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Diverse sensitivity of winter crops over the growing season to climate and land surface temperature across the rainfed cropland-belt of eastern Australia

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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. 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, we found that 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, we identified two critical 8-day periods, 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. Our 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.

1. Introduction

As the world's fourth largest agriculture exporter, Australia, whose crop production accounts for over 13% of its export revenue (ABARES, 2017), has greatly influenced the world grain market in recent decades (Hamblin, 2009; Lawrence et al., 2013). Due to the interactions of three oceans, the Australian climate has the greatest variability among inhabited continents (Cleverly et al., 2016; Ma et al., 2016; Stokes and Howden, 2010; Xie et al., 2016). Rainfall, air temperature and solar radiation are direct growth-defining and limiting factors of broadacre crops (Yu et al., 2001), and their variability poses risks to Australian crop production in terms of reductions in harvest area (Cohn et al., 2016) and grain yield (Barlow et al., 2015; Zheng et al., 2012) as well as changes to the dates that define the crop growing season (Zheng et al., 2012). Recent studies have shown that Australian croplands, which are mostly characterized by a broadacre rainfed planting system, are vulnerable in grain production to current climate variability (Field et al., 2014; Tripathi et al., 2016). While the projected growth of the global human population necessitates an increased crop yield (Godfray et al., 2010; Hochman et al., 2017), growth in annual grain yield in Australia has stalled since 1990, which is majorly caused by the changing climate (Hochman et al., 2017). Thus, it is necessary to quantify the impacts of climate variability on crop growth and to take measures to enhance the development of agricultural early warning systems.

Climate-crop relationships have been intensively researched in recent decades. Based on a recent study, climate variation is responsible for approximately one-third (~32–39%) of global variation in crop yield (Ray et al., 2015). In Australia, climate variation in the state of

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New South Wales (NSW) accounted for 31–47% of inter-annual wheat yield from 1922 to 2000 (Wang et al., 2015a). The results of crop simulations (Asseng et al., 2011) have indicated that variations of 2 °C of the average temperature during the crop growing season can cause up to a 50% reduction in grain production in Australian croplands. Under projected future climate scenarios, wheat yield will decrease by approximately 25% because of the predicted increase of temperature in southeastern Australia in future decades (Anwar et al., 2007). In most previous studies, the approaches of climate-crop relationship can be divided into two major types: observational and statistical models, and crop simulation techniques. The observational and statistical models have been based on data collected from administrative boundaries, which do not reflect the crop-growing process and do not explicitly reflect the spatial relationships identified. Although crop simulation techniques can precisely reconstruct the growth cycles of crops using parameter pre-setting, it is labor 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.

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 the advantage of multiple spatial, temporal and spectral resolutions and the data are from real-time observations (Eamus et al., 2016), which can characterize the full profile of the vegetation growth cycle. Remote sensing methods that have been utilized for crop-climate relationships often focus on estimating the cropland area (Biradar et al., 2009; Potgieter et al., 2011; Wardlow and Egbert, 2008) and detecting vegetation green-up and green-fade dates (Guo et al., 2016; Sakamoto et al., 2013). However, every stage of the crop growth cycle can impact the final crop yield. Currently, there is little knowledge about the different responses of crop performance to regional climate variability at each growth stage.

Understanding the impacts of climate on crop growth over its life span can help farmers and agricultural departments make timely decisions in response to climate variability and reduce potential losses in yield (Rabbinge, 2007) in broadacre rainfed cropping systems in Australia and worldwide. Thus, there is a need to illustrate the relationships between variations in several climate factors and crop growth throughout all crop growth stages and to identify the most sensitive 'windows', that is, the time segments of crop-growth that are most sensitive to climate variability.

Vegetation Indexes (VIs) are widely used remote indicators that characterize the status of land surface vegetation as well as the biophysical properties on global and regional scales (Karnieli et al., 2010; Wan et al., 2004). The VIs measure the 'greenness' of the canopy and monitor vegetation growth and health at various spatial scales (Huete et al., 2002; Ma et al., 2015). The Enhanced Vegetation Index (EVI) used in this study is an optimized VI that can effectively reduce soil background and atmospheric effects (Huete et al., 2002; Huete, 2012; Suepa, 2013).

Rainfall, air temperature and radiation influence crop canopy greenness by directly and indirectly controlling crop transpiration and photosynthesis (Calzadilla et al., 2013; Eamus et al., 2016) within the soil-plant-atmosphere continuum. Both the vegetative growth and reproductive growth stages of crops are dependent on and affected by these factors. The direct effects of variations in these factors on crop growth can be dominant during different growth stages. However, the proportion of the indirect effects of the complex interactions among these factors (Yu et al., 2014) on crops cannot be explained without a comprehensive indicator of the crop water and heat status. The radiative canopy temperature, (the Land Surface Temperature (LST)), is designed to measure the physical processes of the ground surface energy and water balance (Li et al., 2013) and reflects the water and heat status of vegetation and soil. In most cases, a high LST indicates deficient soil moisture and a high canopy heat stress (Karnieli et al., 2010). Thus, we introduced LST as a potentially crop-limiting climate component to describe the indirect impacts of rainfall, air temperature and solar radiation on crop growth.

This study investigated regional inter-annual variations in climate-crop growth relationships by incorporating MODIS land cover maps, time-series Enhanced Vegetation Index (EVI) and Land Surface Temperature (LST) products, ground meteorological station data and *in-situ* trial data across the rainfed cropland belt in NSW during the period from 2001 to 2013. An 8-day time-scale is applied as this is the attainable time step for the satellite that provides the data to produce MODIS EVI and LST. The objectives of this study are to: (1) identify the seasonality, trends and variability for EVI and each climate component during the crop growing season; (2) evaluate the individual and collective impacts of climate and LST variability on crops at the pixel and regional levels; and (3) investigate the relative contribution of the variability of each climate component to variation in crop growth during each 8-day time segment.

2. Materials and methods

2.1. Study area

The land cover map used in this study was obtained from the Dynamic Land Cover Dataset (DLCD) for Australia (http://www.ga.gov.au/) developed by Geoscience Australia. This dataset is based on an analysis of a 16-day MODIS EVI composite at a 250-m resolution during 2000–2008 (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.

Australian rainfed croplands (Fig. 1a) extend over 24.6 million hectares in a crescent around eastern, southern and western Australia and produce approximately 22.9 million tons of grain per year (www.abares.gov.au, 2013). Wheat is the major agriculture commodity across the rainfed cropland belt in Australia (Hochman et al., 2017). The NSW cropland belt (Fig. 1b) stretches across the drier western face of the Australian Great Dividing Range. It accounts for 27.5% of the wheat planted area in Australia and 27% of the total wheat production of the nation (www.abares.gov.au, 2013–14), which makes NSW the second-highest wheat producing state in Australia. The NSW wheat belt (Fig. 1c) has an average elevation of 287.8 m and a gradient of 50 to 750 m from west to east. The annual wheat production during the period from 2003 to 2014 varied between 2.48 and 10.49 million tons, and the yield varied by approximately 5-fold (0.62–2.75 t ha^{-1}) (www.abares.gov.au, 2013–14). Historically, wheat production in NSW has shown vulnerability to climate variability due to high exposure to water and heat stresses (Wang et al., 2015b). The mean annual air temperature and rainfall across the entire cropland belt of NSW vary between 12 and 20 °C and 250–800 mm, respectively, highlighting the significant spatial variation in climate conditions and revealing the complexity of modelling crop yields across broad spatial extents.

2.2. Data processing

2.2.1. Meteorological data and study sites

The meteorological station-based observational data from the Scientific Information for Land Owners (SILO) patched point dataset (http://www.bom.gov.au/silo/) for NSW were collected, and we extracted 161 study sites that were identified as being located in rainfed cropland pixels; both their ground meteorological data and spatially observed data were available. These sites are evenly distributed across our study area (Fig. 1b). As climate-driving parameters, daily rainfall (Rain), maximum air temperature (T_{max}), minimum air temperature (T_{min}), and solar radiation (Radn) from 2000 to 2014 were extracted for