, and the Manchurian plains of China are mostly sensitive to changes in temperature (Navin et al. 2002). Croplands in the Great Plains region of the United States and north-eastern China are mostly sensitive to changes in precipitation (Navin et al. 2002). In Australia, wheat yield has stalled since 1990 due to the reduced rainfall and rising temperature (Hochman et al. 2017) and is expected to decrease by the late 21st century (Wang et al. 2018).

As climate-crop relationship (CCR) research is multi-disciplinary, there is a range of levels of spatial and temporal patterns to focus on to address real-world problems (Challinor et al. 2009). Computer simulation (Asseng et al. 2015; Rosenzweig et al. 2013) and satellite imagery (Potgieter et al. 2010; Shen et al. 2018) have been widely used to understand the complex mechanism of CCR. Meanwhile, regional (e.g. crop outlook https://qaafi.uq.edu.au/industry/crop-outlook) and global (e.g. crop monitor https://cropmonitor.org/) projects on detecting, monitoring and predicting the cropland productivity under the changing climate have also been launched as a mean to enhance the knowledge of researchers, industries, policy makers, and small holder farmers on CCR. However, literature concerning CCR has been relatively fragmented with multiple conclusions. As such, it is timely to undertake a review article on CCR to provide a clear picture of the field to advance researchers' knowledge.

By employing content analysis through the software Leximancer, this paper aims to provide a text-driven analysis of the literature on CCR. By doing so, this paper provides a conceptual map that visually presents the conceptual and relational insights of the previous studies by providing up-to-date knowledge of the CCR field.

This Chapter begins by presenting the results of conventional bibliographic analysis in agro-climatic change variables, crop growth measurements and models employed in current CCR research. Afterwards, the research design using content analysis is then introduced. The results are discussed via the visual representations derived from Leximancer. Thereafter, relevant insights are presented from the results and research gaps and areas for future research then follow. It concludes with a summary of the findings and limitation of this study.

2.2 Research design

2.2.1 bibliographic analysis

In the first step, a keyword-based search for related articles was performed from the scientific database of Scopus. The evolution of electronic age has offered the facilities of many powerful databases for the researchers to search on a particular subject and analyze citation. Scopus, one of the current most popular database, offers the widest coverage of journals in top-level subject fields with consistent accuracy (Falagas et al. 2008). It provides both in keyword searching and citation analysis, although it is limited to recent articles (published after 1995) (Falagas et al. 2008). As search keywords from title, abstract and keywords, The following query (accessed on 26th April 2018) were used:

TITLE-ABS-KEY ("climate change" , "climate variability" , AND crop) AND (LIMIT-TO (EXACTKEYWORD , "Climate Effect ") OR LIMIT-TO (EXACTKEYWORD , "Climate Variability And Change ")) AND (EXCLUDE

(EXACTKEYWORD , "Irrigation") OR EXCLUDE (EXACTKEYWORD , "Irrigation (agriculture)"))

In this way, papers referring to CCR but not applied to the irrigated agriculture domain were filtered. In the second step, only journal articles written in English were selected, as journal articles have been peer-reviewed indicating a good quality. The search then restricted the articles to be published during the latest decade between 2009 to 2018 (inclusive). Thereafter, a small number of interesting efforts which did not qualify in terms of the research approach addressed and the relevance of CCR, were excluded. As a result, a total of 44 papers were selected. A list of these article is provided in Appendix. In the final step, the 44 papers selected were analyzed manually. That is, the author went through each article one-by-one to identity the detailed research focus, agro-climatic change variables and crop growth measurements used, sources of data and models employed.

2.2.2 Content analysis

To better understand the topics discussed the literature, content analysis of the selected literature was performed by using the software - Leximancer. Leximancer is high-level language processing software through the employment of statistical algorithms but also nonlinear dynamics and machine learning. Leximancer transforms 'lexical co-occurrence information from natural language into semantic patterns in an unsupervised manner' through 'two stages of extraction – semantic and relational' (Smith & Humphreys 2006). Previous research demonstrated that Leximancer reduces the per-conception bias that is often associated with manual analysis and generates more objective and text-driven results (Cheng 2016; Nunez - Mir et al. 2016). A detailed description about Leximancer's algorithm can be found in the work of Smith & Humphreys (2006). The concepts that are mapped closed indicate a closer relationship.

All the full texts of the selected papers were analyzed in Leximancer, as Leximancer can provide a systematic and objective analysis of state of the art related work. This would enable the researchers to uncover concepts, themes, and relationships in the texts of articles, and discover unknown qualities about the data to generate valid and trustworthy inferences.

2.3 Main findings

2.3.1 Bibliographic analysis results

2.3.1.1 Agro-climatic change variables

As shown in Table 2.1, the 44 selected papers focus on 4 major aspects of climatic impacts (on dryland crops): terrestrial drought, solar radiation, modelled scenarios, and ocean climate. Drought, a result of the interactions from increased water deficit, warmer average air temperature and elevated atmospheric CO_2, appears to be the major climatic driving component in the CCR related papers published in the recent decade. Precipitation and temperature are two predominant factors that drive the response of crops (Table 2.1). Rainfall, dry days, and terrestrial water storage (TWS) were identified as the indicators of precipitation measurements from the selected papers. Meanwhile, heat stress, maximum temperature, minimum temperature, and diurnal range of temperature were covered as temperature measurements by the surveyed papers. Besides the three independent climatic variables (precipitation, temperature, and CO_2) to describe terrestrial drought, vapour pressure deficit (VPD) and standardized precipitation and evapotranspiration index (SPEI), two computed variables, were also identified by the selected papers (Table 2.1). VPD and SPEI has been recognized as effective indices to measure the climatic stress on dryland crop growth.

Solar radiation is also a fundamental climate factor that governs the physiological and biophysical processes of crop growth in terms of photosynthesis activity and evapotranspiration. Hernández-Barrera & Rodríguez-Puebla (2017) indicated that the performance of the models based on solar radiation is better than that of studies based on temperatures and precipitation variables.

Table 2.1 List of agro-climatic indicators used in selected Climate-Crop research literature

Foci	Climatic driving variables	Indicators
Terrestrial drought (Kristensen et al. 2011; Steiner et al. 2018; Wang et al. 2016)	Precipitation (Dosio & Paruolo 2011; Liu et al. 2016; Rahman et al. 2018; Steiner et al. 2018; Ummenhofer et al. 2015)	-Dry days (Traore et al. 2013) -Rainfall (Armah et al. 2011; Conway & Schipper 2011; Dono et al. 2016; Gichangi et al. 2015; Hakala et al. 2012; Kassie et al. 2013; Milan & Ruano 2014; Omoyo et al. 2015; Paudel et al. 2014) -GRACE TWS (Ndehedehe et al. 2018)
	Temperature (Dono et al. 2016; Dosio & Paruolo 2011; Hakala et al. 2012; Liu et al. 2016; Omoyo et al. 2015; Rahman et al. 2018; Steiner et al. 2018; Tao & Zhang 2013; Ummenhofer et al. 2015)	-Heat stress (Hawkins et al. 2013) -Max/min temperature (Gichangi et al. 2015; Traore et al. 2013) -Diurnal range (Hernandez-Barrera et al. 2017)

	CO_2 (Dono et al. 2016; Tao, Yokozawa, et al. 2009; Tao & Zhang 2013; Tao, Zhang, et al. 2009)
	VPD (Mojid et al. 2015)
	SPEI (Prabnakorn et al. 2018)
Solar radiation	Solar radiation (Hernández-Barrera & Rodríguez-Puebla 2017)
Modelled scenarios	GCMs (Cobon et al. 2016; Tao, Zhang, et al. 2009)
	RCMs (Dosio & Paruolo 2011)
	MIROC 3.2 HI/PRECIS (Naresh Kumar et al. 2016)
	REMO HadRM3 (Mishra et al. 2013)
Ocean climate	SST (Alves et al. 2009)
	Niño-3 / dipole index (Alves et al. 2009)
	NAO index (Marta et al. 2010; Persson et al. 2012)

* Abbreviations: GRACE-Gravity Recovery and Climate Experiment; TWS-Terrestrial Water Storage; SPEI-Standardized Precipitation and Evapotranspiration Index; GCMs-General Circulation Models; MIROC3.2 HI-Model for Interdisciplinary Research on Climate, Japan; PRECIS-Providing Regional Climates for Impact Studies; VPD- vapour pressure deficit; REMO- Regional Model, Max-Plank Institute for Meteorology, Hamburg, Germany; HadRM3- Hadley Regional Model, Hadley Centre for Climate and Meteorology, UK; NAO- North Atlantic Oscillation; SST-sea surface temperature; RCMs- regional climate models.

Modelled scenarios of future and possible climate conditions were generated by the selected papers, which cover a range of spatial scales and complexity. The climate models used were listed in Table 2.1. The climate simulations from the global climate model, General Circulation Models (GCMs), has coarse spatial resolution in the range 100-300 km, while a regional climate model (RCM) typically has the resolution of 10-50 km. Regional models were mostly applied to specific regions, where the model initial conditions were tailored designed to reduce the uncertainty of projections. Efforts in ensemble of multiple climate models was also made to minimize the inherent uncertainties in climate simulations (Dosio & Paruolo 2011; Tao, Zhang, et al. 2009).

Besides conventional meteorological variables (air temperature, precipitation, and CO_2) measured from terrestrial sites, ocean climate has also contributed greatly to the land surface processes in the earth system. The El Niño and La Niña phenomena have multiple climatic and socio-economic consequences globally and regionally (Alves et al. 2009). They associated with dry episodes and flooding over the circum-Pacific regions (Holton & Dmowska 1989). The meridian mode of climate variability in the tropical Indian Ocean is usually indicated by 'dipole index' in academic research. The dipole index is calculated by a latitudinal gradient in the sea surface temperature (SST) anomaly pattern between the north and south of the tropical basin (Black et al. 2003). The North Atlantic Oscillation (NAO) index measures the variation in air pressure difference in the northern Atlantic Ocean, which highly related to the winter conditions in north-western Europe (Persson et al. 2012).

2.3.1.2 Crop growth measurements

The dynamic nature of climate affect crop growth happens during the whole crop life span and eventually limit the final grain yields (van Ittersum et al. 2003). Crop response in aspects of productivity, phenology, photosynthesis, and varieties/types (Table 2.2) were conducted by the selected papers.

Variables for crop productivity included in the selected papers were annual grain yield, reference crop evapotranspiration (ET), extreme yield, leaf area index (LAI), crop production/ Gross domestic product (GDP), and small-holder agriculture (Table 2.2). Crop production and annual grain yield were the two most used variables to measure agricultural productivity in CCR research. While reference crop ET was considered as a hydrological parameter that reflects the integrated effects of various climatic parameters (Mojid et al. 2015). Ummenhofer et al. (2015) explored the seasonal cycle of climatic variables during extreme-yield years and their links to crop growth. LAI is a dimensionless quantity that characterizes crop canopies and is used as a reference tool for crop growth (Wilhelm et al. 2000). The social-economic terms of crop productivity are GDP and small-holder agriculture (farmer's income). These two variables might have relatively lower sensitivity to climate variability because of the protection policy (Conway & Schipper 2011) and the agricultural trading market.

Table 2.2 List of crop growth measurements used in selected Climate-Crop research literature

Aspect of crop response	Variables	References
Crop productivity	Annual grain yield	(Alves et al. 2009; Hawkins et al. 2013; Hernández-Barrera & Rodríguez-Puebla 2017; Hernandez-Barrera et al. 2017; Klink et al. 2014; Kristensen et al. 2011; Liu et al. 2016; Masere & Worth 2015; Naresh Kumar et al. 2016; Ndehedehe et al. 2018; Omoyo et al. 2015; Potgieter et al. 2016; Prabnakorn et al. 2018; Rahman et al. 2018; Sayari et al. 2015; Tao, Yokozawa, et al. 2009; Traore et al. 2013; Traoré et al. 2011; Wang et al. 2016)
	Reference crop ET	(Mojid et al. 2015)
	Extreme yield	(Ummenhofer et al. 2015)
	LAI	(Mishra et al. 2013)
	Crop production/GDP	(Alves et al. 2009; Armah et al. 2011; Cobon et al. 2016; Conway & Schipper 2011; Dono et al. 2016; Estrada et al. 2012; Steiner et al. 2018; Tao, Zhang, et al. 2009)

	Small-holder agriculture	(Kassie et al. 2013; Milan & Ruano 2014; Paudel et al. 2014)
Crop phenology	Greening and browning	(Broich et al. 2015)
	Phenology	(Marta et al. 2010)
	Frost injury	(Persson et al. 2012)
Crop varieties/types		(Gichangi et al. 2015; Hakala et al. 2012)
Crop photosynthesis		(Tao & Zhang 2013)

* Abbreviations: ET- evapotranspiration; LAI-leaf area index; GDP- Gross domestic product

In the research of crop phenology response to climate change, Broich et al. (2015) developed a set of land surface phenology (LSP) remote sensing products characterizing the episodes of greening and browning of the vegetated land surface in Australia. This dataset tracks crop phenology over time and thereby monitor the crop growth response and resilience to climate variability. Persson et al. (2012) conducted the risk of frost injury on winter wheat during the negative NAO phases over the north-western Europe. More specifically, Marta et al. (2010) investigated the timing of crop bud-break, flowering and harvest response to the change of meteorological variables.

In response to climate change and variability, sufficient crop diversity in types and cultivars may enhance the resilience (Gichangi et al. 2015; Hakala et al. 2012). The indigenous knowledge on weather forecasting will be helpful in farming decision making on the types of crops to be planted (Gichangi et al. 2015).

Crop photosynthesis response to climate change was analysed in only one of the selected papers (Tao & Zhang 2013). It has indicated that crop photosynthesis could be enhanced by the rising CO_2 because of its fertilization effects.

2.3.1.3 Models employed in current CCR research

As Figure 2.1 shows, there were two major aspects of efforts in 'modelling' from the 47 selected studies, model assessment and model simulation.

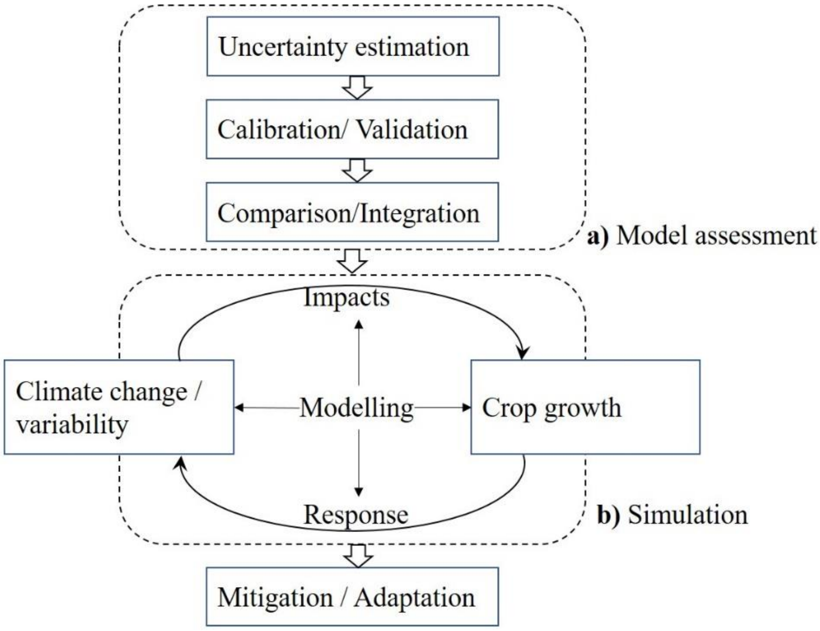

Figure 2.1 scheme of efforts in 'modelling' from the 47 selected studies

The efforts in 'modelling assessment' in the current literature (Figure 2.1) majorly focused on model uncertainty estimation (Estrada et al. 2012; Tao, Zhang, et al. 2009), model calibration and validation (Dosio & Paruolo 2011; Klein et al. 2012; Tingem et al. 2009), and model comparison and integration (Lobell & Asseng 2017; Rosenzweig et al. 2013). The nature of climate forcing and crop growth dynamics is complex and cannot be known precisely, therefore, the inherent uncertainties in CCR simulation and prediction are unavoidable. The uncertainty could be caused by model parameter setting, the predictability of the atmosphere, and the crop response of physical and biological systems (Challinor et al. 2009; Murphy et al. 2004). To assess and minimize such inherent uncertainty, Klein et al. (2012) calibrated a crop system model (CropSyst model) by using farm accountancy data. Tingem et al. (2009) calibrated the same model using observed crop annual yield data and tested the capability of the model to represent the actual performance of crops grown in sub- Saharan Central African. Using multiple models with vary spatial and temporal resolutions (model integration or ensemble) can also give more skilful and reliable results than any single model (Hagedorn et al. 2005; Murphy et al. 2004). The Agricultural Model Inter-comparison and Improvement Project (AgMIP) is a major international effort linking the most cutting-edge CCR models and technology to produce improved crop and economic models and projections for the agricultural sector (Rosenzweig et al. 2013).

The calibrated and optimized models are capable to serve as simulation tools to explore the relationship between climate change and crop growth. The simulations (Figure 2.1) focus on climate change/variability projection, crop growth simulation, and climate impact research. In climate modelling, the simulated climate is sensitive to historical and projected changes to the land surface (Challinor et al. 2009). The importance of water and carbon cycles for representing weather and climate has been recognized in the climate models (listed in Table 2.1) utilized in the selected papers. Meanwhile, the process-based crop modelling can capture the complex biophysical processes associated with climate driving factors by parameterize the environmental factors and management practices during the growing season of a specific crop variety. APSIM (Agricultural Production Systems Simulator) (Liu et al. 2016; Masere & Worth 2015), CropSyst model (a crop system model) (Klein et al. 2012; Tingem et al. 2009), FROSTOL (a model to simulate the frost tolerance of crops) (Persson et al. 2012), and MCWLA (Model to capture the Crop-Weather relationship over a Large Area) (Tao, Yokozawa, et al. 2009; Tao, Zhang, et al. 2009) were the crop response models that mostly employed in the selected papers.

2.3.2 Content analysis results

Figure 2.2 and Table 2.3 indicate four broad area of foci (1) climate change and variability, (2) crop response, (3) CCR approaches, and (4) agricultural adaptation in the selected literature. There are various themes and concepts in each broad area reflecting the diverse perspectives of CCR research.

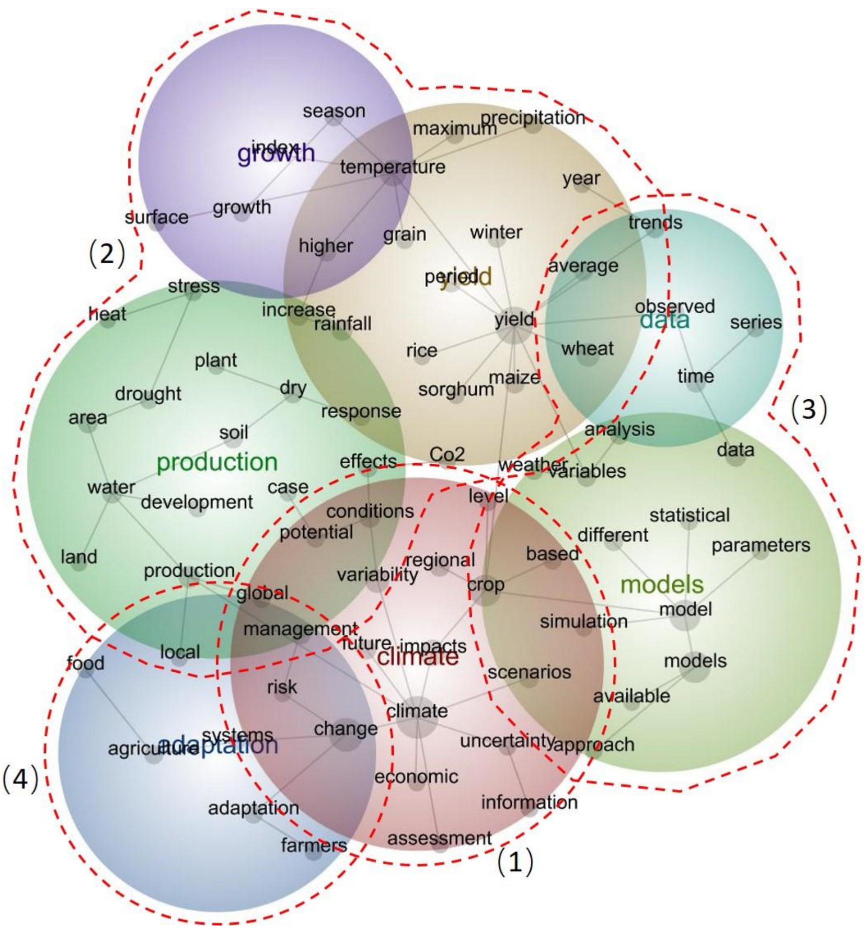

Figure 2.2 Conceptual map of CCR literature published during 2009-2018.
(1) Climate change and variability; (2) Crop response; (3) CCR approaches; (4) Agricultural adaptation

Table 2.3 Themes and Concepts of CCR literature published during 2009-2018

Foci	Themes	Concepts	Frequency
Climate change and variability	Climate	climate, change, crop, impacts, variability, regional, conditions, future, scenarios, management, level, assessment, information, uncertainty, economic	6223
Crop response	Yield	yield, temperature, wheat, rainfall, maize, precipitation, period, increase, higher, maximum, winter, year, grain, CO_2, sorghum, rice	5682
	Production	production, water, soil, effects, area, dry, potential, drought, global, development, stress, response, case, land, plant, heat	3984
	Growth	season, growth, index, surface	984
CCR approaches	Models	models, model, data, different, based, variables, weather, simulation, statistical, approach, parameters, available	3773
	Data	time, trends, observed, analysis, average, series	1989
Agricultural adaptation	Adaptation	agriculture, adaptation, farmers, risk, systems, food, local	1768

2.3.2.1 Climate change/variability

The climate change/variability and its impacts are concerned as the driving component in CCR research. The concept *climate* in close proximity with *change*, *impacts*, *assessment*, *scenarios* and *risk* (Figure 2.2) indicates the rapid growth of research focus on generating the present and the future climate conditions regionally and globally, and evaluating the impacts of the climate scenario on crop growth (Dono et al. 2016) and the corresponding social-economic risks (Estrada et al. 2012). Moreover, the concept *uncertainty* is particularly connected to *risk*, *information*, *scenarios* and *assessment* (Figure 2.2) illustrating that the uncertainty generated from CCR research is an important factor affecting the assessment of the expected agricultural loss and decision-making.

2.3.2.2 Crop response

The broad area of crop response includes 'yield', 'production' and crop 'growth' response, which are highly semantically close. The theme 'yield' and 'production' has the highest occurrence frequency of 5682 and 3984 respectively, while the occurrence of the theme 'growth' has the lowest frequency of 984 (Table 2.2). These indicate the majority of the selected papers in CCR research focus on annual *grain* yield and crop production response.

As for the 'yield' theme, the most related concepts are specific climate variables (*temperature*, *rainfall*, *precipitation*, and CO_2) and crop species (*winter wheat*, *maize*, *sorghum*, and *rice*). While, the 'production' theme includes more general concepts as *water*, *soil*, *area*, *drought*, *land* and *heat*. These indicates that crop grain yield response is the most popular research interest in the selected related works. Researches on agricultural production often links with large scale policy making and social-economic adaptation (Conway & Schipper 2011).

The theme 'growth' describes the crop response to climate change / variability during the crop growing process. The concept *season* reflects the agro-climatic conditions like winter season (Persson et al. 2012), rainy and dry season (Kassie et al. 2013; Mishra et al. 2013; Ndehedehe et al. 2018; Prabnakorn et al. 2018) during crop growing season. While, the concept *surface* provides information about the soil (Hakala et al. 2012) and water (Kassie et al. 2013; Mishra et al. 2013) conditions.

2.3.2.3 CCR approaches

The broad area of CCR approaches includes various types of 'models' and 'data'. The dominant methodology employed in the selected literature is modelling. Table 2.3 listed

30 concepts that have ≥ 20% co-occurrence likelihood to the concept *model*. The related concepts show that the current CCR approaches are highly diverse comprising different *statistical* and *simulation* models, *parameters* calibration, and their *uncertainty* estimation, particular ensemble multiple models (Lobell & Asseng 2017) with *different* spatial and temporal resolution, apply models in *different* sites (Lobell & Asseng 2017) under *different* management practices (Persson et al. 2012), or under the possible *weather* scenarios in the *future*.

Table 2.4 Co-occurrence likelihood ≥ 20% of related-concepts to 'model'

Word	Likelihood	Word	Likelihood	Word	Likelihood
models	93%	Global	30%	Series	22%
Statistical	61%	Regional	30%	Information	21%
Simulation	53%	Approach	30%	Analysis	21%
Parameters	40%	Data	27%	Time	21%
Economic	39%	Crop	27%	Effects	21%
Scenarios	33%	Observed	27%	Available	21%
Uncertainty	33%	Impacts	25%	Soil	21%
Variables	32%	Growth	24%	Future	21%
Assessment	32%	Weather	24%	Case	20%
Different	31%	Wheat	22%	Climate	20%

The performance of models is limited by *data availability* for the study *case* (Lobell & Asseng 2017; Potgieter et al. 2016). 'Data' therefore is the second theme of CCR approaches. The theme 'data' reflects the data used in the selected literature in terms of data source and data analysis. This theme is also connected to the 'yield' theme by the concepts *trends* and *observed* (Figure 2.2) reflecting that the method of processing long term records (such as *time series*) of crop grain yield (Hernández-Barrera & Rodríguez-Puebla 2017; Paudel et al. 2014) and climate change variables (Klink et al. 2014) was mostly applied in current CCR research.

2.3.2.4 Agricultural adaptation

CCR research serves for the decision-making of agricultural adaptation strategies to the changing climate. The broad area agricultural adaptation connected to the broad areas of crop response and climate change/variability by the concepts *local* and *adaptation*, respectively (Figure 2.2). These indicate that climate adaptation requires approaches that address biophysical and socioeconomic considerations at regional and local scales (Steiner et al. 2018), especially include bottom-up approaches from small-scale farming (Steiner et al. 2018). Cobon et al. (2016) and Armah et al. (2011) assessed the agricultural risk and vulnerability to the changing climate at a local scale and identified the impacts and adaptation responses for farmers.

2.4 Discussion

The analysis of extent literature using Leximancer indicates there are four distinct areas within the climate-crop growth relationship (CCR) literature (1) climate change and variability, (2) crop response, (3) CCR approaches, and (4) agricultural adaptation. The specific agro-climatic change variables, crop growth measurements and models employed in current CCR research were identified by manually bibliographic analysis. The following discussion focus on four promising areas for future research, integrated climate driving factor employment, crop phenology and photosynthesis response, multiple source of datasets engagement, bottom-up approaches for agricultural adaptation.

2.4.1 Integrated climate driving factor employment

Efforts in the selected papers focus on one or several lead agro-climatic change variables to explore the climate-crop relationship. However, the conclusions were fragment because the models utilized in current research tend to emphasize the physical side, while the biological processes are rather modelled empirically (Sippel et al. 2018) and the interactions among different climate driving factors are often neglected in controlled-environment experiments. Changes in air temperature, the amount and distribution of precipitation, and elevated atmospheric CO_2 concentration together can have complex and indirect impact on crop growth (Asseng et al. 2004) at different crop phenological stages. Elevated atmospheric CO2 will enhance crop photosynthesis due to its fertilization effects (Tao & Zhang 2013), but it also mean warmer average air temperature and increased water deficit in agricultural systems. Thus, it is critical to adopt an integrated climate driving factor that combines indirect effects of air temperature, effective precipitation, CO_2, and soil conditions within the soil-plant-atmosphere continuum. Li et al. (2013) has introduced the potential to use satellite-derived land surface temperature (LST) to measure the physical processes of the ground surface energy and water balance and reflects the water and heat status of vegetation and soil. LST indicates deficient soil moisture and also a high canopy heat stress (Karnieli et al. 2010). It has proven to be a well-suited ground water and heat measurement at canopy level in large-scale crop monitoring (Karnieli et al. 2010). More possible integrated climate driving factors to be employed in CCR research is worth putting on the agenda.

2.4.2 Crop phenology and photosynthesis response focus

The themes 'yield' and 'production' response were the two major angles of crop growth response in the current CCR related works. However, meteorological variability, such as heatwaves and frost stress, also have strong influence on the main biological processes (setting and ripening of plant organs, onset and duration of different phenological stages) responsible for plant growth and development (Marta et al. 2010). Crop phenology is a sensitive indicator of climate change/variability and has great socio-economic and biological impacts through the changes in productivity and in the carbon and water cycles (Marta et al. 2010). Currently, there is little knowledge about the diverse responses of crop growth to regional climate variability at every growth stage. Understanding the CCR over the life span of crops can help farmers and agricultural departments make timely decisions in response to climate variability and reduce potential losses in yield (Rabbinge 2007).

Another important crop growth and development measurement, crop photosynthesis activity, can be affected by a range of leaf and environmental factors (Gitelson et al. 2015), such as chlorophyll pigment composition, state of stomatal conductance (Yan et al. 2017), changes in leaf and canopy structure, vapor pressure deficit (VPD), CO_2 concentration (Tao & Zhang 2013) and drought stress. Consequently, crop photosynthesis activity varies dynamically over diverse temporal and spatial scales because of the changing climate. These call for urgent agenda to continuously monitor and detect all the changing environmental variables and photosynthesis responses throughout the life span of crops.

2.4.3 Multiple source of datasets engagement

In most previous studies, the ‘models’ of CCR research can be divided into two major types: observational and statistical models, and crop simulation techniques (Figure 2.2, Table 2.3). The data collection of observational and statistical models has been mostly limited from administrative boundaries, which cannot reflect the crop-growing biological process and do not contain information of spatial heterogeneity. Process-based crop simulation models can reconstruct the physical growth cycles of crops using parameter pre-setting. However, it is labour intensive to spatially up-scale the simulations from the field plot to ecosystem or regional scales (Rosenzweig et al. 2013). This is due to the fact that crop simulation needs considerable efforts in data collection and parameter calibration to overcome its limitations in spatial heterogeneity (Shen et al. 2018). These limitations in spatial up-scaling can be overcome by introducing remote sensing detection methods (Reed et al. 1994; Sakamoto et al. 2005) or by combining crop models with satellite observations (Ma et al. 2008; Moulin et al. 1998).

Satellite radiometric observations offer rich spatial-temporal-spectral resolutions (Eamus et al. 2016), from hourly (e.g. Himawari 8 observations) to monthly (e.g. MODIS- The Moderate Resolution Imaging Spectroradiometer datasets), from meters (Landsat datasets) to kilometres, from optical hyperspectral bands (Prasad et al. 2011) to electromagnetic radiation emitted directed from the objects (e.g. Radar- Radio Detection and Ranging). Though extensive independent field-based investigations and specialised research information are required to validate the performance of remote sensing observations (Justice et al. 1998). Remotely sensed indices to measure vegetation health and growth conditions have also been extensively established by many efforts(Huete 2012; Zheng & Moskal 2009), these enriches the wealth of available data and allows to integrate models and data using (Sippel et al. 2018) to minimize the inherent uncertainty associated with climate projections and the complexity of agricultural systems.

2.4.4 Bottom-up approaches for agricultural adaptation

Climate adaptation decision-making, such as cultivars selection, sowing date adjustment, planting density design, fertilization, and irrigation at critical growth stages, have to be undertook by the small-scale farmers. The small-scale farmers often have their indigenous indicators to predict the nature of the season, which have not been tested in a changing climate (Masere & Worth 2015; Steiner et al. 2018). These suggest that CCR research need to include bottom-up approaches to raise farmers' engagement into scientific enquiry (Masere & Worth 2015; Worth 2002). Taking a bottom-up approach, such as learning networks and peer-to-peer communication, whereby practical and efficient adaptation strategies for local and regional scale climate risk assessment is essential (Steiner et al. 2018). Adaptation management options like fertilization and irrigation will require additional economic consideration for farmers and sustainability assessments (Rahman et al. 2018; Reidsma et al. 2010). Including the socio-economic impacts of the available adaptation response options is an issue that is worth putting on the policy agenda. Meanwhile, because management and adaptation can remarkably reduce the potential impact of climate change on crop productivity (Reidsma et al. 2010), future assessment of climatic impacts on crop growth should integrate possible adaptation options into the model simulation, rather than set adaptation alone as a last step conclusion (Reidsma et al. 2010).

2.5 Conclusions

By combining conventional bibliographic analysis and a text-driven approach using Leximancer, this paper presents an objective, systematic and holistic review of current CCR literature. The specific agro-climatic change variables, crop growth measurements and models employed in current CCR research were identified by manually bibliographic analysis. The content analysis using Leximancer illustrated the key concepts, themes and broad area underpinning the CCR field, and further uncovered the research gaps.

In summary, this study has a number of contributions to extant literature. Firstly, it offers a clear-cut representation of the CCR literature by a visual analytics approach to help researchers visibly position themselves in the literature to identify potential new directions as well as to locate their work within the field. Secondly, it can serve as an introduction to the rapidly evolving CCR field by addressing the agro-climatic change variables, crop growth measurements, and models involved for an evidence-informed approach. Thirdly, by aggregating various fragmented evidence in the literature, it also highlights existing barriers and opportunities on collaboration to harness the benefits of CCR research.

The limitations of this study are: 1) examined only academic journal articles published in the current 10 years (2009-2018 inclusive). Future research including wider coverage of publications (such as longer years of retrieval, more databases of searching, government reports, and issues papers), and perhaps a further comparative approach between government-industry-media and academic sources would offer additional insights into the CCR research. 2) Filtered the journal articles only focusing on the direct climate driving factors. The articles focus on the non-climate factors (such as plant diseases, plague of insects, and farmland management), which could be also related to climate change/variability, will be considered in the future.

Appendix

List of the selected papers in Climate-crop relationship research

No.	Authors	Climate indicator (P-precipitation; T-temperature)	Crop growth measurement	Methodology	Aspect of crop response
1.	Rahman et al. (2018)	P/ T	Cotton production/yield	Multi-model ensemble	Crop productivity response
2.	Ndehedehe et al. (2018)	GRACE TWS	Crop yield	Remote sensing	
3.	Prabnakorn et al. (2018)	SPEI	Rice yield	Statistical-based model	
4.	Steiner et al. (2018)	Drought/P/T	Crop production	Decision support tool	
5.	Hernández-Barrera & Rodríguez-Puebla (2017)	Solar radiation	Wheat yield	CMIP5 simulation model	
6.	Hernandez-Barrera et al. (2017)	Diurnal range of temperature	Wheat yield	Statistical-based model	
7.	Cobon et al. (2016)	5 GCMs	Wheat, Sorghum production	'risk matrix' approach	
8.	Dono et al. (2016)	CO_2/ rainfall/T	Crop production	DSP and PDF models	
9.	Liu et al. (2016)	P/T	APSIM-maize yield	Process-based model	
10.	Naresh Kumar et al. (2016)	MIROC3.2 HI (global) /PRECIS(regional)	Mustard production/yield	InfoCrop model (simulation)	
11.	Masere & Worth (2015)	Rainfall	APSIM-maize yield	Focus group discussion	

12.	Omoyo et al. (2015)	Rainfall/T	Maize yield	Statistical-based model
13.	Gichangi et al. (2015)	Rainfall/ maximum and minimum T	Crop types	Statistical / survey
14.	Mojid et al. (2015)	Net radiation/wind speed/ VPD	Reference crop ET	Statistical-based model
15.	Sayari et al. (2015)	Evapotranspiration (P&T)	Chickpea, lentil, bean yield	Statistical-based model
16.		T/ P	Agro-IBIS-Extreme yield	Simulation model
17.	Klink et al. (2014)	T & P variability	Spring barley and oat yield	Statistical-based model
18.	Paudel et al. (2014)	Rainfall/T	Small-holder agriculture	Statistical/ survey
19.	Milan & Ruano (2014)	Rainfall variability	Corn-based cropland system	Survey
20.		REMO HadRM3 model	Rice, wheat yield (LAI)	DSSAT model
21.	Kassie et al. (2013)	T/ rainfall		Survey-small holder farmers
22.	Traore et al. (2013)	maximum and minimum T / dry days	Crop yield	Statistical-based model
23.	Hawkins et al. (2013)	Heat stress	French maize yield	Statistical/ prediction
24.	Persson et al. (2012)	NAO index	Winter wheat-frost injury	FROSTOL model
25.	Armah et al. (2011)	Rainfall	Millet, sorghum production	Markov chain, fuzzy model
26.	Kristensen et al. (2011)	9 agro-climatic indices	Winter wheat yield	Mixed regression model
27.	Conway & Schipper (2011)	Rainfall behavior	Crop production/ GDP	Statistical-based model
28.	Traoré et al. (2011)	GCMs	Millet, sorghum yield	SARRAH simulation model
29.	Tao, Yokozawa, et al. (2009)	CO_2	Crop productivity	MCWLA crop model
30.	Alves et al. (2009)	SST/ Nino-3/dipole index	Crop production, area, yield	Statistical-based model
31.	Potgieter et al. (2016)	Drought conditions	Sorghum, wheat yield	Statistical-based model

32.	Wang et al. (2016)	Drought stress/Aeration stress	Crop yield	SWAT model	Crop phenology response
33.	Broich et al. (2015)	--	Land surface phenology	Remote sensing product	
34.	Marta et al. (2010)	NAO index/ conventional indices	Grapevine phenology	Regression analysis	
35.	Hakala et al. (2012)	Rainfall/ T	Diversity among varieties	Statistical-based model	Crop varieties response
36.	Tao & Zhang (2013)	CO_2/temperature stress	MCWLA-Wheat yield/ET	Ensemble model	Photosynthesis
37.	Estrada et al. (2012)	Climate uncertainty	Coffee production/ income	Risk value assessment	Uncertainty
38.		CO_2/GCMs	Maize production	MCWLA crop model	
39.	Klein et al. (2012)	--	Farm accountancy	CropSyst model	Model calibration and validation
40.	Dosio & Paruolo (2011)	RCMs-T/P	--	ENSEMBLES	
41.	Tingem et al. (2009)	--	Observed yields	CropSyst model	
42.	Lobell & Asseng (2017)	T/ P/ CO_2/ ozone	Crop yield	Process and statistical based	Model comparison and integration
43.	(Rosenzweig et al. (2013))	--	--	AgMIP project	
44.	(Reidsma et al. (2010))	Warmer climate	Crop yield/ farmer's income	Statistical analysis	Adaptation

* Abbreviations: (in 'Climate indicator' column) GRACE-Gravity Recovery and Climate Experiment; TWS-Terrestrial Water Storage; SPEI-(Standardized Precipitation and Evapotranspiration Index; GCMs-General Circulation Models; MIROC3.2 HI-Model for Interdisciplinary Research on Climate, Japan; PRECIS-Providing Regional Climates for Impact Studies; VPD- vapour pressure deficit; REMO- Regional Model, Max-Plank Institute for Meteorology, Hamburg, Germany; HadRM3- Hadley Regional Model, Hadley Centre for Climate and Meteorology, UK; NAO- North Atlantic Oscillation; SST-sea surface temperature; RCMs- regional climate models. (in 'Crop indicator' column) APSIM- Agricultural Production Systems Simulator; ET- evapotranspiration; Agro-IBIS- a dynamic global vegetation model adapted from the Integrated Biosphere Simulator; LAI-leaf area index; GDP- Gross domestic product. (in 'Methodology' column) CMIP5-Coupled Model Intercomparison Project Phase 5; DSP- discrete stochastic programming; PDF- probability distribution functions; DSSAT-Decision Support System for Agro-technology Transfer; FROSTOL- a model to simulate the frost tolerance of crops; SARRAH- Syst`emed'Analyse R´egionale des Risques Agroclimatiques, version H crop simulation model; MCWLA- Model to capture the Crop–Weather relationship over a Large Area; SWAT- Soil and Water Assessment Tool; ENSEMBLES- Europe developed in the framework of the European Union 6th Framework Programme project; AgMIP- Agricultural Model Intercomparison and Improvement Project.

References

Alves, J.M.B., Servain, J. & Campos, J.N.B. 2009, 'Relationship between ocean climatic variability and rain-fed agriculture in northeast Brazil', *Clim. Res.*, vol. 38, no. 3, pp. 225-36.

Armah, F.A., Odoi, J.O., Yengoh, G.T., Obiri, S., Yawson, D.O. & Afrifa, E.K.A. 2011, 'Food security and climate change in drought-sensitive savanna zones of Ghana', *Mitigation and Adaptation Strategies for Global Change*, vol. 16, no. 3, pp. 291-306.

Asseng, S., Foster, I.A.N. & Turner, N.C. 2011, 'The impact of temperature variability on wheat yields', *Global Change Biol.*, vol. 17, no. 2, pp. 997-1012.

Asseng, S., Jamieson, P., Kimball, B., Pinter, P., Sayre, K., Bowden, J. & Howden, S. 2004, 'Simulated wheat growth affected by rising temperature, increased water deficit and elevated atmospheric CO2', *Field Crops Res.*, vol. 85, no. 2-3, pp. 85-102.

Asseng, S., Zhu, Y., Wang, E. & Zhang, W. 2015, 'Crop modeling for climate change impact and adaptation', in V.O. Sadras & D.F. Calderini (eds), *Crop physiology: applications for genetic improvement and agronomy*, Academic press, Academic press, pp. 505-46.

Black, E., Slingo, J. & Sperber, K.R. 2003, 'An Observational Study of the Relationship between Excessively Strong Short Rains in Coastal East Africa and Indian Ocean SST', *Mon. Weather Rev.*, vol. 131, no. 1, pp. 74-94.

Broich, M., Huete, A., Paget, M., Ma, X., Tulbure, M., Coupe, N.R., Evans, B., Beringer, J., Devadas, R., Davies, K. & Held, A. 2015, 'A spatially explicit land surface phenology data product for science, monitoring and natural resources management applications', *Environ. Model. Softw.*, vol. 64, pp. 191-204.

Calzadilla, A., Rehdanz, K., Betts, R., Falloon, P., Wiltshire, A. & Tol, R.J. 2013, 'Climate change impacts on global agriculture', *Clim. Change*, vol. 120, no. 1-2, pp. 357-74.

Challinor, A.J., Osborne, T., Morse, A., Shaffrey, L., Wheeler, T., Weller, H. & Vidale, P.L. 2009, 'Methods and resources for climate impacts research', *Bull. Am. Meteorol. Soc.*, vol. 90, no. 6, pp. 836-48.

Cheng, M. 2016, 'Sharing economy: A review and agenda for future research', *International Journal of Hospitality Management*, vol. 57, pp. 60-70.

Cobon, D.H., Williams, A.A.J., Power, B., McRae, D. & Davis, P. 2016, 'Risk matrix approach useful in adapting agriculture to climate change', *Clim. Change*, vol. 138, no. 1-2, pp. 173-89.

Conway, D. & Schipper, E.L.F. 2011, 'Adaptation to climate change in Africa: Challenges and opportunities identified from Ethiopia', *Global Environmental Change*, vol. 21, no. 1, pp. 227-37.

Dono, G., Cortignani, R., Dell'Unto, D., Deligios, P., Doro, L., Lacetera, N., Mula, L., Pasqui, M., Quaresima, S., Vitali, A. & Roggero, P.P. 2016, 'Winners and losers from climate change in agriculture: Insights from a case study in the Mediterranean basin', *Agricultural Systems*, vol. 147, pp. 65-75.

Dosio, A. & Paruolo, P. 2011, 'Bias correction of the ENSEMBLES high-resolution climate change projections for use by impact models: Evaluation on the present climate', *J. Geophys. Res. Atmos.*, vol. 116, no. 16.

Eamus, D., Huete, A. & Yu, Q. 2016, *Vegetation Dynamics: A Synthesis of Plant Ecophysiology, Remote Sensing and Modelling*, Cambridge University Press, 43-341.

Estrada, F., Gay, C. & Conde, C. 2012, 'A methodology for the risk assessment of climate variability and change under uncertainty. A case study: Coffee production in Veracruz, Mexico', *Clim. Change*, vol. 113, no. 2, pp. 455-79.

Falagas, M.E., Pitsouni, E.I., Malietzis, G.A. & Pappas, G. 2008, 'Comparison of PubMed, Scopus, Web of Science, and Google Scholar: strengths and weaknesses', *The FASEB Journal*, vol. 22, no. 2, pp. 338-42.

Gichangi, E.M., Gatheru, M., Njiru, E.N., Mungube, E.O., Wambua, J.M. & Wamuongo, J.W. 2015, 'Assessment of climate variability and change in semi-arid eastern Kenya', *Clim. Change*, vol. 130, no. 2, pp. 287-97.

Gitelson, A.A., Peng, Y., Arkebauer, T.J. & Suyker, A.E. 2015, 'Productivity, absorbed photosynthetically active radiation, and light use efficiency in crops: Implications for remote sensing of crop primary production', *Journal of Plant Physiology*, vol. 177, no. Supplement C, pp. 100-9.

Hagedorn, R., Doblas-Reyes, F.J. & Palmer, T. 2005, 'The rationale behind the success of multi-model ensembles in seasonal forecasting—I. Basic concept', *Tellus A: Dynamic Meteorology and Oceanography*, vol. 57, no. 3, pp. 219-33.

Hakala, K., Jauhiainen, L., Himanen, S.J., Rötter, R., Salo, T. & Kahiluoto, H. 2012, 'Sensitivity of barley varieties to weather in Finland', *Journal of Agricultural Science*, vol. 150, no. 2, pp. 145-60.

Hawkins, E., Fricker, T.E., Challinor, A.J., Ferro, C.A.T., Ho, C.K. & Osborne, T.M. 2013, 'Increasing influence of heat stress on French maize yields from the 1960s to the 2030s', *Global Change Biol.*, vol. 19, no. 3, pp. 937-47.

Hernández-Barrera, S. & Rodríguez-Puebla, C. 2017, 'Wheat yield in Spain and associated solar radiation patterns', *Int. J. Clim.*, vol. 37, pp. 45-58.

Hernandez-Barrera, S., Rodriguez-Puebla, C. & Challinor, A.J. 2017, 'Effects of diurnal temperature range and drought on wheat yield in Spain', *Theor. Appl. Climatol.*, vol. 129, no. 1-2, pp. 503-19.

Hochman, Z., Gobbett, D.L. & Horan, H. 2017, 'Climate trends account for stalled wheat yields in Australia since 1990', *Global Change Biol.*, vol. 23, pp. 2071-81.

Holton, J.R. & Dmowska, R. 1989, *El Niño, La Niña, and the southern oscillation*, vol. 46, Academic press.

Huete, A.R. 2012, 'Vegetation indices, remote sensing and forest monitoring', *Geogr. Compass*, vol. 6, no. 9, pp. 513-32.

Justice, C.O., Vermote, E., Townshend, J.R., Defries, R., Roy, D.P., Hall, D.K., Salomonson, V.V., Privette, J.L., Riggs, G. & Strahler, A. 1998, 'The Moderate Resolution Imaging Spectroradiometer (MODIS): Land remote sensing for global change research', *IEEE Trans. Geosci. Remote Sens.*, vol. 36, no. 4, pp. 1228-49.

Karnieli, A., Agam, N., Pinker, R.T., Anderson, M., Imhoff, M.L., Gutman, G.G., Panov, N. & Goldberg, A. 2010, 'Use of NDVI and Land Surface Temperature for Drought Assessment: Merits and Limitations', *J. Clim.*, vol. 23, no. 3, pp. 618-33.

Kassie, B.T., Hengsdijk, H., Rötter, R., Kahiluoto, H., Asseng, S. & Van Ittersum, M. 2013, 'Adapting to climate variability and change: Experiences from cereal-based farming in the central rift and kobo valleys, Ethiopia', *Environmental Management*, vol. 52, no. 5, pp. 1115-31.

Klein, T., Calanca, P., Holzkämper, A., Lehmann, N., Roesch, A. & Fuhrer, J. 2012, 'Using farm accountancy data to calibrate a crop model for climate impact studies', *Agricultural Systems*, vol. 111, pp. 23-33.

Klink, K., Wiersma, J.J., Crawford, C.J. & Stuthman, D.D. 2014, 'Impacts of temperature and precipitation variability in the Northern Plains of the United States and Canada on the productivity of spring barley and oat', *Int. J. Clim.*, vol. 34, no. 8, pp. 2805-18.

Kristensen, K., Schelde, K. & Olesen, J.E. 2011, 'Winter wheat yield response to climate variability in Denmark', *Journal of Agricultural Science*, vol. 149, no. 1, pp. 33-47.

Li, Z.-L., Tang, B.-H., Wu, H., Ren, H., Yan, G., Wan, Z., Trigo, I.F. & Sobrino, J.A. 2013, 'Satellite-derived land surface temperature: Current status and perspectives', *Remote Sens. Environ.*, vol. 131, pp. 14-37.

Liu, Z., Yang, X., Lin, X., Hubbard, K.G., Lv, S. & Wang, J. 2016, 'Narrowing the agronomic yield gaps of maize by improved soil, cultivar, and agricultural management practices in different climate zones of Northeast China', *Earth Interactions*, vol. 20, no. 12.

Lobell, D.B. & Asseng, S. 2017, 'Comparing estimates of climate change impacts from process-based and statistical crop models', *Environmental Research Letters*, vol. 12, no. 1, p. 015001.

Ma, Y., Wang, S., Zhang, L., Hou, Y., Zhuang, L., He, Y. & Wang, F. 2008, 'Monitoring winter wheat growth in North China by combining a crop model and remote sensing data', *Int. J. Appl. Earth Obs. Geoinf.*, vol. 10, no. 4, pp. 426-37.

Marta, A.D., Grifoni, D., Mancini, M., Storchi, P., Zipoli, G. & Orlandini, S. 2010, 'Analysis of the relationships between climate variability and grapevine phenology in the Nobile di Montepulciano wine production area', *Journal of Agricultural Science*, vol. 148, no. 6, pp. 657-66.

Masere, T.P. & Worth, S. 2015, 'Applicability of APSIM in decision-making by small-scale resource-constrained farmers: A case of lower Gweru communal area, Zimbabwe', *Journal of International Agricultural and Extension Education*, vol. 22, no. 3, pp. 20-34.

Milan, A. & Ruano, S. 2014, 'Rainfall variability, food insecurity and migration in Cabricán, Guatemala', *Climate and Development*, vol. 6, no. 1, pp. 61-8.

Mishra, A., Singh, R., Raghuwanshi, N.S., Chatterjee, C. & Froebrich, J. 2013, 'Spatial variability of climate change impacts on yield of rice and wheat in the Indian Ganga Basin', *Science of the Total Environment*, vol. 468-469, pp. S132-S8.

Mojid, M.A., Rannu, R.P. & Karim, N.N. 2015, 'Climate change impacts on reference crop evapotranspiration in North-West hydrological region of Bangladesh', *Int. J. Clim.*, vol. 35, no. 13, pp. 4041-6.

Moulin, S., Bondeau, A. & Delecolle, R. 1998, 'Combining agricultural crop models and satellite observations: From field to regional scales', *Int. J. Remote Sens.*, vol. 19, no. 6, pp. 1021-36.

Murphy, J.M., Sexton, D.M., Barnett, D.N., Jones, G.S., Webb, M.J., Collins, M. & Stainforth, D.A. 2004, 'Quantification of modelling uncertainties in a large ensemble of climate change simulations', *Nature*, vol. 430, no. 7001, p. 768.

Naresh Kumar, S., Aggarwal, P.K., Uttam, K., Surabhi, J., Rani, D.N.S., Chauhan, N. & Saxena, R. 2016, 'Vulnerability of Indian mustard (Brassica juncea (L.) Czernj. Cosson) to climate variability and future adaptation strategies', *Mitigation and Adaptation Strategies for Global Change*, vol. 21, no. 3, pp. 403-20.

Navin, R., A., F.J., John, N. & Kevin, M. 2002, 'The global distribution of cultivable lands: current patterns and sensitivity to possible climate change', *Global Ecology and Biogeography*, vol. 11, no. 5, pp. 377-92.

Ndehedehe, C.E., Agutu, N.O. & Okwuashi, O. 2018, 'Is terrestrial water storage a useful indicator in assessing the impacts of climate variability on crop yield in semi-arid ecosystems?', *Ecological Indicators*, vol. 88, pp. 51-62.

Nunez-Mir, G.C., Iannone, B.V., Pijanowski, B.C., Kong, N. & Fei, S. 2016, 'Automated content analysis: addressing the big literature challenge in ecology and evolution', *Methods in Ecology and Evolution*, vol. 7, no. 11, pp. 1262-72.

Omoyo, N.N., Wakhungu, J. & Oteng'i, S. 2015, 'Effects of climate variability on maize yield in the arid and semi arid lands of lower eastern Kenya', *Agriculture and Food Security*, vol. 4, no. 1.

Pachauri, R.K., Allen, M.R., Barros, V.R., Broome, J., Cramer, W., Christ, R., Church, J.A., Clarke, L., Dahe, Q. & Dasgupta, P. 2014, *Climate change 2014: synthesis report. Contribution of Working Groups I, II and III to the fifth assessment report of the Intergovernmental Panel on Climate Change*, IPCC.

Paudel, B., Acharya, B.S., Ghimire, R., Dahal, K.R. & Bista, P. 2014, 'Adapting Agriculture to Climate Change and Variability in Chitwan: Long-Term Trends and Farmers' Perceptions', *Agricultural Research*, vol. 3, no. 2, pp. 165-74.

Persson, T., Bergjord, A.K. & Höglind, M. 2012, 'Simulating the effect of the North Atlantic Oscillation on frost injury in winter wheat', *Clim. Res.*, vol. 53, no. 1, pp. 43-53.

Potgieter, A., Apan, A., Hammer, G. & Dunn, P. 2010, 'Early-season crop area estimates for winter crops in NE Australia using MODIS satellite imagery', *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 65, no. 4, pp. 380-7.

Potgieter, A.B., Lobell, D.B., Hammer, G.L., Jordan, D.R., Davis, P. & Brider, J. 2016, 'Yield trends under varying environmental conditions for sorghum and wheat across Australia', *Agric. For. Meteorol.*, vol. 228, pp. 276-85.

Prabnakorn, S., Maskey, S., Suryadi, F.X. & de Fraiture, C. 2018, 'Rice yield in response to climate trends and drought index in the Mun River Basin, Thailand', *Science of the Total Environment*, vol. 621, pp. 108-19.

Prasad, S., Bruce, L.M. & Chanussot, J. 2011, 'Optical remote sensing', *Advances in Signal Processing and Exploitation Techniques*.

Rabbinge, R. 2007, 'The Ecological Background of Food Production', *Ciba Foundation Symposium 177 - Crop Protection and Sustainable Agriculture*, John Wiley & Sons, Ltd., pp. 2-29.

Rahman, M.H.U., Ahmad, A., Wang, X., Wajid, A., Nasim, W., Hussain, M., Ahmad, B., Ahmad, I., Ali, Z., Ishaque, W., Awais, M., Shelia, V., Ahmad, S., Fahd, S., Alam, M., Ullah, H. & Hoogenboom, G. 2018, 'Multi-model projections of future climate and climate change impacts uncertainty assessment for cotton production in Pakistan', *Agric. For. Meteorol.*, vol. 253-254, pp. 94-113.

Ray, D.K., Gerber, J.S., MacDonald, G.K. & West, P.C. 2015, 'Climate variation explains a third of global crop yield variability', *Nat. Commun.*, vol. 6.

Reed, B.C., Brown, J.F., VanderZee, D., Loveland, T.R., Merchant, J.W. & Ohlen, D.O. 1994, 'Measuring phenological variability from satellite imagery', *J. Veg. Sci.*, vol. 5, no. 5, pp. 703-14.

Reidsma, P., Ewert, F., Lansink, A.O. & Leemans, R. 2010, 'Adaptation to climate change and climate variability in European agriculture: The importance of farm level responses', *Eur. J. Agron.*, vol. 32, no. 1, pp. 91-102.

Rosenzweig, C., Jones, J.W., Hatfield, J.L., Ruane, A.C., Boote, K.J., Thorburn, P., Antle, J.M., Nelson, G.C., Porter, C., Janssen, S., Asseng, S., Basso, B., Ewert, F., Wallach, D., Baigorria, G. & Winter, J.M. 2013, 'The Agricultural Model Intercomparison and Improvement Project (AgMIP): Protocols and pilot studies', *Agric. For. Meteorol.*, vol. 170, pp. 166-82.

Sakamoto, T., Yokozawa, M., Toritani, H., Shibayama, M., Ishitsuka, N. & Ohno, H. 2005, 'A crop phenology detection method using time-series MODIS data', *Remote Sens. Environ.*, vol. 96, no. 3–4, pp. 366-74.

Sayari, N., Bannayan, M., Alizadeh, A., Farid, A., Hessami Kermani, M.R. & Eyshi Rezaei, E. 2015, 'Climate change impact on legumes' water production function in the northeast of Iran', *Journal of Water and Climate Change*, vol. 6, no. 2, pp. 374-85.

Shen, J., Huete, A., Tran, N.N., Devadas, R., Ma, X., Eamus, D. & Yu, Q. 2018, 'Diverse sensitivity of winter crops over the growing season to climate and land surface temperature across the rainfed cropland-belt of eastern Australia', *Agric. Ecosyst. Environ.*, vol. 254, pp. 99-110.

Sippel, S., Reichstein, M., Ma, X., Mahecha, M.D., Lange, H., Flach, M. & Frank, D. 2018, 'Drought, Heat, and the Carbon Cycle: a Review', *Current Climate Change Reports*, pp. 1-21.

Smith, A.E. & Humphreys, M.S. 2006, 'Evaluation of unsupervised semantic mapping of natural language with Leximancer concept mapping', *Behavior research methods*, vol. 38, no. 2, pp. 262-79.

Smith, D.M., Cusack, S., Colman, A.W., Folland, C.K., Harris, G.R. & Murphy, J.M. 2007, 'Improved Surface Temperature Prediction for the Coming Decade from a Global Climate Model', *Science*, vol. 317, no. 5839, pp. 796-9.

Steiner, J.L., Briske, D.D., Brown, D.P. & Rottler, C.M. 2018, 'Vulnerability of Southern Plains agriculture to climate change', *Clim. Change*, vol. 146, no. 1-2, pp. 201-18.

Tao, F., Yokozawa, M. & Zhang, Z. 2009, 'Modelling the impacts of weather and climate variability on crop productivity over a large area: A new process-based model development, optimization, and uncertainties analysis', *Agric. For. Meteorol.*, vol. 149, no. 5, pp. 831-50.

Tao, F. & Zhang, Z. 2013, 'Climate change, wheat productivity and water use in the North China Plain: A new super-ensemble-based probabilistic projection', *Agric. For. Meteorol.*, vol. 170, pp. 146-65.

Tao, F., Zhang, Z., Liu, J. & Yokozawa, M. 2009, 'Modelling the impacts of weather and climate variability on crop productivity over a large area: A new super-ensemble-based probabilistic projection', *Agric. For. Meteorol.*, vol. 149, no. 8, pp. 1266-78.

Tingem, M., Rivington, M., Bellocchi, G. & Colls, J. 2009, 'Crop yield model validation for Cameroon', *Theor. Appl. Climatol.*, vol. 96, no. 3-4, pp. 275-80.

Traore, B., Corbeels, M., van Wijk, M.T., Rufino, M.C. & Giller, K.E. 2013, 'Effects of climate variability and climate change on crop production in southern Mali', *Eur. J. Agron.*, vol. 49, pp. 115-25.

Traoré, S.B., Alhassane, A., Muller, B., Kouressy, M., Somé, L., Sultan, B., Oettli, P., Siéné Laopé, A.C., Sangaré, S., Vaksmann, M., Diop, M., Dingkhun, M. & Baron, C. 2011, 'Characterizing and modeling the diversity of cropping situations under climatic constraints in West Africa', *Atmospheric Science Letters*, vol. 12, no. 1, pp. 89-95.

Tripathi, A., Tripathi, D.K., Chauhan, D., Kumar, N. & Singh, G. 2016, 'Paradigms of climate change impacts on some major food sources of the world: A review on current knowledge and future prospects', *Agric. Ecosyst. Environ.*, vol. 216, pp. 356-73.

Ummenhofer, C.C., Xu, H., Twine, T.E., Girvetz, E.H., McCarthy, H.R., Chhetri, N. & Nicholas, K.A. 2015, 'How climate change affects extremes in maize and wheat yield in two cropping regions', *J. Clim.*, vol. 28, no. 12, pp. 4653-87.

van Ittersum, M.K., Leffelaar, P.A., Van Keulen, H., Kropff, M.J., Bastiaans, L. & Goudriaan, J. 2003, 'On approaches and applications of the Wageningen crop models', *Eur. J. Agron.*, vol. 18, no. 3-4, pp. 201-34.

Wang, B., Liu, D.L., O'Leary, G.J., Asseng, S., Macadam, I., Lines-Kelly, R., Yang, X., Clark, A., Crean, J., Sides, T., Xing, H., Mi, C. & Yu, Q. 2018, 'Australian wheat production expected to decrease by the late 21st century', *Global Change Biol.*, vol. 24, no. 6, pp. 2403-15.

Wang, R., Bowling, L.C. & Cherkauer, K.A. 2016, 'Estimation of the effects of climate variability on crop yield in the Midwest USA', *Agric. For. Meteorol.*, vol. 216, pp. 141-56.

Wilhelm, W., Ruwe, K. & Schlemmer, M.R. 2000, 'Comparison of three leaf area index meters in a corn canopy', *Crop Sci.*, vol. 40, no. 4, pp. 1179-83.

Worth, S. 2002, 'Sustainable Extension: Not Transformation but Renewal', *Proceeding of the 18th Annual Conference of Association for International Agricultural and Extension Education (AIAEE), Durban, South Africa*, pp. 118-20.

Yan, W., Zhong, Y. & Shangguan, Z. 2017, 'Contrasting responses of leaf stomatal characteristics to climate change: a considerable challenge to predict carbon and water cycles', *Global Change Biol.*, pp. 716-26

Yuan, X., Bai, J., Li, L., Kurban, A. & De Maeyer, P. 2017, 'The dominant role of climate change in determining changes in evapotranspiration in Xinjiang, China from 2001 to 2012', *PLoS ONE*, vol. 12, no. 8.

Zheng, G. & Moskal, L.M. 2009, 'Retrieving leaf area index (LAI) using remote sensing: theories, methods and sensors', *Sensors*, vol. 9, no. 4, pp. 2719-45.

Chapter 3. Spatial prediction of rainfed grain yield based on remote sensing gross primary production estimates

Highlights

- The linkage between statistical data and satellite-based dataset were quantified.
- Prediction models of spatial grain annual yield using monthly GPP were built.

Abstract

Spatiotemporal prediction of rainfed agricultural yields as affected by climate variability continues to be a challenging task. This study related satellite-based gross primary production (GPP) estimates to reported agricultural yields for Australia. This study investigated the relative advantages of regression in prediction. The dataset from Australian Bureau of Statistics (ABS) (annual data; 2000-14; State scale) are considered as representative of actual agricultural yields across the Australian cropping belt. Monthly GPP data from 2000-14 with a spatial resolution of 0.05° is applied for the analysis. Here, considering crops types and the growing season across the rainfed cropland belts in Australia, August and September months are specified as optimum triggers for yield prediction (Growing season between June to November). The results showed that it is feasible to predict agricultural yields across our study area of the State of New South Wales (NSW), with an average error of estimations less than 10%. Nonetheless, to reach more accurate results, further research is needed.

Key Words

Spatial prediction, satellite-based GPP, agricultural productivity, stepwise regression approach

3.1 Introduction

Global food demand is expected to increase by at least 60% by 2050, requiring corresponding increases in crop production. Australian wheat yields have stalled during the last two decades, mainly due to increased water stress from declining precipitation and rising air temperature (Hochman et al., 2017). From 2000 to 2013, Australian croplands veered from prolonged water stress conditions during the Millennium Drought (2002-2009) to very wet conditions during the 'Big Wet' (2010-12) (Cleverly et al., 2016; Van Dijk et al., 2013). This resulted in annual nation-average cereal yields varying between 0.6 to 2.6 tons/ha, with an average of 1.7 tons/ha (ABS, 2017). In general, agriculture in Australia follows reactive approaches for agricultural activities. However, a few attempts have been made to proactively estimate agricultural yield based on the spatial conditions at early stages of crop growth (Ray et al., 2015).

Agronomists define cereal crop productivity as crop biological yield, grain yield and harvest index under certain plant density (Donald & Hamblin 1976). In actual practices, farmers and scholars evaluate crop productivity by grain yield (Y) (Lobell et al. 2011; Thompson 1975). In field studies, grain yield is normally calculated by number of grains per square meter multiply weight of 100 grains in grams (Bugbee & Monje 1992), and statistic year books often generally take crop annual yield as the quotient of total grain weight (P) divided by harvested acreage (cropping area, A) within one political unit boundary (Porter et al. 2014). In research, crop grain yield was further narrowed into potential, attainable and actual yield based on crop growth environmental driving factors

(Rabbinge 2007). The gaps between attainable and potential yield is determined by the accessibility of soil water and nutrients and between actual yield and attainable yield based on conditions of pests, weeds, and diseases (Yu et al. 2014). Future climate change is expected to modify regional soil moisture endowments (Calzadilla et al. 2013), and the limitations of soil moisture determine the level of crop attainable yield and could increase the risk of agricultural loss, especially for rainfed cropping systems (Calzadilla et al. 2013). Considering the variation of different cereal crop species and their mechanical properties (Gliński 2011), it is impractical and costly to enumerate each crop species in every field site across the whole Australia cropland belt.

Converting the vegetation productivity to a unified dimension is one of the most challenging tasks. Focusing on this, efforts have been done in many aspects. In a socioeconomic perspective, Lampe et al. (2014) introduced a weighted average price index to compare the outcomes of 10 different global economic models in different scenarios on various economic behaviour and biophysical drivers. Costanza (1998) also calculated the world's total natural capital by estimating the separated 17 ecosystem functions, which contribute to human welfare both directly and indirectly, including food production and nutrient cycling. In an energy aspect, Odum et al. (2000) introduced the concept of 'emergy' for ecological systems. Their accounting method allows us to integrate natural capital and man-made capital by using a consistent energy unit (Wang et al. 2014). Those methods show great advantages in estimation of cropland productivity. However, when it comes to explicit spatial cropping factors, there are still limitations in the regional based calculations that cannot adequately reflect the spatial heterogeneity in crop productivity.

To overcome the disadvantages, many studies turned to estimate the biological yield using various variables derived from remote sensing real-time multi-spectral information (Tao et al. 2005), measure the spatial-temporal gross primary production (GPP) or net primary production (NPP) by incorporating remote sensing fraction of absorbed photosynthetically active radiation (fAPAR) products and crop light-use efficiency model (Lobell et al. 2003; Monteith & Moss 1977; Ruimy et al. 1994; Yebra et al. 2015). Because the growing season GPP (g C m^{-2} yr^{-1}) is directly related to crop dry biomass matter by multiplying the harvest index (ratio of grain mass to total dry mass), the crop biomass allocated to edible products (grain yield) can be obtained (Elliott et al. 2015; Iizumi et al. 2014; Lobell et al. 2003; Reeves et al. 2005). In terms of the relationship between GPP derived grain yield and field observation (or national and subnational statistics), there is a strong positive linear correlations (Iizumi et al. 2014; Lobell et al. 2003), although the correlation coefficients slightly vary for crops in different levels of nitrogen treatment (Lobell et al. 2003).

Thus, this study obtained the monthly 0.05° Global (non-forest vegetation) GPP datasets for Australia (Yebra et al. 2015) as the explanatory variable to estimate vegetation productivity across the Australian rainfed belt. The GPP dataset encompasses the spatial variation of predicted agricultural grain yield. The linear regression fit coefficients between State-wise statistical actual yield and the monthly GPP value averaged over rainfed cropping and pasture grid cells (respectively) from year 2000 to 2013 were calculated for each State. Therefore, the crop productivity temporal variation in my approach basically followed those in the Australia Bureau of Statistics (ABS) State-wise data, as well as those in GPP dataset.

The objectives of this approach are: 1) to quantify the linkage between statistical data and the productivity estimation derived from remote sensing; 2) to examine the possibility of forecasting crop grain yield from monthly satellite-based GPP data across Australian rain-fed cropping and pasture land use belt.

3.2 Study area and data processing

3.2.1 Study area

This approach focuses on the rainfed cropping and pasture land use belts, extending from north-east to south-west Australia (Figure 3.1a). The distribution of rainfed agriculture and pasture was derived from the Dynamic Land Cover Data (version 2), which is produced by Geoscience Australia (Lymburner et al., 2010). The cropping belt experiences temperate to subtropical climate conditions, with a mean annual temperature of 14°C to 26°C and annual precipitation of 250 mm to 1500 mm (Dan et al., 2007). Based on the modified Köppen climate classification (Peel et al., 2007), the major classes are identified predominantly on native vegetation types, with six major groups and 27 sub-groups of climate zones across Australia (Figure 3.1b).

The 250m Australian land cover dataset is produced based on an analysis of 16-day EVI composite at 250 metres resolution using the MODIS satellite during 2002 - 2014. Its classification show a high degree of consistency with extensive independent field based datasets (Lymburner et al. 2010). I extracted the pixels which were identified as rainfed cropping and rainfed pasture as my study area.

The Australian rainfed farming area extends as a crescent alone western, southern, south-eastern, and eastern mainland Australia (Figure 3.1). It covers Köppen climate zones of temperate, grassland, and subtropical and characterized by large spatial variation of climate conditions (Figure 3.1).

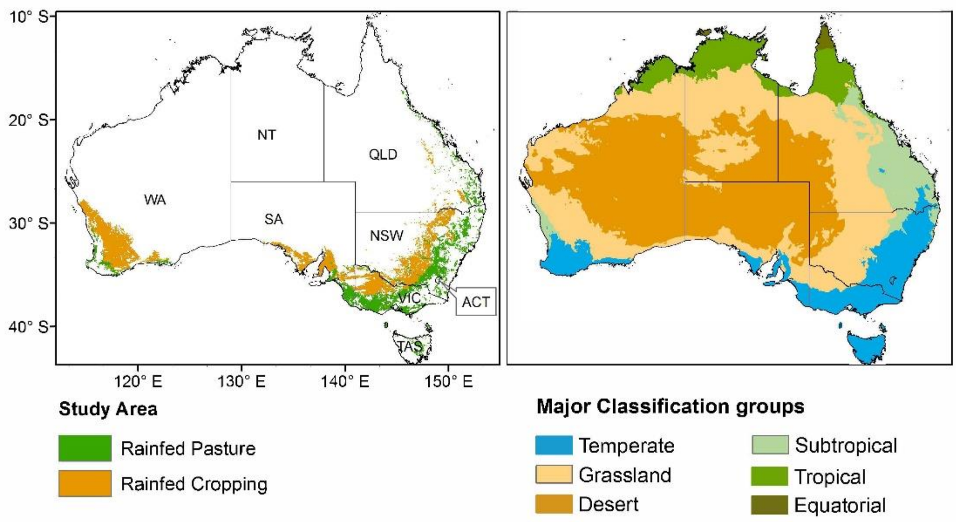

Figure 3.1 Australian rainfed cropping and pasture land use belt (left) and Australian major climate zones based on Köppen classification (right)
* Abbreviations: WA-Western Australia; NT-Northern Territory; SA-South Australia; QLD-Queensland; NSW-New South Wales; ACT-Canberra; TAS-Tasmania.

3.2.2 Grain annual yield

Crop grain production per unit area (yield) is the fundamental metric in agricultural research (Iizumi et al. 2014). This study obtained the grain yield datasets from Australia Bureau Statistics (ABS) (http://www.abs.gov.au/). Grain yield (wheat, barley, oats and cereal), Hay yield, and cattle number (meat cattle, milk cattle, sheep) of each State, across the rainfed farming area, from 2000 to 2013 were combined by reviewing agricultural commodities information from respective crop statistic year. Planting wheat is the major farming activity across Australian rainfed cropland. Pasture cropland are supposed to raise cattle, sheep and other feed animals. Therefore, wheat, barley, oats and cereal (crop species summed-up production/ summed-up area) yields were selected as the ground truth cropland productivity proxies in each State each year. And the increment numbers (number of current year minus number of previous year) of meat cattle, milk cattle, sheep in stock and hay yield (hay production divided by hay area) as the pasture land productivity proxies.

3.2.3 Monthly Gross Primary Production product

The Global vegetation GPP (non-forest) dataset for Australia was collected from the Australian National Computational Infrastructure data collection (http://nci.org.au/) and provided by Australian Water and Landscape Dynamics group, Australian National University (OzWALD, http://www.wenfo.org/wald/). This dataset derived from MODIS remote sensing used an effective method considering radiation and canopy conductance limitations on GPP (Yebra et al. 2015). And it is provided as monthly cumulative GPP (in g C/m^2) (2000-14) at a spatial resolution of 0.05° (accessible via http://www.wenfo.org/wald/data-software/). These GPP estimates have shown stronger or similar correlation to local GPP estimates from flux towers than current alternative GPP products (Yebra et al., 2015).

3.3 Methodology

In this study, a stepwise approach with goodness-of-fit of Bayesian Information Criterion (BIC) was considered for all regression models (both linear and nonlinear regressions (i.e. quadratic regressions) are examined). This combination not only focuses on the accuracy of forecasts but also tries to keep regressions as simple as possible. To address the limited data, a bootstrapping approach with 5000 simulation repetitions was applied, where for each simulation, 75% of data are randomly assigned to the calibration-verification stage and 25% has been allocated to the validation stage (Figure 3.2).

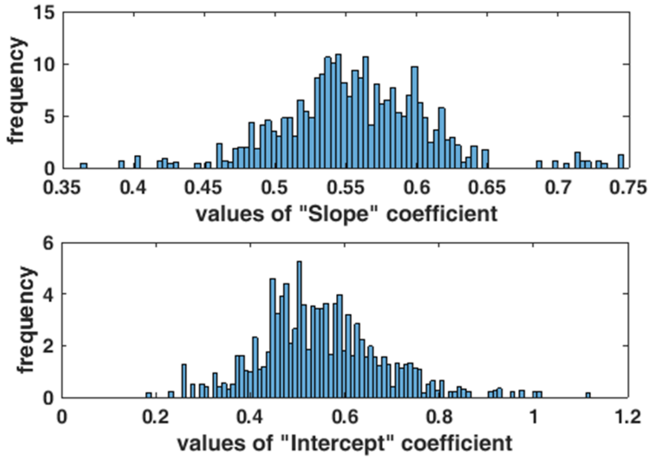

Figure 3.2 Bootstrapping method to estimate model coefficients
* Example for Victoria cereal yield estimation using September GPP as predictor.

The correlations and regressions were between annual-mean GPP and ABS annual yield, and monthly-mean GPP and ABS annual yield respectively for separate species in each State. The GPP values were averaged over the pixels which were identified as cropland and pasture land respectively each year from 2000 to 2013 for each State.

3.4 Results and Discussion

3.4.1 Correlation between GPP and agricultural annual yield in Australia

As noted, several species of cropland and pasture land products from the ABS yearbooks were selected to represent the actual agriculture productivity respectively. By correlating them with corresponding GPP values separately, we can find the best fit agriculture productivity proxy to convert GPP into crop grain yield for cropland, and pasture yield for pasture land.

Figure 3.3 shows that, different species in different States have different correlation performance between their yield and Annual-mean GPP: In western Australia, only meat cattle increment number has significant correlation with GPP; Hay yield was significantly negatively correlated with GPP in Queensland, but significantly positively correlated with GPP in Victoria; Milk cattle increment number has no significant correlation with annual GPP in any of the States during 2000-2013. In NSW, SA and VIC, all the crop species correlated well with annual GPP. These indicate that, in terms of correlation with annual GPP, crop proxies perform better than the pasture proxies.

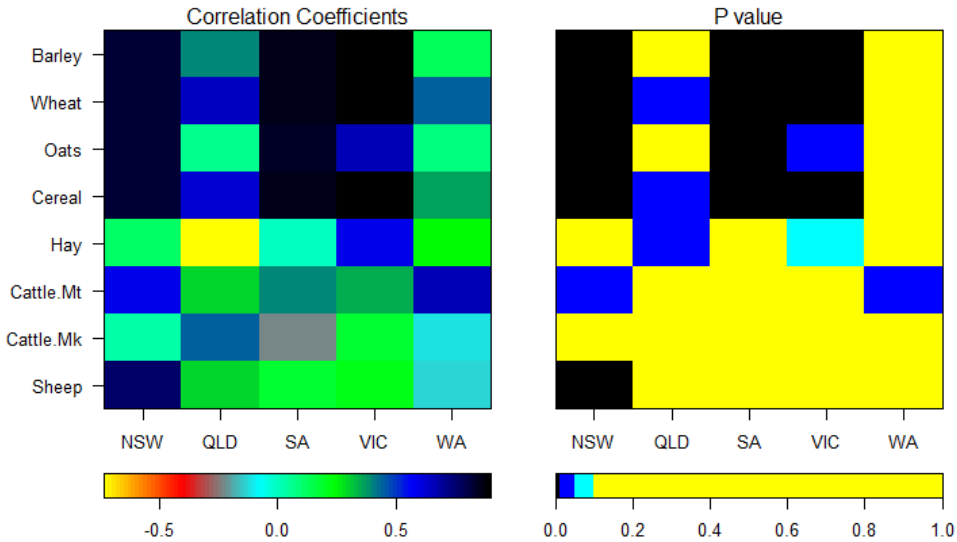

Figure 3.3 Correlation matrixes between annual-mean GPP and ABS annual yields
* In the left matrix: black cells, p<0.01; blue cells, p> 0.05; cyan cells, p<0.1, marginal significant; yellow cells, p>0.1, no significant.

Admittedly, such remarkable differences were caused by diverse geophysical areas and annual average GPP have no information concerning crop growth conditions. Because different species have inconsistent growing season, and the same species have different growing season in different States, I therefore had tests on the correlations between agricultural annual yield and monthly GPP for each species in each State were therefore tested.

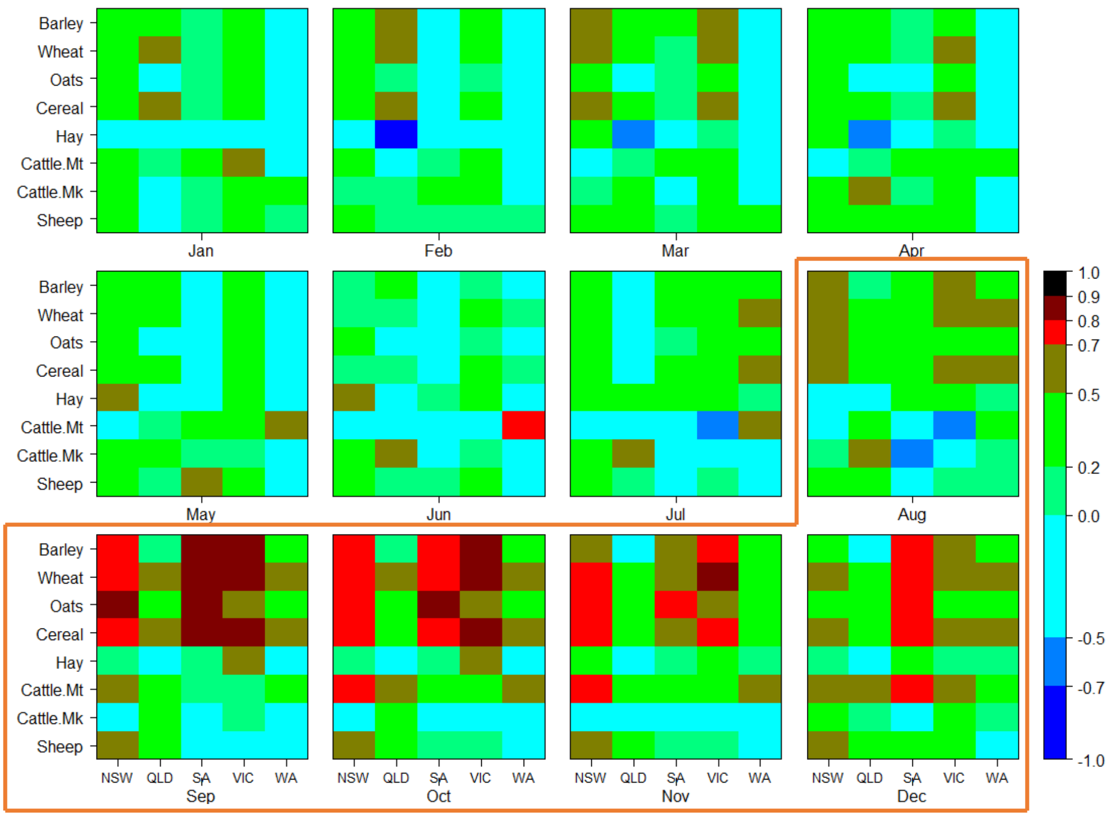

Figure 3.4 Correlation matrixes between monthly-mean GPP and ABS annual yield
* Each matrix plot represents the conditions in each month from January to December. Green and cyan cells, p>0.1, no significant; other color cells, p<0.1, significant or marginal significant.

The monthly GPP and ABS yield correlation matrices (Figure 3.4) show that, the months of most significance and marginal significance correlation between GPP and annual yield were in the last half of a year, especially from August to December, which can be seen as the major cropping season across Australia rainfed farmland belt, and this fact is consistent with the report from the Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES, www.abares.gov.au, 2013) and literature (Wang et al. 2015; Zheng et al. 2012). Average Australian major growing season starts in late May and ends during December. There are two months of winter time from June to July for crop seeds to establish from sowing date to stems tillering and booting. August and September are the best and earliest two months to monitor aboveground cropland vegetation biomass (GPP) at the first half of growing season from remote sensing. Because from these months, cropland vegetation reached the highest density that allow remote sensing radiometer sensors to capture the most of photosynthesis information.

During August and September, wheat and cereal grain yields in the States Western Australia, New South Wales and Victoria were significantly correlated with cropland monthly GPP (Figure 3.4), while nevertheless none of the pasture proxies and pasture land GPP were significantly correlated. The pasture land yield proxies in this study were the increment number of milk cattle, meat cattle and sheep in stock each year, and hay yield. Cattles and sheep are fed by pasture land weeds, their numbers are indirectly correlated and insensitive to pasture land vegetation biomass (GPP). In terms of hay yield, Australian pasture lands have diverse pasture species planted at the same time and their growing season extends over a whole calendar year. No dominant species that produce more than 50% of the annual hay total production regionally and nationally (www.abares.gov.au, 2013), this caused the non-significant correlation between ABS State-wise annual hay yield and annual and monthly GPP.

Based on the statistics of ABS, Western Australia, New South Wales, and Victoria together produce more than 75% of the nation's total cereal productions. Therefore, the prediction model was built only in these three States, and used August and September monthly-mean GPP as separate predictors to estimate cereal grain yield for each rainfed cropland pixel.

3.4.2 Model development using Monthly GPP to forecast Annual yield

Table 3.1 listed the cereal yield estimation equations for WA, NSW and VIC rainfed croplands using August and September monthly-mean GPP as predictor. The Root Mean Square Error (RMSE) of all the models developed were limited to 0.25 t/ha, compared to the average cereal yield across Australia cropland belt, 1.7 t/ha, the magnitudes of the errors in my models using pixel monthly GPP to predict cereal yield are 14.7%.

Table 3.1 Cereal yield models for three States

State	Month	Equation	R^2	P value	RMSE(t/ha)
WA	Aug	Y = 0.96 * GPP + 0.71	0.37	0.021	0.08
	Sep	Y = 0.73 * GPP + 0.89	0.29	0.045	0.09
NSW	Aug	Y = 0.6 * GPP + 0.74	0.31	0.038	0.25
	Sep	Y = 0.45 * GPP + 0.87	0.59	0.001	0.15
VIC	Aug	Y = 0.72 * GPP + 0.59	0.40	0.015	0.22
	Sep	Y = 0.56 * GPP + 0.55	0.74	0.000	0.10

* Y-agricultural annual grain yield

In terms of correlations, regressions show promising results stating that general behavior of Annual grain yield can be approximated reasonably by GPP values in early growing season months (August, and September). Nonetheless, error magnitudes in some cases are not negligible (i.e. RMSE=0.25 t/ha in NSW based on August GPP values). Simultaneous consideration of both goodness-of-fit criteria can imply that estimating annual grain yield would be more accurate in case of benefitting GPP values in Septembers. In addition to temporal estimations of actual agricultural yields, since GPP data contains the attribute of spatial variation, it is practical to use the derived regressions to downscale the actual agricultural yields data from State resolution to grid cell sizes (at current study, 0.05° identical to GPP spatial resolution).

3.5 Conclusion

This approach focused on bridging between monthly GPP (as an indicator of crop growth condition) and actual annual agricultural yield across Australian rainfed farmland belts. The main motivation was the fact that currently, actual agricultural yield datasets have coarse spatiotemporal resolutions (i.e. ABS datasets: annual, State-wide dataset) which can be estimated in finer resolutions (monthly, 0.05°) via the proposed methodology. Results were promising in estimating annual agricultural yield in cropping land across three States of NSW, VIC, and WA. Therefore, although the current methodology will not appropriately be applicable in agricultural business-economy (in which more accurate estimations of supply/demands are required), it can conservatively help agricultural decision makers to have estimations of potential produced crops affected by water and heat stress, which is highly critical to the field of food security in Australia.

The main limitations and difficulties of this study were: 1) availability of actual agricultural yield datasets only for a 14-year period, since 2000. 2) the lack of a reliable and comprehensive proxy for determining actual pasture productivities. 3) high complexity and diversity in crop types, land use, natural geography and climate conditions across the study area (even over each State). 4) available uncertainties/errors in GPP data as modelled based datasets.

The main future directions consist of: 1) concentrating on selected local areas at different States to increase the level of homogeneities in climate conditions, land use and crop types, 2) re-implementing the methodology with up-to-date datasets to investigate the footprint of recent water and heat stress in agricultural productivities as well as the performance of proposed methodology. 3) evaluating the influence of applying more complicated models in predictability of proposed methodology.

References

Australian Bureau of Agriculture and Resources Economics and Science (ABARES) (2017), http://www.agriculture.gov.au.abares, Last accessed: April 2017.

Australian Bureau of Statistics (ABS) (2017), http://www.abs.gov.au/agriculture, Last accessed: April 2017.

Bugbee, B. & Monje, O. 1992, 'The Limits of Crop Productivity', *BioScience*, vol. 42, no. 7, pp. 494-502.

Calzadilla, A., Rehdanz, K., Betts, R., Falloon, P., Wiltshire, A. & Tol, R.S.J. 2013, 'Climate change impacts on global agriculture', *Climatic Change*, vol. 120, no. 1, pp. 357-74.

Cleverly, J., Eamus, D., Luo, Q., Restrepo Coupe, N., Kljun, N., Ma, X., Ewenz, C., Li, L., Yu, Q. & Huete, A. 2016, 'The importance of interacting climate modes on Australia's contribution to global carbon cycle extremes', *Scientific Reports*, vol. 6, p. 23113.

Costanza, R. 1998, 'The value of ecosystem services', *Ecological Economics*, vol. 25, no. 1, pp. 1-2.

Dan, L., Ji, J., & He, Y. (2007), Use of ISLSCP II data to intercompare and validate the terrestrial net primary production in a land surface model coupled to a general circulation model. *Journal of Geophysical Research: Atmospheres*, 112(D2).

Dijk, A.I., Beck, H.E., Crosbie, R.S., Jeu, R.A., Liu, Y.Y., Podger, G.M., Timbal, B. & Viney, N.R. 2013, 'The Millennium Drought in southeast Australia (2001–2009): Natural and human causes and implications for water resources, ecosystems, economy, and society', *Water Resources Research*, vol. 49, no. 2, pp. 1040-57.

Donald, C.M. & Hamblin, J. 1976, 'The Biological Yield and Harvest Index of Cereals as Agronomic and Plant Breeding Criteria', in N.C. Brady (ed.), *Advances in Agronomy*, vol. Volume 28, Academic Press, pp. 361-405.

Elliott, J., Müller, C., Deryng, D., Chryssanthacopoulos, J., Boote, K.J., Büchner, M., Foster, I., Glotter, M., Heinke, J., Iizumi, T., Izaurralde, R.C., Mueller, N.D., Ray, D.K., Rosenzweig, C., Ruane, A.C. & Sheffield, J. 2015, 'The Global Gridded Crop Model Intercomparison: data and modeling protocols for Phase 1 (v1.0)', *Geosci. Model Dev.*, vol. 8, no. 2, pp. 261-77.

Gliński, J. 2011, 'Agrophysical Objects (Soils, Plants, Agricultural Products, and Foods)', *Encyclopedia of Agrophysics*, Springer, pp. 34-5.

Hochman, Z., Gobbett, D.L. & Horan, H. 2017, 'Climate trends account for stalled wheat yields in Australia since 1990', *Global Change Biology*, pp. n/a-n/a.

Iizumi, T., Yokozawa, M., Sakurai, G., Travasso, M.I., Romanenkov, V., Oettli, P., Newby, T., Ishigooka, Y. & Furuya, J. 2014, 'Historical changes in global yields: major cereal and legume crops from 1982 to 2006', *Global Ecology and Biogeography*, vol. 23, no. 3, pp. 346-57.

Lampe, M., Willenbockel, D., Ahammad, H., Blanc, E., Cai, Y., Calvin, K., Fujimori, S., Hasegawa, T., Havlik, P. & Heyhoe, E. 2014, 'Why do global long-term scenarios for agriculture differ? An overview of the AgMIP Global Economic Model Intercomparison', *Agricultural Economics*, vol. 45, no. 1, pp. 3-20.

Lobell, D.B., Asner, G.P., Ortiz-Monasterio, J.I. & Benning, T.L. 2003, 'Remote sensing of regional crop production in the Yaqui Valley, Mexico: estimates and uncertainties', *Agriculture, Ecosystems & Environment*, vol. 94, no. 2, pp. 205-20.

Lobell, D.B., Schlenker, W. & Costa-Roberts, J. 2011, 'Climate trends and global crop production since 1980', *Science*, vol. 333, no. 6042, pp. 616-20.

Lymburner, L., Tan, P., Mueller, N., Thackway, R., Lewis, A., Thankappan, M., Randall, L., Islam, A. & Senarath, U. 2010, '250 metre dynamic land cover dataset of Australia', *Geoscience Australia, Canberra*.

Monteith, J. & Moss, C. 1977, 'Climate and the efficiency of crop production in Britain [and discussion]', *Philosophical Transactions of the Royal Society B: Biological Sciences*, vol. 281, no. 980, pp. 277-94.

Odum, H.T., Brown, M. & Williams, S. 2000, 'Handbook of emergy evaluation', *Center for environmental policy*.

Peel, M.C., Finlayson, B.L., & McMahon, T.A. 2007, Updated world map of the Köppen-Geiger climate classification, *Hydrol. Earth Syst. Sci.*, 11, 1633-1644.

Porter, J.R., Xie, L., Challinor, A., Cochrane, K., Howden, M., Iqbal, M.M., Lobell, D. & Travasso, M.I. 2014, *Food security and food production systems*, Cambridge University Press, Cambridge.

Ray, D. K., Gerber, J. S., MacDonald, G. K., & West, P. C. 2015, Climate variation explains a third of global crop yield variability. *Nature Communications*, 6.

Rabbinge, R. 2007, 'The Ecological Background of Food Production', *Ciba Foundation Symposium 177 - Crop Protection and Sustainable Agriculture*, John Wiley & Sons, Ltd., pp. 2-29.

Reeves, M.C., Zhao, M. & Running, S.W. 2005, 'Usefulness and limits of MODIS GPP for estimating wheat yield', *International Journal of Remote Sensing*, vol. 26, no. 7, pp. 1403-21.

Ruimy, A., Saugier, B. & Dedieu, G. 1994, 'Methodology for the estimation of terrestrial net primary production from remotely sensed data', *Journal of Geophysical Research: Atmospheres*, vol. 99, no. D3, pp. 5263-83.

Tao, F., Yokozawa, M., Zhang, Z., Xu, Y. & Hayashi, Y. 2005, 'Remote sensing of crop production in China by production efficiency models: models comparisons, estimates and uncertainties', *Ecological Modelling*, vol. 183, no. 4, pp. 385-96.

Thompson, L.M. 1975, 'Weather variability, climatic change, and grain production', *Science*, vol. 188, no. 4188, pp. 535-41.

Wang, B., Liu, D.L., Asseng, S., Macadam, I. & Yu, Q. 2015, 'Impact of climate change on wheat flowering time in eastern Australia', *Agricultural and Forest Meteorology*, vol. 209–210, pp. 11-21.

Wang, X., Shen, J. & Zhang, W. 2014, 'Emergy evaluation of agricultural sustainability of Northwest China before and after the grain-for-green policy', *Energy Policy*, vol. 67, pp. 508-16.

Yebra, M., Van Dijk, A.I.J.M., Leuning, R. & Guerschman, J.P. 2015, 'Global vegetation gross primary production estimation using satellite-derived light-use efficiency and canopy conductance', *Remote Sensing of Environment*, vol. 163, pp. 206-16.

Yu, Q., Li, L., Luo, Q., Eamus, D., Xu, S., Chen, C., Wang, E., Liu, J. & Nielsen, D.C. 2014, 'Year patterns of climate impact on wheat yields', *International Journal of Climatology*, vol. 34, no. 2, pp. 518-28.

Zheng, B., Chenu, K., Fernanda Dreccer, M. & Chapman, S.C. 2012, 'Breeding for the future: what are the potential impacts of future frost and heat events on sowing and flowering time requirements for Australian bread wheat (Triticum aestivium) varieties?', *Global Change Biology*, vol. 18, no. 9, pp. 2899-914.

Chapter 4. Diverse sensitivity of dryland winter crops over the growing season to climate and land surface temperature

Highlights

• A new perspective to understand and quantify the observed impacts of climate variability on crop growth at every 8-day time slice from space was provided.

• MODIS Enhanced vegetation Index (EVI) is able to illustrate crop growth cycle and productivity in broad-acre rainfed cropping systems in eastern Australia.

• Land surface temperature (LST) was introduced to be an effective factor that integrates the complex interactions among rainfall, air temperature and solar radiation in large-scale dryland crop-climate relationship study.

• The key 8-day "sensitive windows" during the crop growth cycle, prone to climate and LST variability, were identified for the eastern Australian rainfed cropland-belt.

Abstract

The rainfed cropland belt in Australia is of great importance to the world grain market but has the highest climate variability of all such regions globally. However, the spatial-temporal impacts of climate variability on crops during different crop growth stages across broadacre farming systems are largely unknown. This study aims to quantify the contributions of climate and Land Surface Temperature (LST) variations to the variability of the Enhanced Vegetation Index (EVI) by using remote sensing methods. The datasets were analyzed at an 8-day time-scale across the rainfed cropland of eastern Australia.

First, EVI values were more variable during the crop reproductive growth stages than at any other crop life stage within a calendar year, but nevertheless had the highest correlation with crop grain yield (t ha^{-1}). Second, climate factors and LST during the crop reproductive growth stages showed the largest variability and followed a typical east-west gradient of rainfall and a north-south temperature gradient across the study area during the crop growing season. Last, two critical 8-day periods were identified, beginning on day of the year (DoY) 257 and 289, as the key 'windows' of crop growth variation that arose from the variability in climate and LST. The results show that the sum of the variability of the climate components within these two 8-day 'windows' explained >88% of the variability in the EVI, with LST being the dominant factor. This study offers a fresh understanding of the spatial-temporal climate-crop relationships in rainfed cropland and can serve as an early warning system for agricultural adaptation in broadacre rainfed cropping practices in Australia and worldwide.

Key Words

Climate variability; MODIS EVI; crop growth stages; land surface temperature; rain-fed croplands; eastern Australia

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Chapter 5. Dynamics of light-use efficiency using satellite solar-induced chlorophyll fluorescence and the enhanced vegetation index

Highlights

- GOME-2 solar-induced chlorophyll fluorescence (SIF) and the MODIS enhanced vegetation index (EVI) can be used in large-scale light-use efficiency (LUE) monitoring.

- Spatial pattern of LUE seasonality (2007-2016) were not consistent with seasonality in the spatial patterns of land surface temperature (LST), EVI, nor SIF.

- The optimum LST range for satellite-based LUE across Australian rainfed cropland belts were identified as 16.6-17.6 °C during August.

Abstract

Crop light-use efficiency (LUE) is sensitive to water and heat stress. Consequently, continuous and accurate estimating cropland LUE can serve to provide early warning detection of crop water and heat stress, and therefore can be used to assist in forecasting crop productivity. Space-based monitoring of sun-induced chlorophyll fluorescence (SIF) and the MODIS enhanced vegetation index (EVI) provide direct measurement of cropland vegetation photosynthetic activity and vegetation greenness, respectively. This Chapter explored the potential to remotely monitor real-time LUE by calculating the ratio of photosynthetically active radiation (PAR) normalized SIF to EVI. This calculation was applied to demonstrate spatial patterns and temporal dynamics of LUE in response to land surface temperature (LST) across Australian rainfed croplands (2007-2016). LST was used to provide an integrated measure of vegetation heat and drought stress in this study.

The findings are: spatially, LUE tends to be higher in the geographical middle zones with a mild range of LST level across Australian croplands, than either the hotter northern regions and the colder southern regions; temporally, there was a seasonal hysteresis of LUE in response to surface temperature change throughout the winter crop growing season. The results of one-way ANOVA and *post-hoc* tests revealed that the optimum LST range for satellite-based LUE were 16.6-17.6 °C during August. Pixels with optimum LST across the 10-year sampling period (August of 2007-2016) were distributed in the South-Middle to Middle zones of the Australian rainfed croplands. Practically, these results provide new opportunities for large-scale cropland heat and drought stress detection, and theoretically, for remote analyses of the photosynthetic activities across diverse spatial-temporal scales.

Key words

Solar-induced chlorophyll fluorescence, enhance vegetation index, land surface temperature, light-use efficiency, rainfed croplands

5.1 Introduction

Estimation of large-scale vegetation light-use efficiency (LUE) has both theoretical and practical significance. The LUE model is a physiological model originally conceptualized by Monteith (1972, 1977), and since then (adopted by researchers in the fields of carbon and water flux estimation and remote sensing. Gross primary production (GPP) is mainly determined by the amount of photosynthetically active radiation (PAR) absorbed by vegetation (APAR) (Gitelson et al. 2015). Light-use efficiency (LUE) describes the efficiency of conversion of absorbed light to fixed carbon, that is, GPP. Continuous and accurate monitoring of cropland APAR and LUE not only can forecast crop productivity, but also provides insight to better understand responses of crop photosynthesis to environmental change, and thereby provides information about the impact of climate variability on crop productivity.

In most current GPP estimation models, LUE is often calculated by down-regulating the maximum LUE with scalars of water and heat stress (Dong et al. 2015; Sims et al. 2008), or parameterized as function of meteorological parameter for a given biome (Running et al. 2004; Wang et al. 2010; Xiao et al. 2008). In these cases, LUE models must heavily rely on the parameterizations of many physiological limiting factors. The more factors in the model, the more measurements and calibrations are required. As a result, this can make the model more complex and consequently create more systematic errors.

Physiologically, LUE can be affected by a number of processes (Gitelson & Gamon 2015), ranging from chlorophyll pigment composition, enzyme kinetics, changes in stomatal conductance (Gamon & Qiu 1999; Yan et al. 2017), changes in leaf and canopy structure, vapour pressure deficit, and drought stress (Dong et al. 2015). Consequently, LUE varies dynamically over multiple temporal and spatial scales because of changing environmental conditions. This fact makes it difficult to continuously and rapidly parameterize all the changing environmental variables throughout the life span of vegetation.

To overcome these limitations, efforts have been made to passively estimate LUE and vegetation activities entirely from remotely sensed variables without any ground-based inputs. These include the MODerate-resolution Imaging Spectroradiometer (MODIS)-GPP model (Running et al. 1999; Zhao et al. 2005), and a Vegetation Photosynthesis Model (VPM) (Xiao et al. 2004; Xiao et al. 2005; Yan et al. 2009). However, the LUE values of MODIS-GPP models were obtained from look-up tables for individual vegetation types within each pixel. The EVI-based models rely on two key factors: Land Surface Temperature (LST) and EVI. The optimum temperature for the relationship between photosynthesis activity and LST was set to be 30 °C based on research by Berry & Bjorkman (1980). However, it is still unclear to what extent the optimum LST range changes seasonally. While EVI is effective for measuring vegetation greenness, canopy chlorophyll, and water content (Huete 2012; Xiao et al. 2005; Yang et al. 2013), it is apparent that photosynthetic activities can be highly variable despite vegetation greenness remaining constant. Thus, EVI-based models tend to either overestimate the length of the photosynthetically-active periods (Joiner et al. 2014), or underestimate the impacts of temporal variation in optimum LST.

A newly emerging space-borne retrieval, Solar-Induced Fluorescence (SIF) holds great potential for advancing the capacity to directly measure the photosynthetic status of vegetation (Guan et al. 2016; Jeong et al. 2017; Joiner et al. 2014). Photosynthetic activity generates fluorescence, and the excitation-energy for this process is provided by sunlight. The emission of chlorophyll fluorescence has two peaks near 685 and 740 nm in the red and far-red wavelengths, respectively (Campbell et al. 2008; Joiner et al. 2011). At the canopy level, satellite SIF can be expressed as an integral of contributions over all excitation wavelengths from all the active chlorophyll photosynthesis. Therefore, satellite SIF signal contains not only leaf level photosynthesis activity, but also information about canopy structure, canopy chlorophyll content, and canopy greenness (Yang et al. 2017).

The aims of the study were to: 1) Approximate light-use efficiency (LUE) remotely across broadacre rainfed croplands using satellite Solar-Induced chlorophyll Fluorescence (SIF) and enhanced vegetation index (EVI); 2) characterize seasonal dynamics of the remote sensed measurements of winter wheat cropland in Australia; 3) examine the spatial-temporal performance of LUE in response to Land Surface Temperature (LST) during the crop growing-season.

5.2 Material and methods

5.2.1 Obtaining LUE from SIF and EVI

Current work (Guan et al. 2016; Guanter et al. 2014; Joiner et al. 2014) defines Solar-Induced Fluorescence (SIF) as:

$$SIF(\lambda) = PAR \times fPAR \times LUE_F(\lambda) \times f_{esc}(\lambda) \tag{5.1}$$

Where λ is the excitation wavelength (~740 nm in the GOME-2 retrievals as described in the following section). PAR is the flux of photosynthetic-active radiation at the top of the canopy and the term fPAR is the fraction absorbed of PAR. Thus, the product of PAR and fPAR is APAR, the absorbed photosynthetic-active radiation by vegetation (Monteith 1977). LUE_F is a light-use efficiency for SIF, which is the efficiency of fluorescence photons re-emitted from APAR. And $f_{esc}(\lambda)$ is the fraction of fluorescence photons escaping from the canopy surface. Experiments have shown that the ratio of LUE_P to $LUE_F(\lambda)$ remains relatively constant under strong sun illumination, such as in the late morning when many space-borne observations are made (Berry et al. 2012; Joiner et al. 2014):

$$LUE_P = LUE_F(\lambda) \times a \tag{5.2}$$

Where LUE_P is the term light-use efficiency that I am monitoring in this study, which is the efficiency of carbon uptake per unit APAR. In current reflectance-based GPP estimation models, the Enhanced Vegetation Index (EVI) is an effective measurement for canopy chlorophyll content, the fraction of PAR within the photosynthetic-active period is estimated as a linear function of EVI with a coefficient of 1.0 (Garbulsky et al. 2008; Lobell et al. 2002; Xiao et al. 2004; Xiao et al. 2005; Yan et al. 2009). Thus:

$$fPAR(EVI) = EVI \tag{5.3}$$

The reflectance signature of green leaves shows minimal absorbance in the near-infrared wavelengths (Gitelson & Merzlyak 1996). Therefore, $f_{esc}(\lambda) \approx 1$ was assumed. Therefore, we may expect the LUE_P to be simply estimated as:

$$LUE_P = \frac{SIF(\lambda)_{PAR}}{EVI} \times a \tag{5.4}$$

Where $SIF(\lambda)_{PAR}$ is the PAR normalized satellite solar-induced fluorescence. a is the constant ratio of LUE_P to $LUE_F(\lambda)$, which can be calibrated by field observations (Verma et al. 2017; Zhang et al. 2016). The exact value of a will not influence the comparisons of LUE in diverse spatial temporal scenarios. Thus, we assumed a equals to 1 and examined the spatial distribution and temporal dynamics of LUE in this study.

5.2.2 Statistical analyses

In previous studies, LUE was down-regulated as function of temperature and drought stress from a maximum value of LUE. Land surface temperature measurements by infrared thermometry can adequately estimate the integral stress from those meteorological variables, without explicitly considering each of them (Idso et al. 1977; Sims et al. 2008). Land surface temperature is a measurement of earth “skin” temperature rather than air temperature, and is commonly used in plant physiological studies (Sandholt et al. 2002). The change of evapotranspiration rate is an integrated result of the change of meteorological factors such as rainfall, air temperature, and solar radiation.

Hereafter, LST was used as an integrator of crop temperature and drought stress. One-way analysis of variance (ANOVA) (Welch 1951) was performed to determine whether there were any statistically significant differences among the means of satellite SIF-derived LUE with different LST values. If the one-way ANOVA test gives a significant result, Tukey's honestly significant difference (HSD) *post hoc* test (Salkind 2010) was applied to examine all pairwise comparisons between the LUE means across every LST, and identify all differences between any two LUE means that is larger than the expected standard error.

5.2.3 Applications across Australian croplands

Here, the approach was applied to study spatial patterns and temporal dynamics of satellite SIF-derived LUE across Australian rainfed croplands, where there is a distinct seasonality of vegetation both in greenness and in photosynthesis (Figure 5.1).

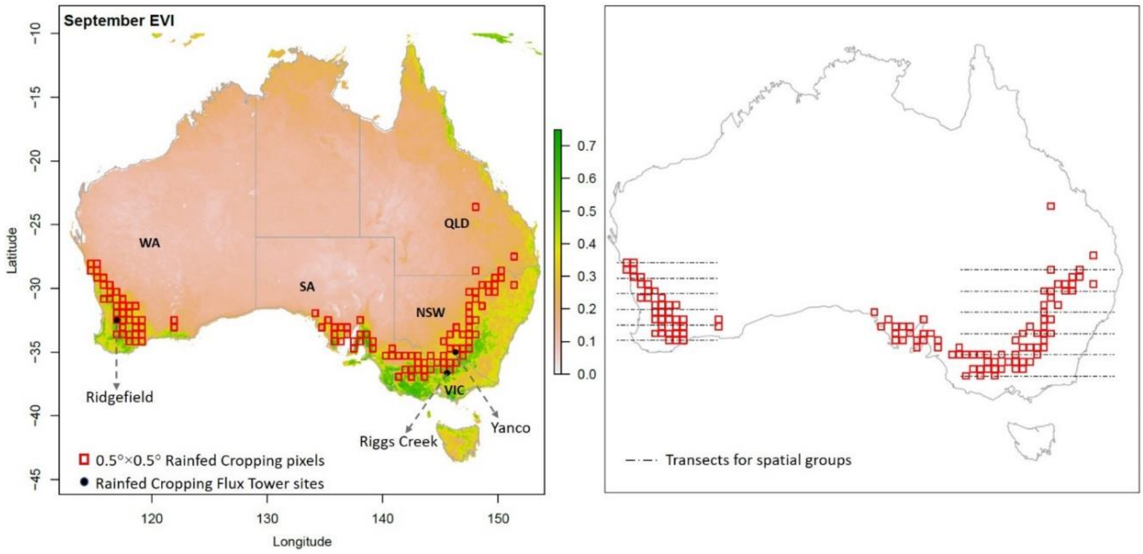

Figure 5.1 Australian rainfed croplands in different levels of spatial resolution (left) and the spatial groups of testing pixels (right)
* The white to green colour range in the left panel is the 10-year (2007-2016) mean MODIS EVI map during September. Western Australia (WA), South Australia (SA), Victoria (VIC), New South Wales (NSW), Queensland (QLD), and Northern Territory (NT) are the 7 States and Territory in Australia. The five groups between the transects for each of the major Australian cropland belts in the right panel were designated as: 1) Southern, (2) Southern-Middle, (3) Middle, (4) Northern-Middle, and (5) Northern zones.

5.2.3.1 Land use classification

The remote sensing datasets used in this study were obtained at two different spatial resolutions. Figure 5.1 shows the extent of Australian rainfed croplands across these two levels of spatial resolution. The Dynamic Land Cover Dataset (DLCD verison 2) for Australia was obtained from Geoscience Australia (http://www.ga.gov.au/). This dataset is based on an analysis of a 16-day MODIS EVI composite at a 250-meter resolution during 2002-2010 (Lymburner et al. 2010). The dataset distinguishes rainfed cropland from irrigated cropland in Australia and shows a high degree of consistency (93%) with extensive independent field-based investigations. To select effective rainfed cropland pixels in 0.5°×0.5° resolution, the 250-meter resolution land use classification map was resampled by using the majority resampling method. The majority land cover type (>75%) within each larger (0.5°×0.5°) pixel is attributed as the land cover type of the certain pixel.

Based on the resampled map, 111 pixels were identified which were classified as rainfed cropping in the study area. The Australian rainfed cropping area extends across Western Australia (WA), South Australia (SA), Victoria (VIC), New South Wales (NSW), and Queensland (QLD), and comprises two belts along western and eastern Australia, respectively.

5.2.3.2 Satellite SIF retrievals

The purpose of resampling the fine resolution map to a coarse one (red boxes in Figure 5.1) across Australia rainfed croplands was to allow comparison with the satellite-SIF dataset. The global satellite-SIF retrievals were obtained from the Global Ozone Monitoring Experiment-2 (GOME-2) sensors on board the MetOp-A platform during 2007-2016 (version 26), and they were processed as 0.5°×0.5° spatial resolution monthly dataset with estimated errors of 0.1-0.4 mW m^{-2} nm^{-1} sr^{-1} by Joiner et al. (2013). The footprint size of GOME-2 sensors is 40×80 km at nadir, but GOME-2 currently provides the longest record of SIF retrieval since 2007. The overpass time of MetOp-A platform is at 9:30 am local time, which is close to the window of peak daily photosynthesis across Australian croplands (Guan et al. 2016). All the data have been processed by quality-filtering, and the level 3 global gridded monthly data (0.5°×0.5°) with PAR normalization process (Joiner et al. 2013) were used.

5.2.3.3 MODIS EVI and LST datasets

The MODIS monthly 0.05°×0.05° Enhanced Vegetation Index (MOD13C2) (Huete et al. 2002) and land surface temperature (MOD11C3, version 06) during 2007-2016 were downloaded from the Land Process Distributed Active Archive Center (LP DAAC) data pool, and were then processed by cloud filtering. Both the MOD11C2 and MOD13C3 are located on board Terra, which has the overpass time of 10:30am local time. The digital numbers (DN value) of EVI (MOD13C2) images were converted to 0-1, while the DN values of LST (MOD11C3) images were converted to °C.

Figure 5.1 shows the 10-year average EVI in September (2007-2016) across Australia with 0.05° spatial resolution. We observed that the September EVI values in the rainfed croplands were larger than in the rest of Australia. September is in Australia's spring season, the rainfed croplands are predominantly planted with winter wheat, with a typical sowing date from May to July (Bowden et al. 2008).

5.2.3.4 Eddy flux sites

There are currently three eddy flux sites located in crop fields in the Australian rainfed croplands, as shown in Figure 5.1 and Table 5.1. I collected eddy flux data from the OzFlux network (http://www.ozflux.org.au/) (Beringer et al. 2017).

The original observations have been processed by Dynamic IN-tegrated Gap-filling and partitioning for OzFlux (DINGO v13) program to half-hourly time series GPP data (Beringer et al. 2017). Monthly flux tower measured GPP were aggregated based on the half-hourly GPP data during daytime and during the morning window 09:00 -11:00 am, separately. Where, daytime was defined as the half hours that have active carbon uptake during a certain day. The purpose to select a morning window from 09:00 to 11:00 am is to keep the consistency of observation time from different sources of satellite data, while ensuring the instantaneous flux GPP during that window can estimate daily GPP.

Table 5.1 Details of the three Australian eddy flux sites

Name	Location (Lat/Lon)	Monitor Period	Annual Rainfall	Temperature Range	Land Cover	State
Riggs Creek	-36.6499, 145.5760	Jan 2011 - Oct 2015	650 mm	12-26 °C	Dryland Agriculture	Victoria
Ridgefield	-32.5061, 116.9668	Mar 2016 -Nov 2016	446 mm	5.5 -31.9 °C	Dryland Agriculture	Western Australia
Yanco	-34.9893, 146.2907	Oct 2012 - Dec 2016	465 mm	12- 37 °C	Dryland Agriculture	New South Wales

The footprint of the flux tower measurement (around 1×1 km) is much smaller than the footprint of GOME-2 satellite measurements (40×80 km). Therefore, to examine the landscape homogeneity around towers, I used MODIS EVIs with 0.05°, 0.1° and 0.5° resolutions to regress with flux site observations (GPP) respectively. If there is no big change in regression determination coefficients (R^2) and the p-values keep significant ($p<0.01$) while changing the EVI from smaller (higher) to a larger (lower) resolution, the footprint of the flux tower could reach the larger (lower) one. Otherwise, it would stay in the smaller (higher) resolution.

In this chapter, data processing and statistical analysis were performed in the R computation environment, and required packages were obtained from The Comprehensive R Archive Network (http://cran.r-prject.org) (RCoreTeam 2013).

5.2.3.5 Spatial division of testing pixels

Rainfall, air temperature and solar radiation are direct growth-defining and limiting factors of broadacre crops (Yu et al. 2001). Land surface temperature (LST) measures the crop canopy temperature and represents an integral of crop stress from those meteorological variables (Shen et al. 2018). To test how EVI, SIF and LUE response to LST change, we need to take account spatial and seasonal variations of LST arising from predictable seasonal changes in sun incident angle but also variation in water and heat distribution across the land surface. Thus, the range of latitudes encompassing the selected rainfed cropland pixels were equally divided into five LST zones for each of the two major Australian cropland belts (Figure 5.1). The eastern belt includes croplands in NSW and VIC, while the western belt only includes WA croplands. The five LST regions were then designated as: 1) Southern, (2) Southern-Middle, (3) Middle, (4) Northern-Middle, and (5) Northern, corresponding to regions from lower to higher mean annual temperature. I then averaged the rainfed cropland pixel values of LST, EVI, SIF, and LUE and plotted their seasonal patterns (Figure 5.3) and variability in each LST zone. Seasonality was calculated from 10-years of monthly means.

5.2.3.6 Temporal division of testing pixels

There were different groups of pixels with different LST values within any given month, both spatially and temporally. For example, in August, there were 111 0.5°×0.5° pixels across the Australian rainfed croplands covering a range of LST values, as shown in Figure 5.1. At each pixel, 10 LST values were recorded in the 10 Augusts from year 2007 to 2016. Consequently, there were a range of LST values levels during each month, which reflect the spatial and inter-annual variations of water and heat condition, and this may be expected to affect LUE. To examine this, the 1110 spatial-temporal datasets each month were divided by percentage quantiles of LST into 10 groups.

5.3 Results and Discussion

5.3.1 Footprint calibration for flux sites

The results of the linear regressions between daytime flux measured GPP with MODIS EVI at 0.05°, 0.1° and 0.5° spatial resolutions, respectively (Figure 5.2 a-c) reveal that there were slight differences among their regression coefficients. The smaller the spatial resolution in EVI, the smaller the slope coefficient, and the larger the R^2 value. When EVI resolution was 0.5°, the regression R^2 dropped from 0.86 to 0.80, and the slope value increased by 4.7%. However, all the p-values are statistically significant ($p<0.01$). Thus, variances of flux GPP and EVI with 0.5° can still linearly explain each other 80%. The direct comparison of flux derived GPP data with the much larger footprint of remotely sensed retrievals at 0.5° spatial resolution produced acceptable regressions for these selected eddy flux sites. Australian rainfed croplands are mostly characterized by broad acre planting (Hochman et al. 2012; Hochman et al. 2017), and the landscape is generally homogenous within several square kilometres.

Thereafter, the fit of linear regressions between satellite SIF_{PAR} and morning (between 09:00 to 11:00 am) flux GPP, and daytime Flux GPP were compared respectively (Figure 5.2 d-e). The determination coefficients, R^2, were the same (0.74) and statistically significant ($p<0.01$) between the two regressions. It should be noted that the photosynthesis activities between 09:00 and 11:00 am at these three flux sites are able to estimate the corresponding daily GPP.

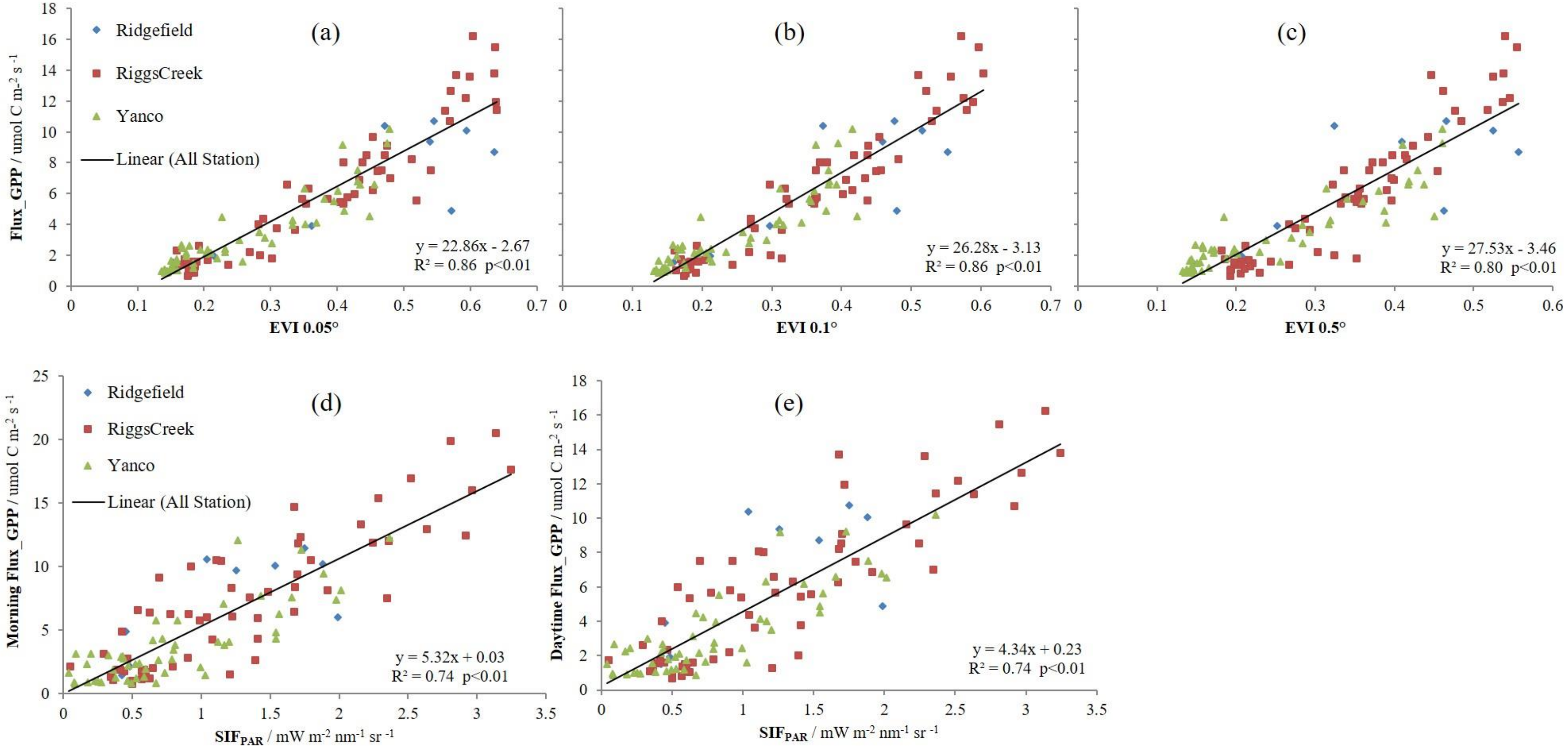

Figure 5.2 Flux tower footprint calibrations

* Moring Flux_GPP is the monthly GPP aggregated from half-hourly GPP during 9:00-11:00 am. Daytime Flux_GPP is aggregated during the daytime. And SIF_{PAR} is PAR normalized SIF.

5.3.2 Spatial pattern of satellite-based vegetation measurements

We found that there was only one major crop growing season across both of the Australian rainfed cropland belts, from June to November, based on canopy greenness (EVI) monthly seasonality curves (Figure 5.3c, d). The start and end dates of each growing season were consistent among the five LST zones, which indicates that spatial variation of LST did not have any significant impact on cropland phenology at a monthly temporal resolution. The EVI values peaked in September across all the zones in the eastern belt (NSW and VIC) and the Southern zone in the western belt (WA). Peaks in EVI were observed in August across all the other zones in WA.

We also observed that the LST curves showed a gradient in spatial pattern of water and heat conditions from North to South across Australian rainfed croplands (Figure 5.3a, b). In the western belt, seasonality curves of surface temperature in the five LST zones were gradually reduced from North to South without intersecting throughout the year. In contrast, in the eastern belt, February (a summer month) temperatures were the same among the five LST zones. The colder the surface temperature, the larger the differentiation among the growing season months of the regions. These characterize the various spatial patterns of surface water and heat conditions across the cropland belts.

The results further show that there was also only one major cycle of increasing, peak and decreasing rates of photosynthesis from around June to November with minimal variation among those LST zones (Figure 5.3e, f). The PAR normalized SIF peaks in August in Northern and Northern-middle zones of the eastern cropland belt and in all the zones of the western belt.

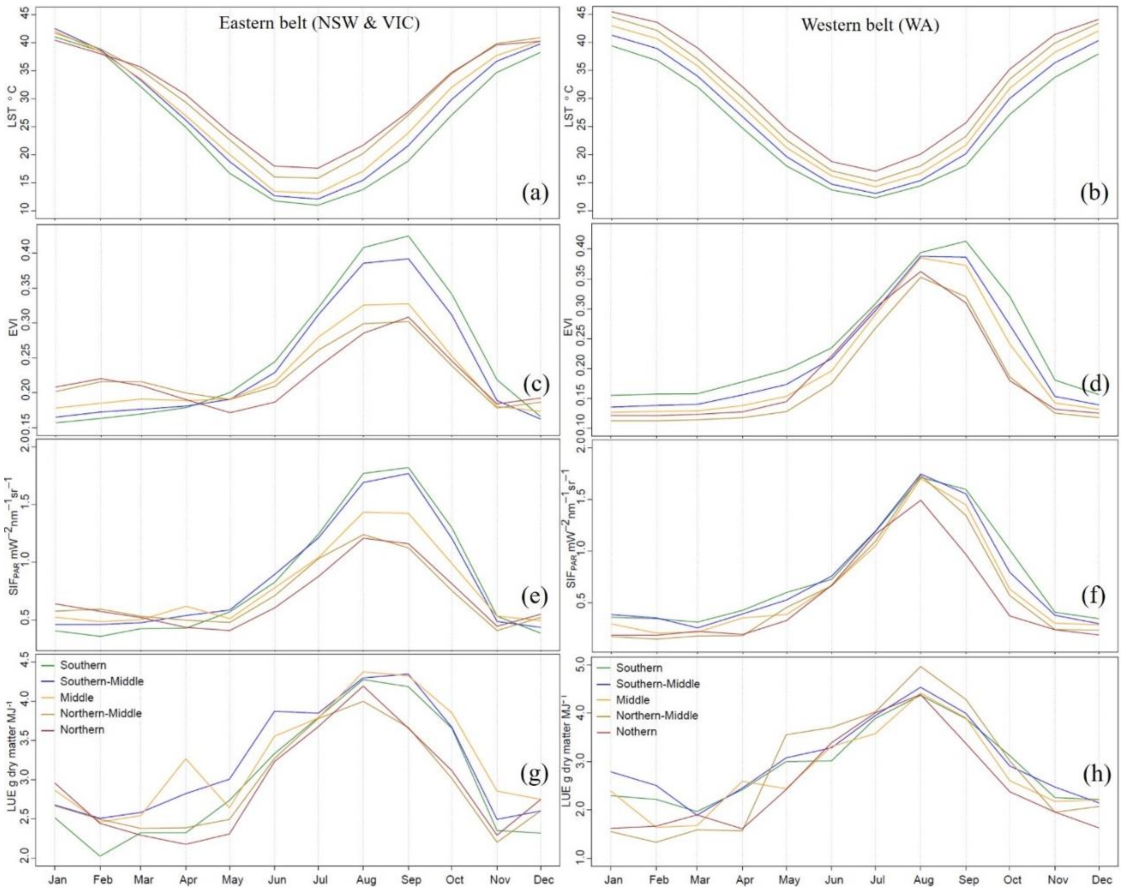

Figure 5.3 Spatial patterns in 10-year mean seasonality of LST, EVI, SIF_{PAR}, and LUE

* SIF_{PAR} is PAR normalized SIF, and LUE is non-parameterized light-use efficiency.

Satellite based LUE ranged 2.1-4.4 and 1.3-4.9 g dry matter MJ^{-1} in the eastern and western belts, respectively (Figure 5.3g, h). Only one major cycle in LUE was present among all the LST zones, although there was more inter-monthly variation in LUE than in LST, EVI, or SIF. August was generally the peak month of LUE across the entire study area, with the exception of the cooler southern LST zone of the eastern belt peaks during September. During the growing season, regions with larger LSTs exhibited larger EVI and SIF_{PAR} values in terms of seasonality, but this was not consistent with the satellite based LUE values. Average LUE in the middle LST zone was the largest in the eastern belt, while in the Northern-middle LST zone was largest in the western belt. This indicates a spatial non-linear relationship between LUE and LST. During the growing season, the rate of decline in LUE after August (the month with optimum LST level) was larger than the rate of LUE rising before August, implying a seasonal hysteresis of LUE in response to surface temperature change across Australian rainfed croplands throughout the winter crop's growing season.

5.3.3 Seasonal dynamics of LUE and related measurements

Temporally, cropland vegetation greenness and photosynthesis-active seasonality are determined by the meteorological cycle. Throughout the growing season LST, EVI, SIF and LUE vary during every month. Consequently, seasonal dynamics of satellite based LST, EVI, SIF and LUE during growing season were summarised across Australian rainfed cropland belts. Table 5.2 shows the 10-year average value for each of these satellite-based vegetation measurements from June to November.

Table 5.2 Statistical summary of satellite based LST, EVI, SIF and LUE across all sites during the growing season

	LST (°C)		SIF_{PAR} ($mW^{-2}nm^{-1}sr^{-1}$)		EVI		LUE (g dry matter MJ^{-1})	
	mean	Se	mean	Se	mean	Se	mean	Se
June	14.4	0.08	0.74	0.01	0.22	0.002	3.27	0.05
July	13.5	0.08	1.11	0.02	0.29	0.002	3.72	0.05
Aug	16.5	0.10	1.54	0.02	0.37	0.003	4.19	0.04
Sep	21.9	0.14	1.45	0.02	0.37	0.003	3.89	0.04
Oct	30.5	0.15	0.92	0.02	0.28	0.003	3.15	0.04
Nov	36.9	0.14	0.43	0.01	0.18	0.002	2.31	0.04

* Se is one standard error.

Table 5.3 Pairwise comparison among each month for satellite based LST, EVI, SIF and LUE

p value	June	July	Aug	Sep	Oct	June	July	Aug	Sep	Oct
	LST (°C)					SIF_{PAR} ($mW^{-2}nm^{-1}sr^{-1}$)				
July	<0.01					<0.01				
Aug	<0.01	<0.01				<0.01	<0.01			
Sep	<0.01	<0.01	<0.01			<0.01	<0.01	<0.01		
Oct	<0.01	<0.01	<0.01	<0.01		<0.01	<0.01	<0.01	<0.01	
Nov	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
	EVI					LUE (g dry matter MJ^{-1})				
July	<0.01					<0.01				
Aug	<0.01	<0.01				<0.01	<0.01			
Sep	<0.01	<0.01	1.00			<0.01	0.09	<0.01		
Oct	<0.01	<0.01	<0.01	<0.01		0.83	<0.01	<0.01	<0.01	
Nov	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01

Across all years, the largest EVI value occurred in September, while SIF and LUE reached their largest value in August. July was the coldest month across all sites, with the lowest surface temperature (LST), but this did not coincide with the smallest greenness index (EVI) nor the lowest photosynthetic activities (SIF and LUE). The smallest EVI, SIF and LUE occurred in November, the hottest month during the growing season (but not the hottest month of the year, which occurs in late summer) across Australian rainfed croplands. By pairwise comparisons of each of the mean satellite-based measurements among the growing season months (Table 5.3), we observed that: (a) among all the growing season months, average EVI during August and September were not statistically different ($p > 0.1$) across all study areas; (b) SIF values varied significantly among the months of growing season ($p < 0.05$); (c) LUE shows distinguish value during August compare to other months of growing season ($p<0.01$), but did not differ significantly during June and October ($p >0.1$). The difference in mean LUE was of marginal significance ($0.1>p>0.05$) between July and September. These imply a non-symmetrical bell-shaped curve of LUE seasonality across Australian rainfed croplands.

5.3.4 Performance of satellite based LUE in response to LST

Table 5.4 summarizes the LST range and means of each spatial-temporal percentage quantile LST value within each month of the growing season. The range of LST in a specific month overlapped with the range of LST in the month before and after. Furthermore, all the levels of mean LST within each month were significant different with each other (all pairwise $p < 0.05$). The standard deviation (Sd) in the first and last 10% quantiles of LST, especially the last, were greater than that of other percentage quantiles in each month from June to November. This indicates that every month during growing season has pixels with extreme high LST values.

By comparing the mean values of satellite based LUE across different groups of LST each month using one-way ANOVA and *post-hoc* testing, the spatial-temporal LST each month were regrouped into several ranges (Figure 5.4). Thereafter, we attribute each of the statistical LST ranges as slight cold, normal, optimum, slight hot, medium hot, and extreme hot group for LUE based on their means of LST range (Figure 5.4). Mean LUE significantly ($p < 0.1$) peaked at the LST range of 16.6-17.6 °C during August (Figure 5.4, Table 5.4), which is the optimum LST range for Australian rainfed cropland photosynthetic activity. LST that were lower or higher than this range in August resulted in lower LUE values. It is noteworthy that the mean LUE values are significantly reduced ($p < 0.05$) when LST was in the highest 10% quantile during August, September and October. Every month has its certain water and heat patterns, corresponding to the certain stages of crop growth over specific crop life span. The pixels with the uppermost 10%

quantiles of LST during each month exhibit extreme water and heat conditions, which lead to stresses on photosynthetic efficiency. Furthermore, the non-linear relationship between LUE and LST was also observed among the re-grouped spatial-temporal LST levels (Figure 5.4). During June and July, there was no significant LUE increase among all the 10% quantiles of LST groups. However, there were significant LUE decreases in the uppermost 10% quantile of LST group in October and 6 groups of the 10% quantile of LST in November. These facts indicated that LUE increased more slowly (was less sensitive) as temperature increased from the minimum range to the optimum range (16.6-17.6 °C during August), but then declined more rapidly (was more sensitive) as LST increased from supra-optimal values, especially during October and November. Consequently, assigning a single threshold of LST at 30 °C as that has been applied in most formulations of current GPP models can result in significant errors without considering spatial and temporal variation in optimum temperature.

Table 5.4 Statistical summary of spatial-temporal percentage quantile LST levels each month from June to November

Interval		0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
	Jun	9.3	11.5	12.2	12.7	13.2	13.8	14.4	15.4	16.8	18.5	25.1
	Jul	8.4	10.9	11.4	11.9	12.3	12.8	13.4	14.2	15.4	17.3	26.6
	Aug	9.8	12.7	13.8	14.4	15.1	15.6	16.6	17.6	19.1	21.4	31.7
	Sep	12.7	16.4	18.0	19.2	20.2	21.4	22.6	24.0	26.0	28.3	37.3
	Oct	16.7	23.7	26.0	27.6	29.1	30.6	32.0	33.7	35.1	36.8	43.8
	Nov	22.4	31.2	33.3	34.7	35.8	37.0	38.4	39.6	41.0	42.8	49.5
Mean	Jun		10.9	11.8	12.4	13.0	13.5	14.1	14.9	16.0	17.6	19.7
	Jul		10.2	11.2	11.6	12.1	12.5	13.1	13.7	14.7	16.3	19.3
	Aug		11.8	13.3	14.1	14.7	15.3	16.1	17.0	18.3	20.1	23.9
	Sep		15.1	17.2	18.6	19.7	20.7	22.0	23.2	24.9	27.0	31.1
	Oct		21.6	24.9	26.9	28.4	29.8	31.3	32.9	34.4	35.9	38.8
	Nov		28.6	32.4	34.0	35.3	36.4	37.7	39.0	40.3	41.9	44.4
Sd	Jun		0.05	0.02	0.01	0.01	0.02	0.02	0.03	0.04	0.05	0.13
	Jul		0.06	0.02	0.01	0.01	0.01	0.02	0.02	0.04	0.05	0.17
	Aug		0.06	0.03	0.02	0.02	0.02	0.02	0.03	0.04	0.06	0.20
	Sep		0.08	0.04	0.03	0.03	0.03	0.04	0.04	0.06	0.06	0.23
	Oct		0.16	0.06	0.04	0.04	0.04	0.04	0.05	0.04	0.05	0.16
	Nov		0.18	0.06	0.04	0.03	0.03	0.04	0.03	0.04	0.05	0.14

* All pairwise comparison test in mean of temperature among LST levels each month have a statistically significant p value of < 0.05.

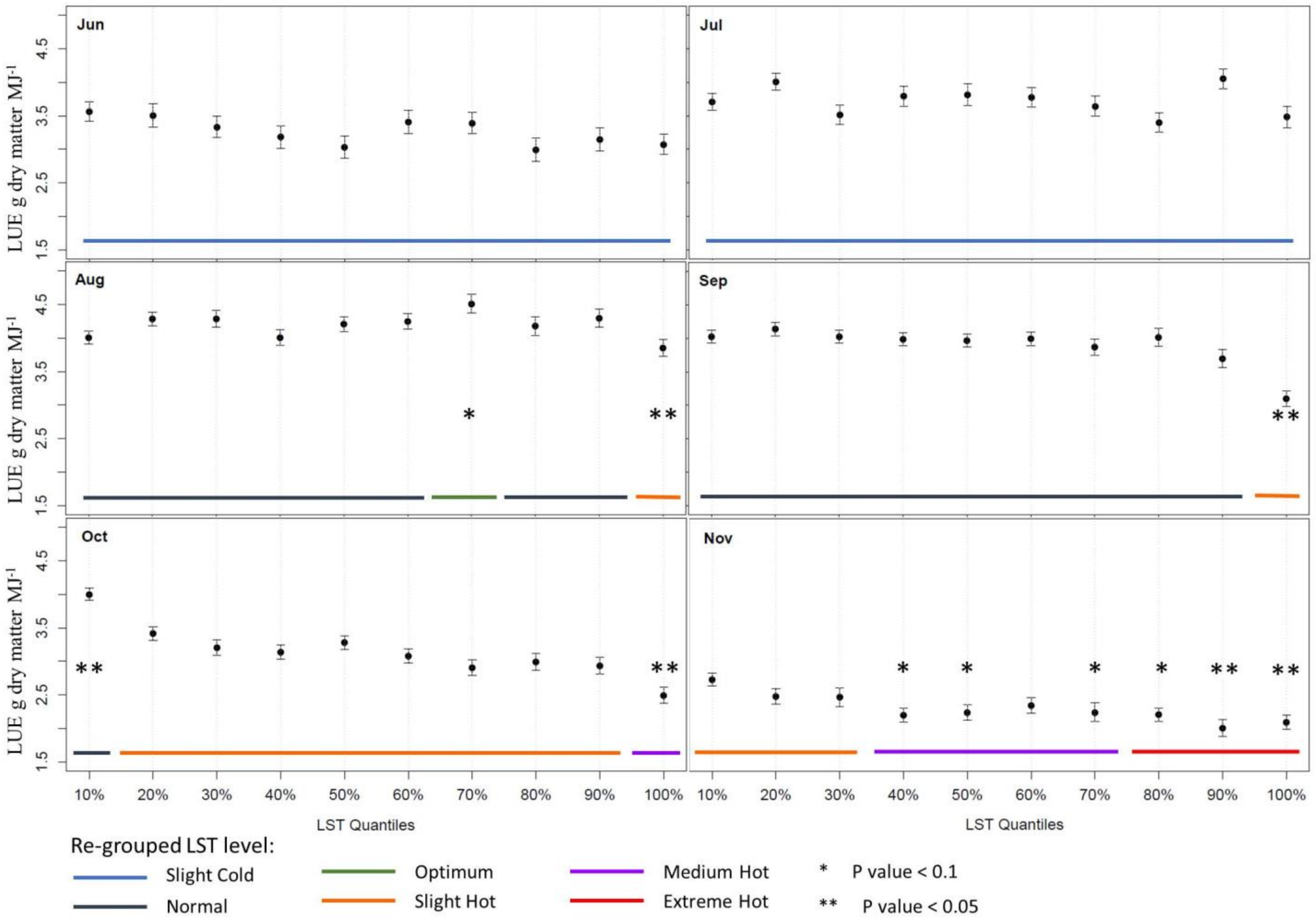

Figure 5.4 Re-grouped spatial-temporal LST levels within each month divided by one-way ANOVA and *post hoc* test

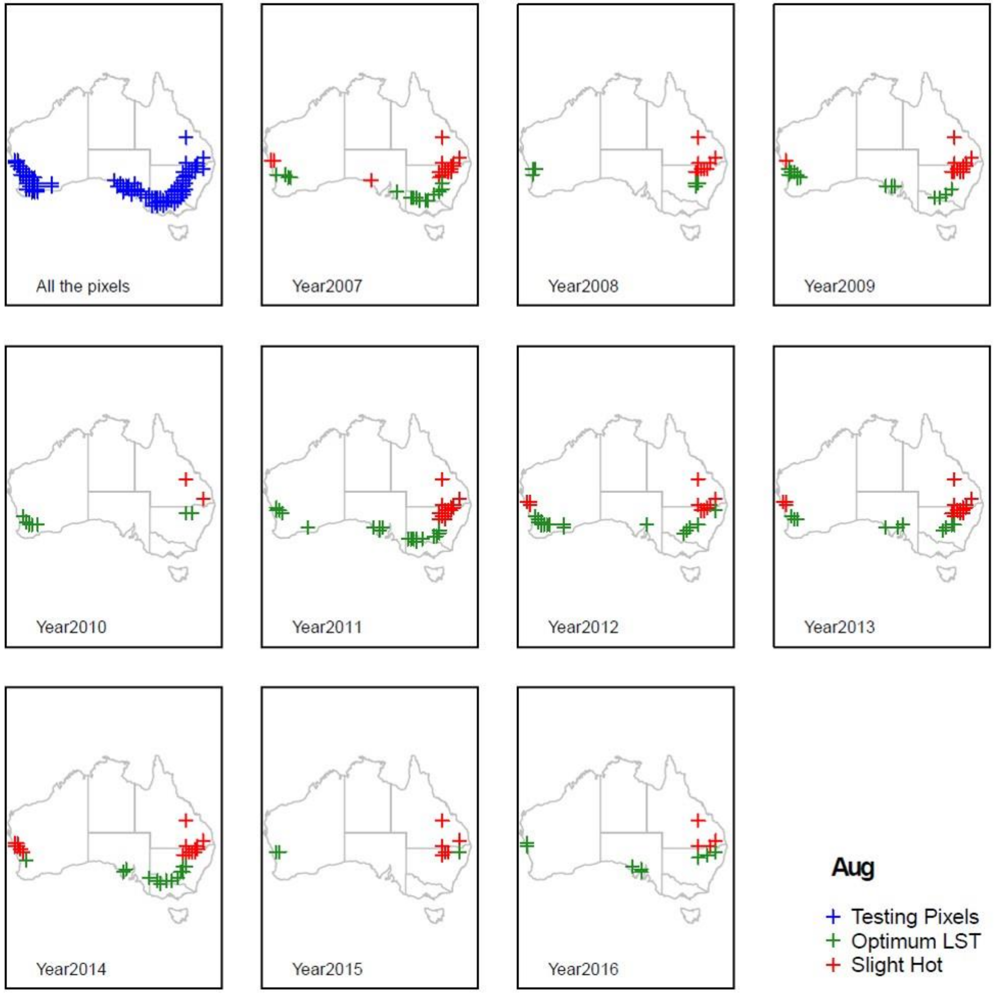

Figure 5.5 Spatial-temporal distributions of pixels with the re-grouped LST levels during August across all 10 years

Since three spatial-temporal LST groups during August (Normal, Optimum, and slight hot) were identified, the spatial-temporal distributions of pixels in each of the groups were then examined (Figure 5.5).

Pixels having the optimum and slightly hot LST range were distributed in different regions across Australian rainfed croplands. The pixels in the optimum LST group and with the highest LUE level (green crosses in Figure 5.5) in August were distributed across western, southern, and eastern regions, with the exception of Queensland (QLD). Pixels having the slightly hot LST range were distributed in the upper northern part of the eastern belt, and also the western belt in some hydrologically dry years (2007, 2009, 2012, 2013 and 2014) (Cleverly et al. 2016; Dijk et al. 2013). Year 2011 had the most pixels (19) with an optimum LST value in August, and year 2008, 2010, 2015, and 2016 had the smallest number of pixels within the optimum LST range (6, 7, 3 and 8, pixels respectively). For the slightly hot LST range, 18 were recorded in 2007, while 2 and 4 pixels were recorded in 2010 and 2016, respectively.

In summary, the eastern belt of Australian rainfed croplands recorded a larger number of slightly hot pixels than the western belt in August. Pixels within the optimum LST range in August were distributed in the South-middle to Middle zones of both cropland belts, while the rest of the rainfed cropland pixels either had colder or hotter surface temperature and this resulted in a lower LUE. Years 2008, 2010, 2015, and 2016 recorded fewer than 10 pixels both in the optimum LST range and the slightly hot LST group, while years 2007, 2009, and 2011-2014 recorded more than 10 pixels in these two ranges of LST in August.

5.4 Conclusions

This study monitored real time cropland light-use efficiency from space by calculating the ratio of SIF_{PAR} to EVI, (followed by multiplication by a constant coefficient). Satellite based solar-induced chlorophyll fluorescence (SIF) and the enhanced vegetation index (EVI) provided direct measurements of vegetation photosynthetic activity and greenness, respectively. The link between SIF and crop photosynthesis is instantaneous, but the satellite SIF signal often contains additional information pertaining to canopy structure and total canopy chlorophyll content (Yang et al. 2017). The methodological advance was to effectively and accurately remove the constant greenness level, so as to estimate the real-time photosynthetic activity entirely from remotely sensed variables.

This study further demonstrated the spatial pattern and temporal dynamics of satellite based vegetation measurements both among the cropland growing season and within each of the months across a range of land surface temperature values. LST is a measure of vegetation canopy temperature and was demonstrated to be an effective climate component that integrates complex interactions among the climate-driving factors (Shen et al. 2018) in this study. LST is closely related to plant evapotranspiration because increases in LST reflect decreased partitioning of radiation to latent heat flux compared to sensible heat flux. Spatially, although there were gradients in seasonality of in LST, EVI and SIF from northern to southern regions of the western and eastern croplands of Australia, LUE values in the northern (hottest) zones and southern (coldest) zones were not the largest recorded. Temporally, LUE peaked at the LST range of 16.6-17.6 °C during August (Figure 5.4, Table 5.4). The results also indicated a hysteresis of LUE in response to surface temperature spatially, seasonally and during certain month. Thus, the contributions of the study are that I’ve: 1) approximated the real-time LUE entirely by remote sensing; and 2) taken spatial and temporal variation into consideration when estimating the optimum temperature for vegetation activity. The results of this study have significant implications for large-scale detection and monitoring of cropland water and heat stress, as well as application of remotely sensed analyses of photosynthetic activities at leaf and canopy scales.

5.5 Limitation and future research

This study is not without limitations. Firstly, the linear relationship between LUE_P and LUE_F is a debatable issue in current research. PAR absorbed by vegetation chlorophyll (APAR) was theoretically divided into three distinctive fractions: the energy to fix carbon, generate fluorescence and dissipate non-radiative heat (Verma et al. 2017). These three pathways may compete with each other (Meroni et al. 2009) especially at the instantaneous scale and leaf level. However, many recent empirical studies indicated that SIF linearly related to GPP is more robust at the coarse spatial and temporal resolution (such as ecosystem and regional scale) (Guanter et al. 2014; Joiner et al. 2014; Smith et al. 2018; Zhang et al. 2016) than the theory based on leaf-level processes (Verma et al. 2017). At the same time, SIF better captures the dynamics of seasonal and inter-annual GPP than other remote sensing observations, especially across dryland ecosystems (Smith et al. 2018). The relationship between LUE_P and LUE_F at 0.5°×0.5° spatial resolution therefore can be simplified as linearly based on the concepts that SIF and GPP were roughly estimated as APAR multiply LUE_F and LUE_P, respectively. Meanwhile, Figure 2 (d-e) has indicated the linear relationship (R^2=0.74, $p<0.01$) between satellite SIF and Flux GPP both during the morning window and during the photosynthesis-active daytime in Australian rainfed cropland. Thus, the assumption of linearity in LUE_P:LUE_F for this study is appropriate, though the linear relationship in SIF:GPP under different environmental conditions (Verma et al. 2017) is required to be tested in future research.

Secondly, the value of the constant coefficient value a, calculated as the ratio of LUE_P to $LUE_F(\lambda)$, will be enhanced by conducting field validations. I applied a constant value of 1 in this study. One reason for this was because this study examined spatial and temporal changes in LUE by comparing those relative values, rather than directly utilizing it in GPP estimation models. In addition, previous experimental studies (Charles-Edwards 1982; Garcia et al. 1988) have estimated a similar range of LUE values (upper limit to be 6.4 g dry matter MJ^{-1}) for crops as the satellite estimation (1.2 to 4.9 g dry matter MJ^{-1}). Thus, the assumption of a equals to 1 is appropriate.

Thirdly, we acknowledge that GOME-2 SIF retrieval has a coarse spatial resolution of 0.5°×0.5°, which may contain noises of LUE estimation. The EVI dataset I utilized in this study is derived from MODIS, which is a well-tested instrument for land monitoring, and the current EVI product is mature (version 6). As Figure 5.2 shows, both of the correlations of Flux GPP-SIF and Flux GPP-EVI are statistically significant, and their R^2 only have a difference of 0.06 at 0.5°×0.5° resolution. My intension was to perform a first test using existing spaceborne SIF products as such the first test is valuable. Thus, there is no major concern with the spatial resolution.

Fourthly, the physiological responses of LUE to LST vary dynamically over different time scales, ranging from hourly-to-monthly-to-seasonally. In the present study, I only examined variation at monthly and seasonal scales due to data availability. Finer spatial and temporal resolutions of SIF data can be conducted in future studies.

Lastly, the exact range of optimum LST values during August depend on the method of statistical division, the resolution of percentage quantiles determines the thresholds of each level within each growing season month. One-way ANOVA and its *post-hoc* testing helped us to identify and re-classify the equally divided groups into several significantly different levels. As such, we still have high confidence in the conclusion that the range of optimum LST level for satellite-based LUE across Australian croplands was 16.6-17.6 °C.

References

Beringer, J., McHugh, I., Hutley, L.B., Isaac, P. & Kljun, N. 2017, 'Technical note: Dynamic INtegrated Gap-filling and partitioning for OzFlux (DINGO)', *Biogeosciences*, vol. 14, no. 6, pp. 1457-60.

Berry, J. & Bjorkman, O. 1980, 'Photosynthetic response and adaptation to temperature in higher plants', *Annual Review of plant physiology*, vol. 31, no. 1, pp. 491-543.

Berry, J.A., Frankenberg, C., Wennberg, P., Baker, I., Bowman, K.W., Castro-Contreas, S., Cendrero-Mateo, M.P., Damm, A., Drewry, D. & Ehlmann, B. 2012, 'New methods for measurement of photosynthesis from space', *Geophys. Res. Lett*, vol. 38, p. L17706.

Bowden, P., Edwards, J., Ferguson, N., Nee, T.M., Manning, B., Roberts, K., Schipp, A., Schulze, K. & Wilkins, J. 2008, *Wheat growth and development*, NSW Department of Primary Industries.

Campbell, P.K.E., Middleton, E.M., Corp, L.A. & Kim, M.S. 2008, 'Contribution of chlorophyll fluorescence to the apparent vegetation reflectance', *Science of The Total Environment*, vol. 404, no. 2, pp. 433-9.

Charles-Edwards, D.A. 1982, *Physiological determinants of crop growth*, vol. 1, Academic Press Sydney.

Cleverly, J., Eamus, D., Luo, Q., Restrepo Coupe, N., Kljun, N., Ma, X., Ewenz, C., Li, L., Yu, Q. & Huete, A. 2016, 'The importance of interacting climate modes on Australia's contribution to global carbon cycle extremes', *Sci. Rep.*, vol. 6, p. 23113.

Dijk, A.I., Beck, H.E., Crosbie, R.S., Jeu, R.A., Liu, Y.Y., Podger, G.M., Timbal, B. & Viney, N.R. 2013, 'The Millennium Drought in southeast Australia (2001–2009): Natural and human causes and implications for water resources, ecosystems, economy, and society', *Water Resour. Res.*, vol. 49, no. 2, pp. 1040-57.

Dong, J., Xiao, X., Wagle, P., Zhang, G., Zhou, Y., Jin, C., Torn, M.S., Meyers, T.P., Suyker, A.E., Wang, J., Yan, H., Biradar, C. & Moore, B. 2015, 'Comparison of four EVI-based models for estimating gross primary production of maize and soybean croplands and tallgrass prairie under severe drought', *Remote Sens. Environ.*, vol. 162, pp. 154-68.

Gamon, J. & Qiu, H. 1999, 'Ecological applications of remote sensing at multiple scales', *Handbook of functional plant ecology*, vol. 805, p. 846.

Garbulsky, M.F., PeÑUelas, J., Papale, D. & Filella, I. 2008, 'Remote estimation of carbon dioxide uptake by a Mediterranean forest', *Global Change Biol.*, vol. 14, no. 12, pp. 2860-7.

Garcia, R., Kanemasu, E.T., Blad, B.L., Bauer, A., Hatfield, J.L., Major, D.J., Reginato, R.J. & Hubbard, K.G. 1988, 'Interception and use efficiency of light in winter wheat under different nitrogen regimes', *Agric. For. Meteorol.*, vol. 44, no. 2, pp. 175-86.

Gitelson, A.A. & Gamon, J.A. 2015, 'The need for a common basis for defining light-use efficiency: Implications for productivity estimation', *Remote Sens. Environ.*, vol. 156, pp. 196-201.

Gitelson, A.A. & Merzlyak, M.N. 1996, 'Signature Analysis of Leaf Reflectance Spectra: Algorithm Development for Remote Sensing of Chlorophyll', *Journal of Plant Physiology*, vol. 148, no. 3, pp. 494-500.

Gitelson, A.A., Peng, Y., Arkebauer, T.J. & Suyker, A.E. 2015, 'Productivity, absorbed photosynthetically active radiation, and light use efficiency in crops: Implications for remote sensing of crop primary production', *Journal of Plant Physiology*, vol. 177, no. Supplement C, pp. 100-9.

Guan, K., Berry, J.A., Zhang, Y., Joiner, J., Guanter, L., Badgley, G. & Lobell, D.B. 2016, 'Improving the monitoring of crop productivity using spaceborne solar-induced fluorescence', *Global Change Biol.*, vol. 22, no. 2, pp. 716-26.

Guanter, L., Zhang, Y., Jung, M., Joiner, J., Voigt, M., Berry, J.A., Frankenberg, C., Huete, A.R., Zarco-Tejada, P., Lee, J.-E., Moran, M.S., Ponce-Campos, G., Beer, C., Camps-Valls, G., Buchmann, N., Gianelle, D., Klumpp, K., Cescatti, A., Baker, J.M. & Griffis, T.J. 2014, 'Global and time-resolved monitoring of crop photosynthesis with chlorophyll fluorescence', *Proc. Nat. Acad. Sci. U.S.A.*, vol. 111, no. 14, pp. E1327-E33.

Hochman, Z., Gobbett, D., Holzworth, D., McClelland, T., van Rees, H., Marinoni, O., Garcia, J.N. & Horan, H. 2012, 'Quantifying yield gaps in rainfed cropping systems: A case study of wheat in Australia', *Field Crops Res.*, vol. 136, no. 0, pp. 85-96.

Hochman, Z., Gobbett, D.L. & Horan, H. 2017, 'Climate trends account for stalled wheat yields in Australia since 1990', *Global Change Biol.*, vol. 23, pp. 2071-81.

Huete, A., Didan, K., Miura, T., Rodriguez, E.P., Gao, X. & Ferreira, L.G. 2002, 'Overview of the radiometric and biophysical performance of the MODIS vegetation indices', *Remote Sens. Environ.*, vol. 83, no. 1–2, pp. 195-213.

Huete, A.R. 2012, 'Vegetation indices, remote sensing and forest monitoring', *Geogr. Compass*, vol. 6, no. 9, pp. 513-32.

Idso, S.B., Jackson, R.D. & Reginato, R.J. 1977, 'Remote sensing for agricultural water management and crop yield prediction', *Agric. Water Manage.*, vol. 1, no. 4, pp. 299-310.

Jeong, S.-J., Schimel, D., Frankenberg, C., Drewry, D.T., Fisher, J.B., Verma, M., Berry, J.A., Lee, J.-E. & Joiner, J. 2017, 'Application of satellite solar-induced chlorophyll fluorescence to understanding large-scale variations in vegetation phenology and function over northern high latitude forests', *Remote Sens. Environ.*, vol. 190, pp. 178-87.

Joiner, J., Guanter, L., Lindstrot, R., Voigt, M., Vasilkov, A., Middleton, E., Huemmrich, K., Yoshida, Y. & Frankenberg, C. 2013, 'Global monitoring of terrestrial chlorophyll fluorescence from moderate spectral resolution near-infrared satellite measurements: methodology, simulations, and application to GOME-2', *Atmospheric Measurement Techniques*, vol. 6, no. 2, pp. 2803-23.

Joiner, J., Yoshida, Y., Vasilkov, A.P., Corp, L.A. & Middleton, E.M. 2011, 'First observations of global and seasonal terrestrial chlorophyll fluorescence from space', *Biogeosciences*, vol. 8, no. 3, pp. 637-51.

Joiner, J., Yoshida, Y., Vasilkov, A.P., Schaefer, K., Jung, M., Guanter, L., Zhang, Y., Garrity, S., Middleton, E.M., Huemmrich, K.F., Gu, L. & Belelli Marchesini, L. 2014, 'The seasonal cycle of satellite chlorophyll fluorescence observations and its relationship to vegetation phenology and ecosystem atmosphere carbon exchange', *Remote Sens. Environ.*, vol. 152, pp. 375-91.

Lobell, D.B., Hicke, J.A., Asner, G.P., Field, C.B., Tucker, C.J. & Los, S.O. 2002, 'Satellite estimates of productivity and light use efficiency in United States agriculture, 1982–98', *Global Change Biol.*, vol. 8, no. 8, pp. 722-35.

Lymburner, L., Tan, P., Mueller, N., Thackway, R., Lewis, A., Thankappan, M., Randall, L., Islam, A. & Senarath, U. 2010, '250 metre dynamic land cover dataset of Australia', *Geoscience Australia, Canberra*.

Meroni, M., Rossini, M., Guanter, L., Alonso, L., Rascher, U., Colombo, R. & Moreno, J. 2009, 'Remote sensing of solar-induced chlorophyll fluorescence: Review of methods and applications', *Remote Sens. Environ.*, vol. 113, no. 10, pp. 2037-51.

Monteith, J.L. 1972, 'Solar Radiation and Productivity in Tropical Ecosystems', *Journal of Applied Ecology*, vol. 9, no. 3, pp. 747-66.

Monteith, J.L. 1977, 'Climate and the Efficiency of Crop Production in Britain [and Discussion]', *Philosophical Transactions of the Royal Society of London. B, Biological Sciences*, vol. 281, no. 980, pp. 277-94.

RCoreTeam 2013, 'R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.[WWW document]', *URL* http://www. *R-project. org/.*

Running, S.W., Nemani, R., Glassy, J.M. & Thornton, P.E. 1999, 'MODIS daily photosynthesis (PSN) and annual net primary production (NPP) product (MOD17) Algorithm Theoretical Basis Document', *University of Montana, SCF At-Launch Algorithm ATBD Documents (available online at: www. ntsg. umt. edu/modis/ATBD/ATBD_MOD17_v21. pdf)*.

Running, S.W., Nemani, R.R., Heinsch, F.A., Zhao, M., Reeves, M. & Hashimoto, H. 2004, 'A Continuous Satellite-Derived Measure of Global Terrestrial Primary Production', *BioScience*, vol. 54, no. 6, pp. 547-60.

Salkind, N. 2010, 'Encyclopedia of Research Design'.

Sandholt, I., Rasmussen, K. & Andersen, J. 2002, 'A simple interpretation of the surface temperature/vegetation index space for assessment of surface moisture status', *Remote Sens. Environ.*, vol. 79, no. 2–3, pp. 213-24.

Shen, J., Huete, A., Tran, N.N., Devadas, R., Ma, X., Eamus, D. & Yu, Q. 2018, 'Diverse sensitivity of winter crops over the growing season to climate and land surface temperature across the rainfed cropland-belt of eastern Australia', *Agric. Ecosyst. Environ.*, vol. 254, pp. 99-110.

Sims, D.A., Rahman, A.F., Cordova, V.D., El-Masri, B.Z., Baldocchi, D.D., Bolstad, P.V., Flanagan, L.B., Goldstein, A.H., Hollinger, D.Y., Misson, L., Monson, R.K., Oechel, W.C., Schmid, H.P., Wofsy, S.C. & Xu, L. 2008, 'A new model of gross primary productivity for North American ecosystems based solely on the enhanced vegetation index and land surface temperature from MODIS', *Remote Sens. Environ.*, vol. 112, no. 4, pp. 1633-46.

Smith, W.K., Biederman, J.A., Scott, R.L., Moore, D.J.P., He, M., Kimball, J.S., Yan, D., Hudson, A., Barnes, M.L., MacBean, N., Fox, A.M. & Litvak, M.E. 2018, 'Chlorophyll Fluorescence Better Captures Seasonal and Interannual Gross Primary Productivity Dynamics Across Dryland Ecosystems of Southwestern North America', *Geophys. Res. Lett.*, vol. 45, no. 2, pp. 748-57.

Verma, M., Schimel, D., Evans, B., Frankenberg, C., Beringer, J., Drewry, D.T., Magney, T., Marang, I., Hutley, L., Moore, C. & Eldering, A. 2017, 'Effect of environmental conditions on the relationship between solar-induced fluorescence and gross primary productivity at an OzFlux grassland site', *J. Geophys. Res.: Biogeosci.*, vol. 122, no. 3, pp. 716-33.

Wang, Z., Xiao, X. & Yan, X. 2010, 'Modeling gross primary production of maize cropland and degraded grassland in northeastern China', *Agric. For. Meteorol.*, vol. 150, no. 9, pp. 1160-7.

Welch, B. 1951, 'On the comparison of several mean values: an alternative approach', *Biometrika*, vol. 38, no. 3/4, pp. 330-6.

Xiao, J., Zhuang, Q., Baldocchi, D.D., Law, B.E., Richardson, A.D., Chen, J., Oren, R., Starr, G., Noormets, A., Ma, S., Verma, S.B., Wharton, S., Wofsy, S.C., Bolstad, P.V., Burns, S.P., Cook, D.R., Curtis, P.S., Drake, B.G., Falk, M., Fischer, M.L., Foster, D.R., Gu, L., Hadley, J.L., Hollinger, D.Y., Katul, G.G., Litvak, M., Martin, T.A., Matamala, R., McNulty, S., Meyers, T.P., Monson, R.K., Munger, J.W., Oechel, W.C., Paw U, K.T., Schmid, H.P., Scott, R.L., Sun, G., Suyker, A.E. & Torn, M.S. 2008, 'Estimation of net ecosystem carbon exchange for the conterminous United States by combining MODIS and AmeriFlux data', *Agric. For. Meteorol.*, vol. 148, no. 11, pp. 1827-47.

Xiao, X., Hollinger, D., Aber, J., Goltz, M., Davidson, E.A., Zhang, Q. & Moore, B. 2004, 'Satellite-based modeling of gross primary production in an evergreen needleleaf forest', *Remote Sens. Environ.*, vol. 89, no. 4, pp. 519-34.

Xiao, X., Qingyuan, Z., Hollinger, D., Aber, J. & Moore, B. 2005, 'Modeling Gross Primary Production of an Evergreen Needleleaf Forest Using Modis and Climate Data', *Ecol. Appl.*, vol. 15, no. 3, pp. 954-69.

Yan, H., Fu, Y., Xiao, X., Huang, H.Q., He, H. & Ediger, L. 2009, 'Modeling gross primary productivity for winter wheat–maize double cropping system using MODIS time series and CO2 eddy flux tower data', *Agric. Ecosyst. Environ.*, vol. 129, no. 4, pp. 391-400.

Yan, W., Zhong, Y. & Shangguan, Z. 2017, 'Contrasting responses of leaf stomatal characteristics to climate change: a considerable challenge to predict carbon and water cycles', *Global Change Biol.*, pp. 716-26

Yang, H., Yang, X., Zhang, Y., Heskel, M.A., Lu, X., Munger, J.W., Sun, S. & Tang, J. 2017, 'Chlorophyll fluorescence tracks seasonal variations of photosynthesis from leaf to canopy in a temperate forest', *Global Change Biol.*, vol. 23, no. 7, pp. 2874-86.

Yang, Y., Shang, S., Guan, H. & Jiang, L. 2013, 'A novel algorithm to assess gross primary production for terrestrial ecosystems from MODIS imagery', *J. Geophys. Res.: Biogeosci.*, vol. 118, no. 2, pp. 590-605.

Yu, Q., Hengsdijk, H. & Liu, J.D. 2001, 'Application of a progressive-difference method to identify climatic factors causing variation in the rice yield in the Yangtze Delta, China', *Int. J. Biometeorol.*, vol. 45, no. 2, pp. 53-8.

Zhang, Y., Guanter, L., Berry, J.A., van der Tol, C., Yang, X., Tang, J. & Zhang, F. 2016, 'Model-based analysis of the relationship between sun-induced chlorophyll fluorescence and gross primary production for remote sensing applications', *Remote Sens. Environ.*, vol. 187, pp. 145-55.

Zhao, M., Heinsch, F.A., Nemani, R.R. & Running, S.W. 2005, 'Improvements of the MODIS terrestrial gross and net primary production global data set', *Remote Sens. Environ.*, vol. 95, no. 2, pp. 164-76.

Chapter 6. Summary and future research

6.1 Summary

Climate in Australia is well known to have the highest variability around the world as it is influenced by multiple components. Accordingly, the total annual wheat production in Australia has varied dramatically, especially during the most recent decade. By incorporating multi-source observed datasets, this thesis illustrated the relationship between climate variability and crop growth spatially and temporally across the Australian rainfed cropland belts.

To deal with the increasing challenges of climate change/climate variability, the complex climate-crop relationship (CCR) needs to be better understood. This thesis provided a systematic, holistic and objective review of the dryland CCR academic literature by combining Leximancer, a content analysis tool, to conventional bibliographic analysis. Forty-four publications on climatic impacts on croplands from 2009 to 2018 (inclusive) have been identified. The findings revealed four broad areas of foci with CCR research: (1) climate change and variability, (2) crop response, (3) CCR approaches, and (4) agricultural adaptation. The specific agro-climatic change variables, crop growth measurements and models employed in current CCR research were identified by manual bibliographic analysis. This thesis calls for a future agenda on integrated climate driver factor employment, crop phenology and photosynthesis response focus, multiple source of datasets engagement, and bottom-up approaches for agricultural adaptation. Focusing on the broad angle of crop response, the responses of crop productivity, crop phenology and crop photosynthesis activities were subsequently addressed in three major chapters in this thesis.

Spatiotemporal prediction of rainfed agricultural yields as affected by climate variability is a challenging task. This thesis related monthly satellite-based gross primary production (GPP) estimates to reported agricultural yields for Australia. The findings indicate that August and September are the optimum triggers for yield prediction (Growing season between June to November) across the rainfed cropland belts in Australia. The results showed that it is possible to spatially predict agricultural yield, especially in the State of New South Wales (NSW).

In terms of the spatial-temporal impacts of climate variability on crops during different crop growth stages. This thesis quantified the contributions of climate and Land Surface Temperature (LST) variations to the variability of the Enhanced Vegetation Index (EVI) by using remote sensing methods. The datasets were analyzed at an 8-day time-scale across the rainfed cropland areas of eastern Australia. The results indicated that: (1) EVI values were more variable during the crop reproductive growth stages than at any other crop life stage within a calendar year, but nevertheless had the highest correlation with crop grain yield (t ha^{-1}). (2) two critical 8-day periods, beginning on day of the year (DoY) 257 and 289, were identified as the key 'windows' of crop growth variation that arose from the variability in climate and LST. (3) the sum of the variability of the climate components within those two 8-day 'windows' explained >88% of the variability in the EVI, with LST being the dominant factor.

Crop Photosynthesis is highly sensitive to water and heat stress. Consequently, continuous and accurate estimation of cropland photosynthesis activity can serve to provide early warning detection of crop water and heat stress, and therefore can be used to assist in forecasting crop productivity. Space-based monitoring of sun-induced chlorophyll fluorescence (SIF) and the MODIS enhanced vegetation index (EVI) provide direct measurement of cropland vegetation photosynthetic activity and vegetation greenness, respectively. This thesis explored the potential to remotely monitor real-time light-use efficiency by calculating the ratio of photosynthetically active radiation (PAR) normalized SIF to EVI. This thesis applied this calculation to demonstrate spatial patterns and temporal dynamics of LUE in response to land surface temperature (LST) across Australian rainfed croplands (2007-2016). LST was used to provide an integrated measure of vegetation heat and drought stress in this study. The results showed that: spatially, LUE tends to be higher in the geographical middle zones with a mild range of LST level across Australian croplands, than either the hotter northern regions and the colder southern regions; temporally, there was a seasonal hysteresis of LUE in response to surface temperature change throughout the winter crop growing season. The results of one-way ANOVA and *post-hoc* tests revealed that the optimum LST range for satellite-based LUE were 16.6-17.6 °C during August. Pixels with optimum LST across the 10-year sampling period (August of 2007-2016) were distributed in the South-Middle to Middle zones of the Australian rainfed croplands.

6.2 Contributions

This thesis has a number of contributions to dryland crop stress detection and adaptation: From a theoretical perspective, it offers enhanced spatial temporal models in quantifying the observed impacts of climate variability on crop productivity and photosynthesis activity, especially on crop phenology at 8-day time step. As such, it identifies the impacts of heat variation to outweigh rainfall variation on crops across rainfed croplands. It also identified the optimum surface temperature range for Australian cropland photosynthesis activity; From a methodological point of view, it contributes to extant literature on the exploration of crop-climate relationship (CCR) not only by introducing Leximancer, a content analysis tool into the study to visualize the state-of-art related works, but also by putting efforts on closing the gaps identified from the literature review: climate driving factor employment, crop phenology and photosynthesis response focus, and multiple source of datasets engagement; From a practical point of view, the results of this thesis have significant implications for large-scale detection and monitoring of cropland water and heat stress, as well as application of remotely sensed analyses of crop productivity, phenology and photosynthetic activities at leaf and canopy scales. This thesis paves a way for timely understanding the influence of climate variability on crop growth and productivity and can serve as an early warning system for agricultural adaptation.

6.3 Limitations and future research

From the findings, the main future directions have become clearer:

1) The literature review in Chapter 2 examines only academic journal articles published in the current 10 years. Future research including grey literature (such as government reports, policy statements and issues papers), and perhaps a further comparative approach between industry and academic sources would offer additional insights into the climate-crop growth relationship research.

2) The research findings were limited to data availability and accessibility. Re-implementing the methodology with up-to-date datasets to investigate the climatic impacts on crop productivity, phenology and photosynthesis activity, as well as the performance of proposed methodology will be necessary.

3) The performance of climate-crop growth relationships can be variable under various spatial-temporal scales. Evaluating the influence of applying combination of datasets with vary spatial-temporal resolutions and process-based models in the reliability of proposed methodology is a logical progression.

4) In this thesis, sensitivity and resilience of crop growth response to climate change and variability were analysed without time-lag considerations. Conducting analysis of the time-lag effects in the measurements of crop growth to specific agro-climatic change variables spatially and temporally is an important future research direction.

5) Soil moisture, which negatively impacts on crop growth by either water deficiency or excess water stress, is one of the environmental factors that directly limit crop growth, especially in dryland agriculture systems. Assessment of the impacts of soil moisture change on crop growth based on both satellite and *in-situ* observations will be my next future step work.