Multi-Temporal Remote Sensing for Estimation of Plant Available Water-holding Capacity of soil

A thesis submitted to the University of Adelaide in fulfillment of the requirement for the degree of Doctor of Philosophy

Sofanit Girma Araya

B.Sc. in Geology, Addis Ababa University, Ethiopia
M.Sc. in Geoinformatics, University of Twente, The Netherlands

School of Biological Sciences

The University of Adelaide

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Abstract

Soil maps are fundamental for agricultural management. However, mapping soils is a difficult task because of their high spatial variability and the challenge of choosing representative field sites for soil analysis. Globally, soil information is becoming a prioritized agenda, due to the increasing demand for soil information for quantitative ecological, environmental and agronomic modelling. Hence, improved digital soil mapping techniques are required to fulfill this demand.

The Plant Available Water-holding Capacity (PAWC) is a key soil property in most agricultural management activities as it determines the maximum water that can be readily extracted by plants. Globally, there is an increasing demand for spatially explicit soil PAWC data for understanding the potential consequences of climate change and development of adaptation strategies. The coarse resolution of current PAWC information limits the spatial detail of future predictions and decision support.

Plant growth in water-limited Mediterranean climates is predominantly controlled by soil water availability. In rain-fed cropping systems, differences in PAWC can explain a large proportion of the spatial and temporal crop yield variability. The overall aim of this research was to develop a methodology to estimate spatial pattern of PAWC at a high spatial resolution using satellite-based remote sensing techniques. The underlying hypothesis is that the spatio-temporal plant growth patterns contain integrated information about soil properties and plant-soil-water interaction in the profile. The objective was to evaluate if phenological metrics derived from MODIS-NDVI (Moderate Resolution Imaging Spectroradiometer Normalized Difference Vegetation Index) can be used to infer about PAWC. The study was conducted in the South Australian agricultural region, which is one of the major grain producing regions of the country.

Central to facilitating the research was the design and development of a flexible software package (CropPhenology) to extract phenological metrics that are indicators of crop condition at different growth stages. The CropPhenology package was developed in R to be used for analyzing data for all later stages of the project. It is available in the public domain repository GitHub.

Initially, the sensitivity of remote sensing phenological metrics for differences in soil PAWC was assessed in a controlled situation. Phenological metrics for crop grown in soils of contrasting PAWC values under identical agricultural management were compared. The results identified potential phenological metrics to be used as indicators for soil PAWC. The findings support that the soil signal can be extracted from time-series vegetation growth dynamics.

The research further evaluated the efficacy of the phenological metrics for assessment of spatio-temporal crop growth variability for management practices. The association between phenological metrics and management zones were analyzed in a South Australian cropping field. The result shows that phenological metrics have potential to inform about both spatial variability and temporal variability, highlighting a pathway towards alternative approaches for assessing the spatio-temporal variability in cropping fields.

Finally, an approach was developed for spatial PAWC estimation. Multiple linear regression models were developed that analytically associate of the measured soil PAWC values with MODIS-NDVI phenological metrics. The PAWC map shows significant agreement with the landscape-scale soil map of the region with realistic detail of PAWC variability within the soil map units across management units. The evidence from this result indicates the potential of phenological metrics from satellite remote sensing for soil PAWC mapping at unprecedented detail over a broad regional extent. Advances in PAWC mapping as demonstrated in this thesis will improve models assessing future climate change development of adaptation strategies and will narrow the gap in spatial detail between regional decision making and farm-based precision agriculture.

Publications arising from this thesis

Refereed

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Araya, S, Lyle, G., Lewis, M., and Ostendorf, B. (2016) "Phenologic metrics derived from MODIS NDVI as indicators for Plant Available Water-holding Capacity." *Ecological Indicators* 60:1263-72. doi: http://dx.doi.org/10.1016/j.ecolind.2015.09.012.

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My little boy Michael, I am ever grateful to be your mom.

I Love you million times to the moon and back!

Finally, and most importantly

*To **God**, my strength,*

"How awesome are your deeds!"

"I know that you can do all things; no purpose of yours can be thwarted"

This thesis is dedicated

To

My ***MOM, Amsale Atle***

Who paid ultimate sacrifices for me to be the person I am today.

And

My ***Husband, Abay Teshome***

Who has been constantly and tirelessly supporting and encouraging me during the challenging time of my study.

This would never been possible without you being next to me.

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Acronyms

AVHRR	Advanced Very High Resolution Radiometer
MODIS	MODerate resolution Imaging Spectroradiometer
NDVI	Normalized Difference Vegetation Index
PAWC	Plant Available Water-holding Capacity
PA	Precision Agriculture
SSCM	Site Specific Crop Management
SA	South Australia
EP	Eyre Peninsula

Chapter 1

Introduction

1.1 Introduction

Soil sustains human life on earth, supplying nutrients and water for plants. It is estimated that 95 % of global food production depends on soil (FAO, 2015). With the increasing global population, projected to reach 9.7 billion in 2050 (United Nations, 2015), and reductions in agricultural yield due to climate change (IPCC, 2014), global food security hinges on having sustainable agricultural management systems that promote productivity. Consequently, the demand for high resolution, up-to-date soil maps is increasing at global, national, regional and field scale (Hartemink, 2008, Hartemink and McBratney, 2008, Koch et al., 2013, Amundson et al., 2015, Folberth et al., 2016). However, soil mapping is a difficult task due to the high spatial variability and the challenge of choosing representative field sampling for soil analysis (Ostendorf, 2011). Digital soil mapping has evolved from the conventional soil mapping through the use of indicative environmental factors to spatially predict soil properties (McBratney et al., 2003, Hempel et al., 2008).

Globally, consistent soil information is required for decisions in ranges of issues such as food production and climate change (Amundson et al., 2015, Arrouays et al., 2017). The global consortium GlobalSoilMap aims to produce a new digital soil map for selected key soil properties, such as soil organic carbon, electrical conductivity and Plant Available Water-holding Capacity, at a spatial resolution of 90m for the entire world (Sanchez et al., 2009, Hartemink et al., 2010, MacMillan et al., 2010). These soil maps will be produced by participants across the world implementing the GlobalSoilMap specifications. The Soil Landscape Grid of Australia (SLGA) is one example of continental GlobalSoilMap implementation (Grundy et al., 2015, Viscarra Rossel et al., 2015). The SLGA presents Australian wide soil maps estimated using digital soil mapping techniques integrating historical soil data and new measurements (Odgers et al., 2014, Odgers et al., 2015).

Plant Available Water-holding Capacity (PAWC) is a key soil property included in the GlobalSoilMap specification (MacMillan et al., 2010). It determines the maximum water that can be readily extracted from soils by plants. Therefore, PAWC is essential information in most agricultural management systems (Cook et al., 2008). Under similar climatic conditions plants grown in high PAWC soils have access to more water than plants grown in low PAWC soils. Temporally, PAWC also has a strong interaction with seasonal rainfall to change plant growth response from season to season. PAWC therefore modulates the vegetation responses to changes in climatic conditions (Oliver et al., 2006, Wong and Asseng, 2006). Accordingly, a map of PAWC is recognized as a key element in the assessment of climate change impacts on agricultural production (Wang et al., 2009, Yang et al., 2014, Folberth et al., 2016, Yang et al., 2016).

In Mediterranean climates, characterized by hot, dry summers and cool, wet winters, plant growth is predominantly controlled by soil water availability (French and Schultz, 1984, Turner and Asseng, 2005). A large portion of yield variability experienced in rain-fed cropping systems can be explained by the variability in PAWC (Turner and Asseng, 2005, Wong and Asseng, 2006, Hayman et al., 2012, Whelan and Taylor, 2013). Hence, most of the agronomic management systems in these regions promote maximum water use efficiency, balancing the strong seasonality of rainfall with plant water requirements (Jacobsen et al., 2012), and this demands soil PAWC information.

Despite the high demand for soil PAWC information, the availability of high resolution PAWC maps is very limited globally (Grunwald et al., 2011). This is largely because the field measurement of soil PAWC is very difficult and time consuming, as it needs repeated measurements at dry and wet seasons at a range of depth in the soil profile (Burk and Dalgliesh, 2013). Trying to overcome this limitation, numbers of researchers have produced estimated soil PAWC maps using single or combinations of predictive environmental factors at national (Poggio et al., 2010, Hong et al., 2013, Ugbaje and Reuter, 2013), regional (Poggio et al., 2010, Padarian et al., 2014) and catchment (Malone et al., 2009, Poggio et al., 2010) geographic extents. While these methods were successful for mapping PAWC regionally, a high degree of uncertainty was reported in locations that had limited sampling density of the predictive factors. Hence, there remains a need for alternative ways of PAWC estimation to satisfy the need.

Remote sensing has long been used to identify and map soil properties either through the use of reflectance directly from bare soil (eg. Ben-Dor et al., 2009, Lagacherie et al., 2010, Summers et al., 2011) or through interpretation of the reflectance from vegetation cover (eg. Lozano-Garcia et al., 1991, Cole and Boettinger, 2006, Sharma et al., 2006, Li et al., 2012, Maynard and Levi, 2017). Due to the fact that the land surface is predominantly covered by vegetation, most of the remote sensing applications in digital soil mapping involve vegetation indices for soil prediction.

The effectiveness of vegetation index data for soil property prediction depends on the relationship between the soil property of interest and the remotely sensed vegetation change in response to change in that soil property (Maynard and Levi, 2017). Single vegetation images have used to infer temporally stable soil properties such as parent material (Lozano-Garcia et al., 1991, Boettinger et al., 2008, Eldeiry and Garcia, 2008). On the other hand, PAWC integrates soil-water properties over the entire rooting depth and its interaction with seasonality of rainfall controls the crop growth patterns. Therefore, multiple vegetation index data reflecting temporal vegetation change appears to be a promising avenue to identify a predictive spatial indicator of PAWC.

Multi-temporal vegetation index data has been used to quantify the seasonal vegetation dynamics that can be used to estimate the timing of biophysical growth stages (phenology) (Roerink et al., 2011, Henebry and de Beurs, 2013). As soil PAWC is a key soil property influencing the vegetation response, it can be hypothesized that phenological information derived from temporal vegetation dynamics is related to soil PAWC. This implies that, soil PAWC information is concealed in the growth dynamics captured from the time-series of vegetation index data. Therefore the potential of multi-temporal vegetation index data for soil PAWC mapping needs to be examined. With the increasing availability of remote sensing vegetation index data, this approach can potentially provide a new paradigm for mapping soil PAWC in agricultural regions.

1.2 The aim and objective of the study

This research has the overarching aim of developing a methodological framework to estimate PAWC at improved spatial resolution using less expensive and more robust techniques. Multi-temporal remote sensing vegetation index data from Moderate Resolution Imaging Spectroscopy (MODIS), rainfall data and existing soil PAWC data were recognized as being crucial inputs to achieve this aim.

The framework was tested and implemented at different spatial scales within the South Australian agricultural region. This region is one of the main wheat-producing areas in Australia (Trewin, 2006), accounting for more than 17% of the national wheat production in 2009-10 (Pink, 2012).The South Australian agricultural region is characterized by Mediterranean climate. The agriculture in the region is dominantly rain-fed mono cropping systems, wheat being the dominantly grown crop followed by barley (Australian Bureau of Statistics, 2016).

The outcome from this research can potentially provide a robust method to address the increasing demand for soil PAWC information. Furthermore it can improve the understanding of spatial and temporal variability across agricultural fields, which can in turn improve agricultural management decisions.

The specific objectives were:

1- To develop a methodology for analysing vegetation index data into quantifiable metrics that can summarize the vegetation growth dynamics and enable assessment of spatio-temporal growth variability across the cropping fields. This is central to facilitate this research project and the outcome can potentially help future similar projects.
   This objective involves design and development of a flexible and easy to use software package that extracts phenological metrics from time-series satellite vegetation index data without lengthy pre-processing steps and so allow hypothetical linking of phenological metrics with crops biophysical growth stages.

2- To gain a better understanding of the soil – climate interaction by analysing the relationship between the seasonal vegetation dynamics and rainfall data. This objective examines the sensitivity of remote sensing derived phenological metrics to differences in soil PAWC under identical agricultural management, i.e within the same cropping field. This objective identifies the phenological metrics that can be used as indicators for soil PAWC, providing a pathway towards estimation of soil PAWC using indicators derived from multi-temporal vegetation index data.

3- To assess the efficacy of crop phenological metrics for crop management practices, addressing the spatial and temporal variability across cropping fields. This can potentially lead to a new pathway for agricultural management zone delineation, especially in fields where there is no or limited yield data.

4- To assess the possibility of creating high resolution estimates of soil PAWC at a broad scale, using multi-temporal vegetation index data. This objective utilized archived measured soil PAWC data, remote sensing vegetation index data and rainfall data. It involves modelling the empirical relationship between the measured soil PAWC and the remote sensing derived phenological metrics. Producing these estimates can provide a new approach for PAWC estimation and potentially narrow down the gap in spatial detail between regional modelling and farm based management models.

1.3 Thesis structure

This thesis is divided into six chapters. The Chapters 2 to 5 are presented as published or submitted research papers, therefore there may be some repetition of material as they are written for different audiences.

Chapter 1

Introduction

The first chapter (this chapter) provides the general overview of the soil property Plant Available Water-holding Capacity (PAWC) and highlights the motivation behind the research. It summarises the aim and objective of the study and outlines the structure of the thesis.

Chapter 2

Araya, S., Ostendorf, B., Lyle, G., Lewis, M. CropPhenology: An R package for extracting crop phenology from time-series remotely sensed vegetation index imagery. *Ecological Informatics* (*under review*)

This chapter addresses objective one of the research. It presents a software package, CropPhenology, designed in the R software environment to extract phenological metrics from time-series of vegetation index data. The CropPhenology package is easy to use, allowing the user to progress from downloaded images to crop phenological information with only minor data pre-processing steps. The paper further presents inference of the phenological metrics in relation to their corresponding physiological crop growth stages. Practical examples are presented to demonstrate the utility of the package in a Southern Australian broadacre, rain-fed cereal cropping region. The source code for the package is available on GitHub repository at https://github.com/SofanitAraya/CropPhenology. The documentation and practical guide for the package are included on this thesis at Appendix A and Appendix B, respectively

Chapter 3

Araya, S., Lyle, G., Lewis, M., and Ostendorf, B. 2016. Phenologic metrics derived from MODIS NDVI as indicators for Plant Available Water-holding Capacity. *Ecological Indicators* 60:1263-72. http://dx.doi.org/10.1016/j.ecolind.2015.09.012

This chapter addresses objective two of the research. It assesses the usability of phenological metrics as indicators for soil PAWC. The study was conducted in two South Australian cropping fields with paired contrasting (high and low) PAWC soils. The phenological metrics were extracted from time series of MODIS vegetation indices data for 13 years (2001-2013). The paired ranked test analysis between the contrasting paired soils reveal that some of the phenological metrics show persistent differences which can, therefore, be used as indicators for soil PAWC. The findings of this research component were initially presented as a conference paper at the 20th International Congress on Modelling and Simulation (MODSIM2013), held in Adelaide, South Australia (Appendix C).

Chapter 4

Araya, S., Ostendorf, B, Lyle, G., and Lewis, M. Remote Sensing Derived Phenological Metrics to Assess the Spatio-Temporal Crop Yield Variability. *Advances in Remote Sensing.* (I*n press*).

This chapter addresses objective three of this research. It examines the potential of remote sensing phenological metrics for agricultural management purposes to assess the spatial and temporal variability in cropping fields. The associations between the phenological metrics and pre-defined management zones were statistically analysed. The result indicate strong potential of some of the phenological metrics to indicate site quality in cropping fields. This highlights a pathway towards the potential use of phenological metrics for agricultural management applications. The findings from this research were presented at the 2014 Australia National Soil Science Conference, held in Melbourne, Victoria. The abstract is published in the conference preceding under the title "Time Series analysis of Satellite Imagery to improve agricultural soil management" (Appendix D).

Chapter 5

Araya, S., Ostendorf, B, Lyle, G., and Lewis, M. Spatial estimation of Plant Available Water-holding Capacity using phenological indicators. *Ecological Indicators.* (*Under review*).

Objective four is addressed in this chapter. An empirical model was developed to associate the phenological metrics with the measured soil PAWC values located across the South Australian agricultural region. The designed model was tested for spatial PAWC estimation across the South Australian agricultural region and the correspondence between the resulting PAWC map and the existing landscape-scale PAWC map was assessed. The estimated PAWC map shows an overall good correspondence with the existing landscape-scale PAWC map, with relatively higher detail than the existing dataset. The result indicated that there is a strong potential of remote sensing derived phenological metrics to be used for soil PAWC estimation, and thus providing unprecedented detail at broad spatial scale.

Chapter 6

Conclusions

The last chapter summarises the main findings of the research, its significance, and contributions. The key contribution of this research is the comprehensive methodology of utilizing the remote sensing vegetation index data to analyse the growth dynamics of crops to estimate soil property. Future research directions in this area of research are also recommended in this chapter.

Chapter 2

CropPhenology: An R package for extracting crop phenology from time-series remotely sensed vegetation index imagery

This chapter is submitted for publication as

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Principal Author

Name of Principal Author (Candidate)	Sofanit Araya		
Contribution to the Paper	Development, conceptualization and realisation of the research, wrote the scripts and codes and wrote the manuscript		
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Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	5/10/17

Co-Author Contributions

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

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

Name of Co-Author	Bertram Ostendorf		
Contribution to the Paper	Supervised development of the research, assisted in analysis and code writing and evaluated manuscript		
Signature		Date	13-9-17
Name of Co-Author	Megan Lewis		
Contribution to the Paper	Co-Supervised the development of the research and evaluated the manuscript		
Signature		Date	25/9/17
Name of Co-Author	Gregory Lyle		
Contribution to the Paper	Co-supervised development of the research, assisted analysis and code writing, and evaluated manuscript		
Signature		Date	26/9/17

Abstract

Remotely sensed vegetation indices to measure crop growth through phenological metrics have a high potential for agricultural management. However, implementing the analytical routines from remote sensing data acquisition to relating vegetation index information to in-situ plant development is complex to even the most experienced user. We present the CropPhenology package, a free, easy to use package designed in the R environment which allows the user to progress from downloading remote sensing images to crop phenology analysis with only minor pre-processing steps. The package computes 15 phenological metrics which can be easily visualised and used for successive spatio-temporal analysis. The system is specifically designed to identify crop growth stages by relating theoretical phases of crop growth to satellite-based NDVI dynamics. The metrics are theoretically related to Zadoks growth stages which explicitly characterise cereal crop growth conditions, including new leaf emergence, flowering, ripening, and yield. These metrics provide a systematic understanding of characterisation of the plant-soil-climate interactions. We present an example that illustrates the utility of our package in a Southern Australian broad acre, rain-fed cereal cropping region.

Keywords: Phenological metrics; R package; MODIS; cereals; Remote sensing; Zadoks growth stage

2.1 Introduction

Phenology, the sequence and timing of plant developmental stages and their relationship with climate, provides essential information for many agricultural applications such as crop yield estimation (Hill and Donald, 2003, Sakamoto et al., 2013), enhancement of management practices (You et al., 2013) and digital soil mapping (Zhang et al., 2015, Araya et al., 2016, Maynard and Levi, 2017). Conventional phenological measurement involves periodical physical observation of plant growth development using internationally recognized growth scales. Examples of these scales include the Zadoks decimal growth scale (Zadoks et al., 1974, GRDC, 2005) which is the most widely used and complete description of growth stages for cereal crops (Lee et al., 2009). Other frequently used scales also include Haun (Haun, 1973), which is mainly used for growth stage description before the booting stage, and Feekes (Large, 1954), which focuses on the development period from start of stem elongation to end of flowering. These observations, however, are subjective and can vary between reporters, location, and time, which impedes reliable information exchange between farmers, advisers and researchers.

The Normalized Difference Vegetation Index (NDVI) is one of the most widely used vegetation indices derived from satellite images, which can be related to photosynthetic status, relative coverage and plant biomass (Smith et al., 1995, Mkhabela et al., 2011). Crop phenology information can be acquired from multi-temporal vegetation observation using such vegetation indices (Reed et al., 1994, Reed et al., 2009). Phenology from satellite imagery is applied in a wide range of agricultural applications (eg. Schnur et al., 2010, You et al., 2013). One satellite sensor that has been extensively used to derive phenological information is the Moderate Resolution Imaging Spectroradiometer (MODIS). Applications of MODIS data include crop type mapping and classification (Wardlow et al., 2007, Zhong et al., 2011), global and regional yield estimation (Becker-Reshef et al., 2010, Kouadio et al., 2012, Sakamoto et al., 2013), and yield forecasting (Bolton and Friedl, 2013). Its high temporal frequency of acquisition makes it particularly appropriate for characterising crop phenology. Several phenology products have been developed at different spatial resolutions from the MODIS sensor. These include the 500m Land Cover Dynamic Product (MCD12Q2) (Gray, 2012) and 5.6km Australian Land Surface Phenology (Broich et al., 2015). These products provide valuable inputs to inform policy and decision making but their usefulness is dependent on the problem at hand. For example, the MCD12Q2 product works very well within the northern hemisphere but has limitations in retrieving phenology in arid, evergreen or cloudy environments (Ganguly et al., 2010, Gray, 2012).

With increased availability of multi-temporal images, software tools have been developed to analyse these images. TIMESAT (Jönsson and Eklundh, 2004) and PhenoSat (Rodrigues et al., 2011, 2012) are two such software packages which analyse the vegetation index temporal curve through extraction of seasonal parameters. TIMESAT has been used for the estimation of sowing date using MODIS and SPOT(Satellite Pour l'Observation de la Terre) images, as part of a study which focused on the effect of early sowing on wheat yield in India (Lobell et al., 2013). TIMESAT has also been used to improve the accuracy of mapping abandoned agricultural land, in eight eastern Europe countries (Alcantara et al., 2012). The PhenoSat software has a special focus on extraction of phenological metrics for double cropping seasons and has the ability to select a sub-region of interest in order to reduce the data processed (Rodrigues et al., 2011). A comparative study of on-ground vegetation phenology using PhenoSat within three different environments (vineyard, semi natural meadows and low shrub-lands) has shown good correlation particularly for start of season and maximum vegetation development metrics (Rodrigues et al., 2013).

While these software tools have successfully utilised satellite imagery in crop management, they have several limitations. An important limitation is the lack of a physiological foundation of the metrics in terms of crop growth conditions: relationships between the derived metrics and physiological crop growth stages are often unclear (Song et al., 2002, Fisher et al., 2006). Phenological metrics are defined in different ways. TIMESAT provides 11 metrics using fitted functions that can be customised with a number of user-defined input parameters (Lars and Per, 2010, Eklundh and Jönsson, 2015), whereas PhenoSat provides seven metrics using the maximum and minimum of the curvature change of the fitted vegetation index curve (Rodrigues et al., 2013). This variation in the number and definition of metrics may exist because of their perceived importance within their study environments and perhaps their complexity of derivation. Additionally, variation in the definition of these metrics is due to the application of different mathematical techniques to pre-process and smooth the NDVI dynamics curve to remove measurement noise such as cloud or sensor errors. However, while defined differently, the underlying fundamental concepts of these metrics are similar. They estimate the start of growing season, maturity or maximum growth, and the end of the season or senescence. These fundamental metrics are then used to derive additional metrics based on the measurement of crop growth over the duration of season such as rate of increase and decrease, length of growing season or time integrated vegetation index. This group of metrics represent important phenological events of the plants (White et al., 1997, Hill and Donald, 2003). Current software packages, however, do not have a comprehensive range of metrics which can be used. Furthermore, they do not include additional metrics which have been shown to be beneficial information for agricultural management (Poole and Hunt, 2014). For example, the curve integral before maximum NDVI and after maximum NDVI can indicate the cumulative biomass before and after anthesis, which provides information about the crop yield potential and grain quality.

The usability of the current software tools is somewhat cumbersome. For example, the user is required to arrange the vegetation index data into an array of NDVI values in a text file for input. Although there is an option of using the image as an input, there is still a requirement to provide a text file input with a list of image file names and the number of images. At the output and analysis phases, output metrics are also provided as text files, which require post- processing to obtain graphic representations. These processes make it particularly hard for new users and those who are not technically savvy to consider undertaking such analyses.

The objective of this study was to build on the basics of the previous phenology software and develop a new easy to use freely available package. We present the CropPhenology package that easily extracts 15 crop phenological metrics from time series of satellite vegetation index images. The package builds on the concepts highlighted in past literature to bring together the majority of ad hoc metrics to provide for the user ten fundamental phenological metrics and five new metrics which have not been implemented previously. The package also incorporates a multipoint analysis tool which enables the user to plot and examine the NDVI dynamics curves for up to five individual pixels. We demonstrate the utility of the package using a time series of MODIS imagery which encompasses rain-fed cereal cropping farms on the western region of the Eyre Peninsula in South Australia. In addition, we assess broad-scale predictability of the metric.

2.2 Materials and Methods

2.2.1 Time-series MODIS NDVI Data

NDVI is one of the most widely used indexes applied in vegetation related studies as it can be related to photosynthetic status, relative coverage and plant biomass (Smith et al., 1995, Mkhabela et al., 2011). The index derived from daily MODIS imagery is available as a sixteen-day composite data product at 250m spatial resolution (MOD13Q1), which is freely available for download from NASA (Didan, 2015). This product uses the Constrained View Angle Maximum Value Composite algorithm which extracts the maximum NDVI value for each pixel within each 16 day intervals to create a cloud-free composite image (Huete et al., 2002, Solano et al., 2010). The imagery is in a sinusoidal projection which has to be reprojected to a cartographic coordinate system using the freely available MODIS Reprojection Tool (USGS, 2011).

2.2.2 Image data pre-processing

The CropPhenology package does not require specific naming conventions for the image files or folder names that hold them. However, in order to undertake time series analysis the names need to represent the chronological sequence in alphabetic order. This flexibility allows direct use of the default file names of each MODIS image given by NASA at the time of downloading as image names incorporate year and sequential day number.

2.2.3 Data extraction

Past phenology software has utilized mathematical techniques such as function fitting (Jönsson and Eklundh, 2004) and temporal filtering (Rodrigues et al., 2011) to pre-process and smooth the NDVI dynamics curve before the metrics are extracted. The filters and other smoothing techniques have been previously used to remove the noise inherent within the raw unprocessed image data, particularly due to cloud and aerosol contamination (Reed et al., 1994, Sakamoto et al., 2005) . In previous studies, good empirical relationships with ground observations were found when smoothing was applied (Sakamoto et al., 2010). However, smoothing eliminates spatial and temporal variability that may be an important information source to understand environmental conditions that affect crop development. An obvious consequence of smoothing is the reduction of NDVI peaks, hence potentially removing crop-relevant information (Reed et al., 1994). Furthermore, with the implementation of improved pre-processing techniques such as the Maximum Value Composite algorithm used widely on MODIS images for the creation of composite images, these problems are less severe (Didan and Huete, 2006, Solano et al., 2010). Validation studies have suggested that the MODIS composite vegetation index shows good correlation with ground observation for pheonologic representation (Huete et al., 2002). In the CropPhenology package, we provide an option for moving average smoothing. In the CropPhenology package, we provide an option for moving average smoothing. For our example we opted to use unsmoothed vegetation index imagery in order to preserves detail of the curve dynamics. Further smoothing may affect the calculation of the metrics particularly in the identification of the start, maximum and end of crop growth (Reed et al., 1994). The consecutive NDVI values across the temporal sequence of images are extracted for every pixel in the image to define a space-time cube (a three-dimensional dataset representing the time series of NDVI values (x, y, time)).

2.2.4 Phenological metrics extraction

We analysed this dataset to extract the 15 phenological metrics (Figure 2.1) which represent the seasonal growth condition of the crop for each pixel.

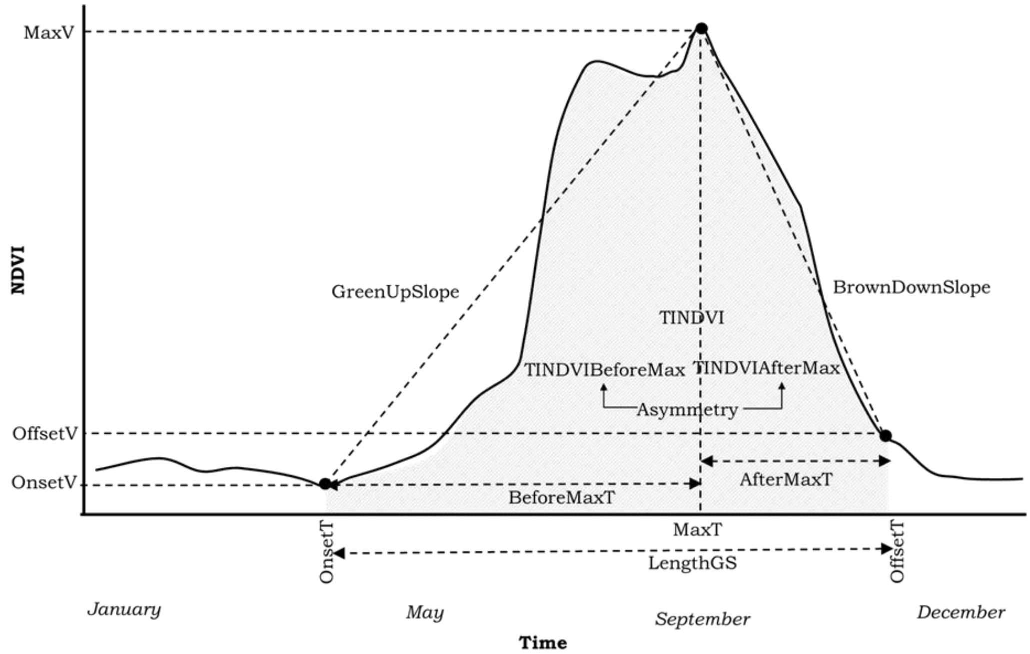

Figure 2.1. *The NDVI dynamics curve showing the defined phenological metrics (Explained in Table 2.1)*

The derivation of metrics from the NDVI dynamics curve starts by calculating OnsetV, OnsetT, OffsetV, OffsetT, MaxV, and MaxT (Figure 2.1) (Table 2.1). The derivation of MaxV and MaxT (maximum NDVI value and time of the maximum recoded during the growth period) is similar to the previous literature, but our package differs by giving users the option to employ smoothing algorithm (eg. Jönsson and Eklundh, 2004) or fitting time series curves (eg. Reed et al., 1994, Hill and Donald, 2003). Moreover, the user can implement other smoothing techniques prior to the CropPhenology function call as required. In CropPhenology, MaxV and MaxT are defined as the maximum NDVI value of the season and the time this value is attained.

In the literature, Onset and Offset metrics have been estimated using thresholds (White et al., 1997, Eklundh and Jönsson, 2015), harmonic analysis (Moody and Johnson, 2001), moving averages (Reed et al., 1994, Duchemin et al., 1999), or inflection points (Dash et al., 2010). Threshold methods have often achieved improved estimation accuracy when compared to the ground based phenologic measurements (You et al., 2013). However, NDVI curve characteristics of different crop types are influenced by phenological stages during their growth period

(Pan et al., 2012) and complex climatic and environmental conditions. Therefore a threshold value has to be flexible. CropPhenology provides the option to customize threshold values, acknowledging that it may be important to vary threshold values dependent on crop type or other environmental conditions (Cong et al., 2012; You et al., 2013) based on experimental or other evidence describing local conditions (i.e. occurrence of weeds).

In CropPhenology, the threshold is mainly used to avoid spuriously high NDVI increases due to weed growth prior to sowing. Estimation of OnsetT is implemented by starting at MaxT and analysing NDVI changes between previous NDVI values, searching for local minima (dips) in NDVI close to the global maximum MaxT. The first dip below the user defined NDVI threshold is defined as OnsetT and hence determines OnsetV (the NDVI value at time Onset). The default threshold value is 10% of the maximum NDVI. If no local minimum (dip) can be recognized, the point closest to MaxT below the threshold is identified as OnsetT. OffsetT and OffsetV are estimated similarly, moving forwards in time from MaxT. Conceptually, OffsetT is the time when the crop reaches maturity and loses all greenness. A local minimum (dip) in NDVI at harvest time is possible, but it is generally less distinct and occurs less often than during onset.

In South Australia, with a Mediterranean climate and predominantly winter rainfall, the onset most often occurs between late April and early June, or between 7th and 12th MODIS 16 days composite imaging periods. Similarly, OffsetV and OffsetT are defined as the NDVI value and time at the point where the NDVI dynamics curve finishes its decline over the later growth period and calculated as the last minimum below the threshold value, starting from MaxT.

Once Onset, Offset and Max are defined, nine other metrics are calculated. The slope of the lines connecting OnsetV and MaxV and MaxV and OffsetV on the curve are then defined as GreenUpSlope and BrownDownSlope metrics, respectively (Figure 2.1 and Table 2.1). This is a simpler calculation than in TIMESAT which derives these metrics as the ratio of the difference between 20% and 80% level of NDVI and their corresponding time differences, in the left and right sides of the curve, respectively (Jönsson and Eklundh, 2004). Table 2.1 defines the metrics and their biophysical inferences based on the Zadoks scale and description of crop growth and development.

Table 2.1. *Definition of the phenological metrics, biophysical description of growth conditions and inferred physiological growth stages on the Zadoks scale.*

Metrics	Definition on the NDVI curve, Formula, and description	Theoretical and physiological inferences	Crop growth and environmental factors description
OnsetV (in NDVI value)	NDVI value measured at the start of continuous positive slope over a threshold between successive NDVI values. The threshold is user defined percentage above the minimum NDVI value before the NDVI peak.	The start of the crop growth measured by the development of leaf and canopy emergence. It represents early growth stages (seedling growth) – Zadoks growth stage 11-20.	New leaf emergence depends on environmental factors of the season like temperature and available soil water (Stapper, 2007). Values are usually above 0.1, which represents NDVI of bare soil (Guerschman et al., 2009).
OnsetT (in MODIS image time period)	MODIS acquisition time when OnsetV is derived.	The time of the start of Zadoks growth stage 11-20 (Seedling growth) representing leaf and canopy emergence.	OnsetT is dependent on planting date across large areas. It is mainly controlled by the season break (French et al., 1979). Low values represent an early start to plant establishment.
MaxV (in NDVI value)	Maximum NDVI value achieved during the season MaxV= Maximum (NDVI1 : NDVI23)	Full canopy coverage, representing Anthesis/Flowering - Zadoks growth stage 60-69.	High MaxV values indicate better growing season and productivity (Smith et al., 1995)
MaxT (in MODIS imaging period)	MODIS acquisition time when MaxV is derived.	Time recorded for complete canopy closure (Zadoks growth stage 60-69).	Lower MaxT values indicate Anthesis/Flowering is achieved earlier.
OffsetV (in NDVI value)	NDVI value measured at the lowest slope below a threshold between successive NDVI values. The threshold is defined as the user defined percentage of the minimum NDVI value after maximum. Values are higher than 0.2 (Guerschman et al., 2009, Hill et al., 2013).	Signifies the end of the crop growth period. (Zadoks growth stage 90-99).	Crop canopy has ripened.

OffsetT (in MODIS imaging period)	MODIS acquisition period when OffsetV is derived.	A time when the crop has ripened (Zadoks stage 89-99).	Water stress and high temperatures late in the season cause the crop to senescence earlier (McMaster and Wilhelm, 2003b).
LengthGS (in MODIS imaging period)	The duration of time that the crop takes to go through all the stages of crop growth $LengthGS = OffsetT - OnsetT$	Higher values indicate longer time between start and end of the season, which relates to shorter growth period.	The length of growing season is influenced by the environmental factors that control crop growth such as temperature and rainfall.
BeforeMaxT (in MODIS image time period)	The length of time from OnsetT to the MaxT $BeforeMaxT = MaxT - OnsetT$	The duration of time the crop takes from emergence to anthesis.	Pre-anthesis growth stages determine the number of ears and grain kernels produced (Satorre and Slafer, 1999, Acevedo et al., 2002). A short time indicates less time within the pre anthesis growth stages, forming lower numbers of ears and kernel producing lower yields (Acevedo et al., 2002).
AfterMaxT (in MODIS image time period)	The length of time from MaxT and OffsetT $AfterMaxT = OffsetT - MaxT$	The duration of time the crop takes from anthesis to ripening.	Post anthesis growth stages determine grain filling and grain weight (Satorre and Slafer, 1999). A shorter time of post-anthesis growth relates to less time for grain filling resulting in low grain weight and yield(Poole and Hunt, 2014).
GreenUpSlope	The rate at which NDVI increases from the OnsetV to MaxV over the time difference between MaxT and OnsetT $GreenUpSlope = \frac{(MaxV - OnsetV)}{(MaxT - OnsetT)}$	Measures how fast the crop undergoes the pre-anthesis growth stages to reach to MaxV.	The pre-anthesis time is when the crop ears are formed and grown (Satorre and Slafer, 1999, Poole and Hunt, 2014). A high or steeper slope indicates a high rate of change, as NDVI values increase over a short time period, in the initial phases of development.
BrownDownSlope	The rate at which NDVI decreases from MaxV to OffsetV over the difference between OffsetT and MaxT. $\mathrm{BrownDownSlope} = \frac{(\mathrm{MaxV} - \mathrm{OffsetV})}{(\mathrm{OffsetT} - \mathrm{MaxT})}$	Measurement of how fast the crop undergoes the post-anthesis growth stages to reach to its ripened stage.	During the post-anthesis stages the sugars produced by photosynthesis are transported to fill the grain, influencing grain size and final yield (Poole and Hunt, 2014). A high value (steep slope) indicates a high reduction in NDVI over a short period of time, in the final phases of development.

TINDVI (in Accumulated NDVI value)	Area under the NDVI curve between OnsetT and OffsetT. TINDVI is estimated using trapezoidal numerical integration.	A measure of the biomass productivity of the growing season (Holm et al., 2003).	High TINDVI value indicates high crop productivity (Hill and Donald, 2003).
TINDVIBeforeMax (in Accumulated NDVI value)	Numerical integration of NDVI between OnsetT and MaxT. This metric indicates the pre-anthesis crop growth.	Pre-anthesis crop canopy growth is important for reducing evaporation of water from the soil surface. High value shows high biomass cumulated before anthesis, which can indicate lower water evaporation from soil and high number of tillers and kernels being formed.	Pre-anthesis crop growth contributes directly to yield through the storage of sugar produced by photosynthesis, which is accumulated in the stem and translocated to the grain after anthesis. Crops that have produced large dry matter before anthesis can have large yield potential. Alternatively, plant stress during the pre-anthesis period affects the amount of biomass produced and the number of tillers (Armstrong et al., 1996). This will affect the number of grains per head and the potential grain size, resulting in a reduction of yield potential (Fischer, 2008, Poole and Hunt, 2014).
TINDVIAfterMax (in Accumulated NDVI value)	Numerical integration of NDVI between MaxT and OffsetT. This metric indicates the post-anthesis growth.	High values indicate smaller reductions in accumulated biomass during the post anthesis period, which relate to a slower and longer process of grain filling and ripening. Small values show, faster and shorter process of grain filling, indicates low yield (Plaut et al., 2004, Poole and Hunt, 2014).	During post-anthesis the growth products are transported in to the grain and water is used efficiently. Limited water supply during this growth period affects the yield potential (Plaut et al., 2004). Large canopy crops might face difficulty to fill the grain due to water loss through evapotranspiration (Poole and Hunt, 2014).
Asymmetry (in NDVI value)	The symmetry of the NDVI curve. It measures which part of the growing season attain relatively higher accumulated NDVI values. $Asymmetry = TINDVIBeforeMax - TINDVIAfterMax$	Describes the relative crop canopy size before and after anthesis for the season. Comparison of Asymmetry indicates the difference between the establishment of a crop canopy and canopy ripening. High values indicate high biomass cumulated pre anthesis than post anthesis.	Yield potential is best explained in terms of the number of grains per unit area and the size or weight of the grain (Poole and Hunt, 2014). However, it is more sensitive to number of grains produced, measured by TINDVIBeforeMax, than the grain weight (Acevedo et al., 2002). Furthermore, in dry environments, the crop is often unable to fill the grain directly through photosynthesis due to water stress. This water/temperature stress can be measured by the lower magnitudes of TINDVIAfterMax. Here, a higher proportion of yield comes from pre anthesis stored sugar (Poole and Hunt, 2014).

2.2.5 The CropPhenology R package

The R software (The R core team, 2015) is a free computing environment which is gaining considerable popularity in recent years (Tippmann, 2015). The CropPhenology package contains three functions; SinglePhenology for calculating single phenologic metrics for a single pixel, PhenoMetrics for calculating and mapping phenological metrics and MultiPointsPlot for visualising time series of NDVI.

2.2.5.1 PhenoMetrics functions

The PhenoMetrics inputs are described in Figure 2.2a. The Path parameter determines the disk location of the time series of downloaded images. The Region Of Interest (ROI) parameter requires the user to indicate if there is a polygon or a point shapefile to define a subset study region of the image for which metrics are to be calculated. If there is an ROI, the user has to set the ROI argument to TRUE and provide the ROI boundary as a shapefile in the directory specified by Path. If the user sets the ROI to FALSE, the metrics will be extracted for the whole image. The PhenoMetrics function has 2 optional parameters: Smoothing and Percentage Treshold. The smoothing parameter (default values is FALSE) allows the user to indicate if smoothing is desired. The Percentage Threshold parameter allows the user to define the threshold value for defining Onset and Offset of the dynamics curve (explained above). The Percentage Threshold value defaults to 10% if not given. The PhenoMetrics function then calculates the 15 phenological metrics; in the order of OnsetV, OnsetT, MaxV, MaxT, OffsetV, OffsetT, LengthGS, BeforeMaxT, AfterMaxT, GreenUpSlope, BrownDownSlope, TINDVIBeforeMax, TINDVIAfterMax, TINDVI, and Asymmetry.

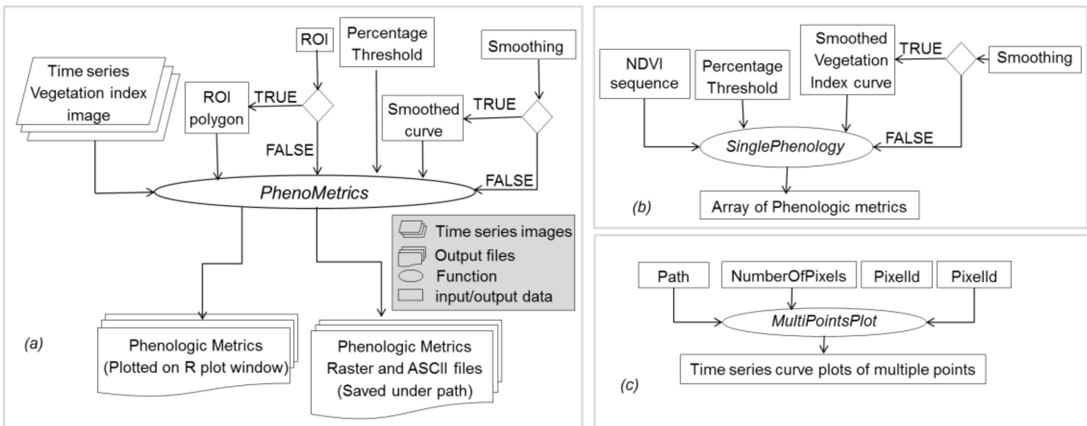

Figure 2.2. *Workflow of the functions for the CropPhenology package (a) PhenoMetrics function, (b) SinglePhenology function, and (c) MultiPointsPlot function.*

The outputs of the metrics are shown as maps within the R software for fast and easy visualisation. The metrics are represented spatially by 15 raster images, saved in the IMG format in the same projection as the input data which can be viewed from a geographic information system and are also exported as a generically formatted ASCII text file. The ASCII file is formatted as text in the sequence of pixelID, X-coordinate, Y coordinate, and the metrics value. Each of the ASCII files is named as the metrics name, for example OnsetT.txt. The spatial output of the metrics is saved with file names which are also the same as the metric name; for example OnsetT.img. Additionally, an overview file is provided, named as 'AllPixels.txt', which lists all pixels with their NDVI time series data values in the format: pixel number, x and y coordinates of the centroid of the pixel and NDVI value. These output metrics are saved in a folder which name is hard coded as "Metrics" in the directory specified in the Path parameter.

2.2.5.2 SinglePhenology function

SinglePhenology takes a time series of vegetation index values and results phenological metrics as an array. The function has three input parameters: Vegetation Index timeseries, Smoothing, and Percentage (Figure 2.2b). The Vegetation Index timeseries can be provided as an array, list, timeseries, or vector data type. Smoothing and Percentage are both optional parameters with default values of FALSE and 10 percent respectively. When Smoothing is set to TRUE, a moving average filter will be applied on the Vegetation Index curve. The user can also define the percentage of maximum Vegetation Index attained above which the Onset and Offset defined. The output is provided as an array of 15 values for the 15 metrics.

2.2.5.3 MultiPointsPlot function

The MultiPointsPlot function provides the user with the ability to visualise the NDVI curve by plotting the temporal sequences of NDVI values of user selected raster pixels. The function provides plots of a maximum of five pixels together. The input parameters are Path, the file path where AllPixels.txt is located, NumberofPixels, the number of pixels to be plotted, and the PixelId, the pixel Id number for each pixel (Figure 2.2c). Pixel Id numbers can be easily located and accessed from the AllPixels.txt file. Visually, the function plots the pixels in different colours in their order in the function call: the first curve in black the second in red, the third in green, the fourth in blue, and the fifth in yellow. The plotted output allows the user to observe the spatial and temporal differences in relative dynamics of the vegetation index for the selected points.

2.3 Example of the CropPhenolgy package

In order to illustrate the utility of the CropPhenology package we used MODIS MOD13Q1 imagery of the years 2001, 2003, and 2007 for a cropping region located on the western Eyre Peninsula of South Australia (Figure 3). The years were selected to represent differing rainfall amount and seasonality with 352.4mm, 261.2mm, and 261.5mm of annual rainfall respectively. The year 2001 had higher than average rainfall whilst the years 2003 and 2007 were selected because of low rainfall and differing rainfall seasonality. 2007 had early season dominating rainfall, with low rainfall in June, whereas in 2003 rainfall was relatively regularly distributed with highest falls during the June – August. The region of interest (ROI) was set to include approximately 30 paddocks with a total area of 131 hectares (Figure 2.3). The ROI is characterised by cereal cropping with some patches of natural vegetation. A total of 69 images, 23 images per year, were downloaded for three seasons and projected to the South Australian Lambert Conformal Conical projection.

At the R console, the function can be called as follows:

```
> PhenoMetrics("E:/MODIS_2001", TRUE, 15); *
```

In this example the path E:/MODIS_2001 points to the directory that contains the images and ROI boundary. The Percentage Threshold (explained above) is defined as 15% and smoothing is set to FALSE by default. The call results in a computation of all 15 metrics that are saved as output rasters in the newly created directory E:\MODIS_2001\Metrics. The call also creates maps of the indices in the plot window of R. The key benefits of using phenological indicators as compared to the raw time series is that the method reorganises the information in the time series according to what is known about crop growth (Table 2.1) hence providing a means for a systematic comparison of NDVI dynamics in space and across years. This is demonstrated in Figure 2.3 and Figure 2.4 below.

The resulting maps of all 15 metrics for 2001, 2003, and 2007 are collated in Figure 2.3. The different metrics are organised in groups of three for the three

* **Note:** The valid path separator in R is / or \\ rather than the default windows path separator \.

years. This allows a comparison of patterns of crop growth as influenced by the different climatic conditions of the years. This figure also includes a Google Earth high resolution colour satellite image of the study area that shows patches of native vegetation and field boundaries within the ROI. As expected, the year with the highest rainfall (2001) had overall larger values of TINDVI and MaxV. These metrics are indicative of leaf area progression during the entire season and hence strongly related to the variability in yield and biomass production (Hill and Donald, 2003, Calera et al., 2004, Lyle and Ostendorf, 2011) (see also Table 2.1). The figure also shows that some metrics (OffestV, OnsetV, and to some degree GreenUpSlope) show a spatial patterns that are time-invariant and hence less sensitive to climatic conditions. The metrics OffestV, OnsetV are consistently high in areas covered by native vegetation and are therefore good indicators for land-use differences among the fields. Other metrics (GreenupSlope, MaxV, and MaxT) have been shown to bear a significant relationship with soil conditions (Araya et al., 2016). In order to identify differences in soils, or in other words long-term consistent spatial differences, these need to characterise the responsiveness of plant growth to different environmental conditions. TINDVIAfterMax is indicative of leaf area after anthesis. This may be important for canopy management and can help to optimize fertilizer applications. Some metrics also appear to show a relatively detailed spatial pattern that seems unrelated to seasonal rainfall or management boundaries. In the case of OnsetT and the related metrics BeforeMaxT and LengthGS this may be noise arising from the difficulty of unambiguously identifying onset of growth.

These simple examples show how different indices may be selected for varying purposes such as yield estimation, land use classification, or the identification of soils: these contrasting applications benefit from different groups of phenological metrics. For studies using phenological metrics as an indicator of yield, TINDVI or MaxV (Hill and Donald, 2003, Calera et al., 2004, Lyle and Ostendorf, 2011) may be most suitable. In contrast, spatial patterns of soil or land cover do not vary strongly in time. Hence phenological metrics that are less dependent of rainfall are more indicative (Araya et al., 2016). The maps in Figure 2.3 qualitatively show the potential benefits of the approach and the usefulness of an easy-to-apply package to systematically quantify spatio-temporal variability in the vegetation index and hence reduce high volume spatio-temporal data into a limited number of metrics with specific crop growth meaning.

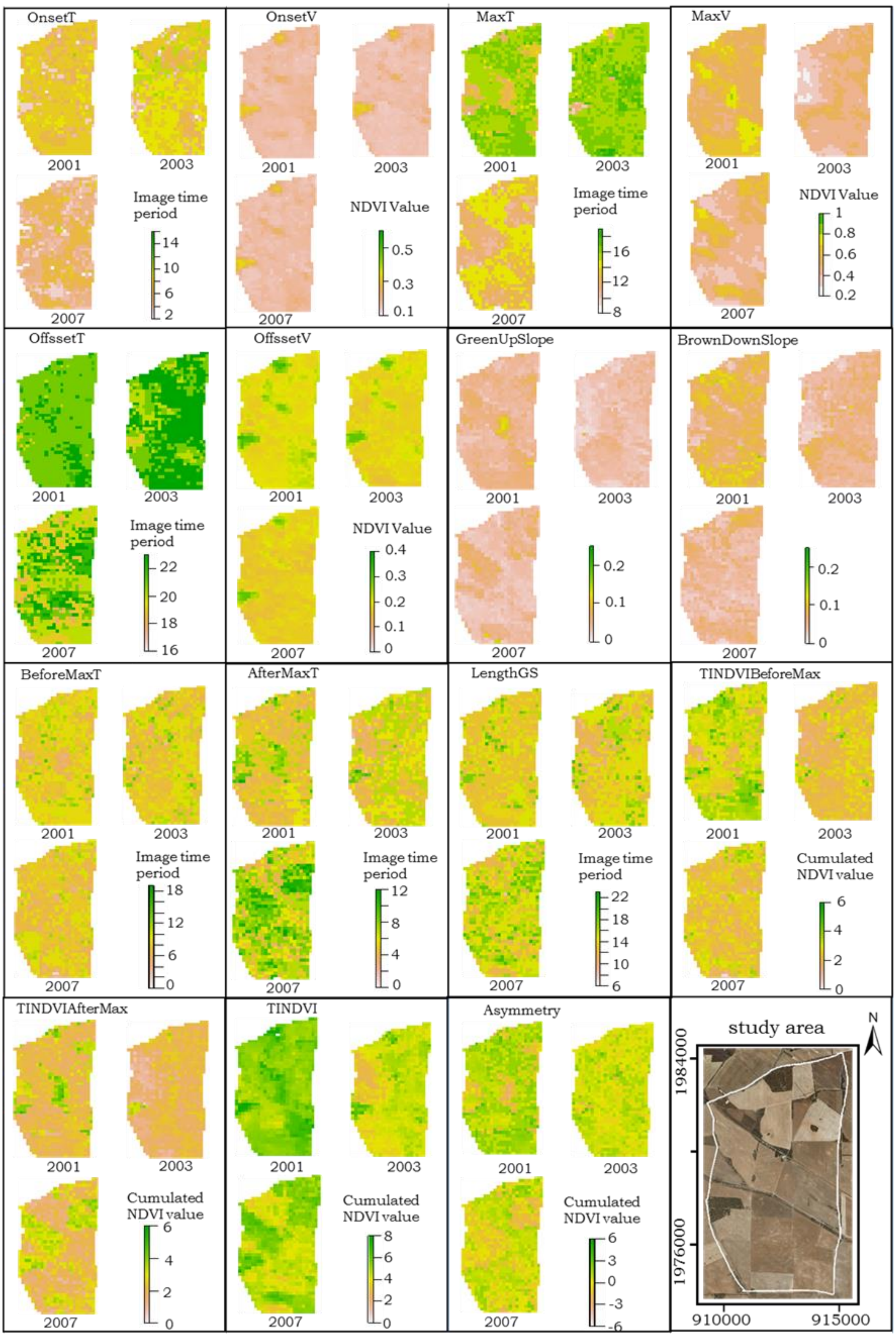

Figure 2.3. *The 15 phenological metrics of the example landscape for the years 2001, 2003, 2007 in the western region of the Eyre Peninsula in South Australia. Included is a Google Earth image of the study area for reference with boundaries of the overall rgion of interest (white)*

Figure 2.4 presents NDVI dynamics resulting from six calls of the MultiPointsPlot function extracting time series from cropping and native vegetation for all years, respectively. At the command prompt, the function can be called as:

```
> MultiPointsPlot("E:/MODIS_2001/Metrics", 3, 18, 10, 12).
> MultiPointsPlot("E:/MODIS_2003/Metrics", 3, 18, 10, 12)
> MultiPointsPlot("E:/MODIS_2007/Metrics", 3, 18, 10, 12)

> MultiPointsPlot("E:/MODIS_2001/Metrics", 3, 54, 75, 94)
> MultiPointsPlot("E:/MODIS_2003/Metrics", 3, 54, 75, 94)
> MultiPointsPlot("E:/MODIS_2007/Metrics", 3, 54, 75, 94)
```

Here, we extract time series for 2001 at three locations (18,10,12). The function makes use of the file AllPixels.txt located at "E:/MODIS_2001/Metrics". The second argument qualifies the number of pixels to be plotted (3) while the three other parameters represent PixelIds.

These plots show the detailed dynamics of NDVI and a convenient possibility to comparing individual locations, here a difference within a paddock across years compared to native vegetation. Similar comparisons can show the spatial and temporal differences in crop growth for different paddocks. This can reveal relationships between the soil and climatic interaction through crop growth development.

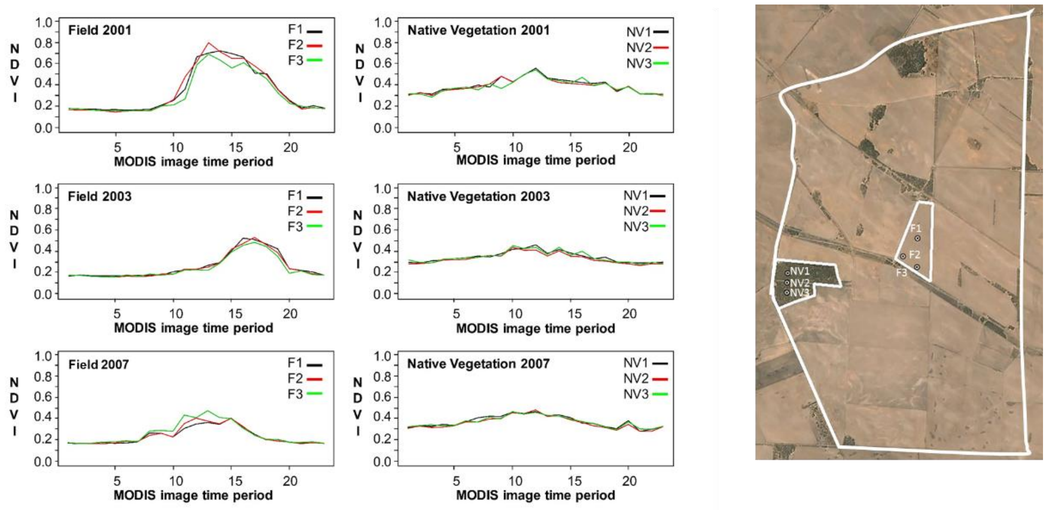

Figure 2.4. *The NDVI time series curve for the three selected points for the field and native vegetation study areas, and GoogleEarth image of the study area boundaries of the native vegetation and the farm with selected point locations (white).*

A further example shows the versatility of CropPhenology within the R programming environment. The example code below uses MODIS NDVI values at the location F1 (see above-Figure 2.4) and passes the time series through the Savitzky Golay smoothing procedure. The code below is fully operational and includes installation procedure. It installs "devtools", which is required for GitHub downloads and "signal" for the Savitzky-Golay smoothing filter (‘sgolayfilt‘ function). The code applies smoothing and call the function ‘singlePhenology‘ to computes the phenological metrics for location F1. Figure 2.5 shows the time series plot of the row and smoothed NDVI curve together.

```
> install.packages(c("signal", "devtools"))
> lapply(c("signal", "devtools"), library, character = TRUE)
> # install CropPhenology
> install_github("SofanitAraya/CropPhenology")
> # NDVI test data for location F1
>  MODIS_2015<-c(0.15,  0.1488,  0.152,  0.1526,  0.1699,  0.1634,
0.1647,  0.1693,  0.1899  ,0.2369  ,0.2594,  0.2274,  0.2382,  0.2168,
0.2033, 0.198, 0.183, 0.183, 0.1797, 0.1635, 0.1468, 0.1621, 0.1487)
> # Savitzky-Golay smoothing filter
> sg_MODIS2015 <- sgolayfilt(MODIS_2015)
> ts.plot(ts(MODIS_2015), ts(sg_MODIS2015), col=1:2, lwd=2)
> # Apply CropPhenology to smoothed NDVI time series
> SinglePhenology(sg_MODIS2015))
> ts.plot(ts(MODIS_2015), ts(sg_MODIS2015), col=1:2, lwd=2)
```

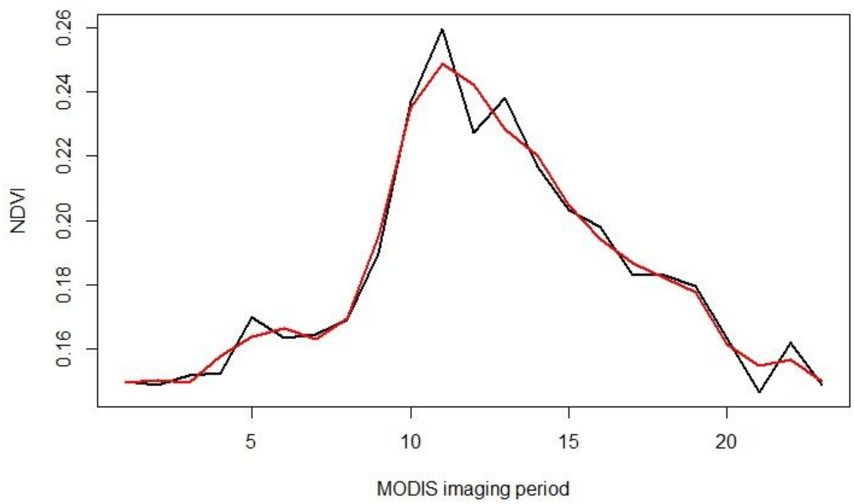

Figure 2.5. *Example time series plot of raw (black) and Savitzky-Golay smoothed (red) MODIS NDVI for 2015 at location F1.*

In a similar way, different smoothing and curve fitting algorithms could be implemented with relative ease in the R software environment for integration with the CropPhenology package.

2.4 Corroboration

Ground truthing of broad-scale remote sensing is difficult because of the logistic problems related to conduct representative field sampling at the spatial scale imagery (Ostendorf, 2011, Lawley et al., 2014). Irrespective, phenological metrics have successfully been used to estimate physiological events at regional scales. The time integrated NDVI (TINDVI) has proven to be a reliable indicator of the total biomass accumulated (Reed et al., 1994, Hill and Donald, 2003, Holm et al., 2003).

In order to test CropPhenology, we obtained wheat yield statistics between 2009-2015 for 14 cropping districts in South Australia (PIRSA, 2016). The cereal cropping regions and district boundaries were obtained from Department of Water Land and Biodiversity Conservation (DWLBC), (DWLBC Information Management, 2003). The MODIS imagery was masked and CropPhenology was applied. Figure 2.6(a) shows the resulting TINDVI raster for the cropping districts for 2011. The mean TINDVI value was calculated for all districts and years and compared with the annual yield estimates. A significant correlation was observed between the district crop estimate and TINDVI (p<0.0001, R2= 0.8, n=84) (Figure 2.6(b)). This result suggests that the derived metric TINDVI is an excellent indicator of crop yield.

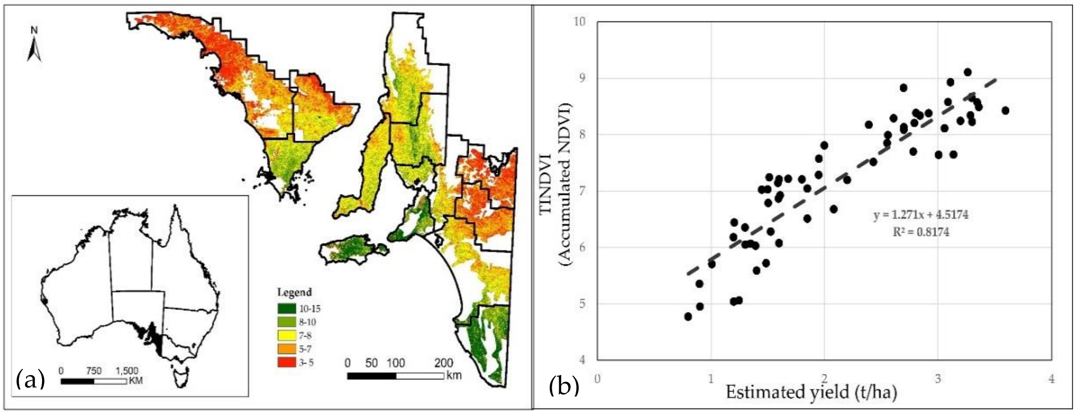

Figure 2.6. *Comparison of TINDVI metrics with broad-scale crop yield statistics. (a) TINDVI of the cropping farms of the districts of South Australia for the year 2015. (b) Scatterplot comparing the mean TINDVI of the districts with the seasonal crop yield estimate.*

2.5 Results and Discussion

CropPhenology builds on past software and literature to provide a state of the art software package to extract phenological metrics from temporal sequences of images. Minimising the technical difficulties involved in the data pre-processing and processing stages allows increased adoption of its use and access to new users and those who are less technically proficient.

The CropPhenology package provides further enhancements to existing software. The package produces 15 raster layers, offering additional metrics such as Asymmetry, BeforeMaxT and AfterMaxT which can provide important information for crop management. Built into the package is an ability to provide a spatially-explicit graphical representation of each metric for user-defined regions of interest. The package includes pixel level visualisation of time series using the MultiPointsPlot function. The package can thus inform crop monitoring and management for specific locations and areas.

CropPhenology assumes low NDVI during the initial growth phase after sprouting with a mid-season peak followed by senescence. This is a very typical crop growth scenario that is valid for a wide variety of crops. But there are some inherent limitations. The package is designed to provide a single set of phenological metrics and cannot automatically handle double or triple cropping systems. In order to obtain phenological information for multiple crops per year, the user has to manually separate input image sequences for individual growth periods as CropPhenology does not attempt to find multiple growing seasons.

The package assumes that the image sequence corresponds to the alphabetical order of the file names. Time is treated as a discrete order of images. The outputs of the temporal metrics (i.e. OnsetT and OffsetT) are integer numbers, which the user may convert to dates if required. This implies that in different parts of the globe with sowing season late in a year and harvest in the next year, images across years need to be collated in a single folder and named in sequence. Note that the MODIS imagery is named correctly by default. In addition, care needs to be taken to avoid dependent metrics in statistical analysis. For example, LengthGS is the difference between OffsetT and OnsetT and hence does not provide an independent variable.

Several R packages have recently been developed to facilitate access of remote sensing data and analysis. Being in an R software environment, CropPhenology can easily be integrated into a pipeline of processing using these tools. For example, MODIStsp package (Busetto and Ranghetti, 2016a) automatically downloads MODIS images as direct input of CropPhenology, similarly, the output raster from CropPhenology can further be analysed using RStoolbox package (Leutner and Horning, 2015), i.e. for unsupervised classification.

The CropPhenology package potentially enhances precision agriculture management by allowing improved understanding of the comprehensive physiological characteristics of the crop growth over space and time. Whereas yield mapping produces the end-result of a growing season, phenology characterises the pathway to the yield. It therefore complements information from traditional precision agriculture techniques by utilising information of how the plant canopy changes over time within a season and allows objective and quantitative interpretations of plant/climate/soil interactions. CropPhenology provides a comprehensive physiological characterisation of crop growth over space and time and hence enables users to increase understanding of the spatial and temporal growth variability of their crops, drilling down into relative plant performance in different growth stages. The availability of now 16 years of continuous coverage of MODIS image composites provides a long-term perspective of plant growth, which has proven useful in many applications (Wardlow and Egbert, 2008, Duveiller et al., 2012).

However, farm-based adoption of phenological mapping has been limited in the past because cloud-free temporal satellite imagery has only been available at a limited spatial resolution, i.e. 250m for MODIS or 260m for MERIS and 1000m for historic AVHRR. This consequently limits the application to broad-acre cropping. But even in such broad-scale applications, yield mapping can be conducted at spatial resolutions an order magnitude higher, rendering spatio-temporal satellite imagery inferior. Full use of the methodology for farm-based management may come with increased availability of temporal series of higher spatial resolution multispectral imagery. Imagery is currently being collected by different agencies including NASA (LANDSAT), ESA (Sentinel), and numerous commercial providers at a range of different spatial resolutions. It is therefore in principle possible to obtain more detailed spatio-temporal NDVI sequences. However, cloud and cloud shadow effects during the growing season limits use for phenology studies. Whilst currently spatio-temporal imagery is costly to obtain from commercial providers, prices may lower if demand increases. Furthermore, as the length of time series archives increases, fusing imagery from different publicly available sensors will become more likely (Feng et al., 2006, Fu et al., 2013). As CropPhenology will work for different spatial and temporal resolutions, is not limited to MODIS and it can be readily adopted to different imagery.

2.6 Conclusion

The use of remotely sensed vegetation indices to measure crop growth through phenological metrics has a high potential for agricultural management. However, the process from remote sensing data acquisition to relating vegetation index information to on-ground crop development is complex to even the most experienced user. While improvements have been made in the ease of access, useability and robustness of remote sensing products, fewer advances have been made in the software that is needed to manipulate, analyse and visualise these products.

We present the CropPhenology package which is designed to extract crop phenology metrics from time-series vegetation index data. The package is easy to use allowing the user to progress from downloaded image to crop phenology analysis with only minor data pre-processing steps. CropPhenology provides an option of using the moving average filter for smoothing the vegetation index curve. As the source code is openly available for users with GNU license, modification can be done to implement other smoothing techniques that have been used previously.

The package provides the user with 15 phenological metrics, which build upon those available from previous software and include new metrics suggested by the agricultural remote sensing literature. These metrics are presented in raster and text data formats for user's convenience. Furthermore, we have provided the theoretical biological inferences of how these metrics can be interpreted for crop management practices. CropPhenology was tested using MODIS 16-day NDVI composites but it can also be used with other imagery. It is freely available, on a GitHub repository for use in the R computing environment, which has gained popularity in recent years.

CropPhenology also offers a function, MultiPointsPlot function that plots vegetation index time series at selected pixel locations. Our worked example illustrates the utility of our package to provide a means of observing spatial and temporal crop growth variability across multiple years. This provides important information about the environmental factors influencing crop growth, potentially improving crop management. The CropPhenology package has been designed for cropping environments and tested in an environment with a distinct annual growth peak, but its generic design makes it also useful in other more complex environments.

2.7 Availability of CropPhenology package

CropPhenology is freely available from the most commonly used online package distributor and repository, GitHub (Chacon and Straub, 2009) at https://github.com/SofanitAraya/CropPhenology. The CropPhenology package manual and other relevant information are also available at http://cropphenology.wixsite.com/package.

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Author Contributions:

“Sofanit Araya designed the algorithm, wrote the R code, debugged and ran the program run and wrote the manuscript; Gregory Lyle assisted in algorithm design and provided critical evaluation of the manuscript; Bertram Ostendorf contributed to code development, manuscript writing and editing, Megan Lewis revised and edited the manuscript.

Conflicts of Interest:

The authors declare no conflict of interest.

Chapter 3

Phenologic metrics derived from MODIS NDVI as indicators for Plant Available Water-holding Capacity

This chapter is published.

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Principal Author

Name of Principal Author (Candidate)	Sofanit Araya
Contribution to the Paper	Development, conceptualization and realisation of the research, collected and organized data, undertaken analysis and interpreted results, wrote manuscript.
Overall percentage (%)	85
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.
Signature	Date 5-10-17

Co-Author Contributions

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

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

Name of Co-Author	Bertram Ostendorf
Contribution to the Paper	Supervised the development of the research, assisted interpretation of the result and evaluated manuscript
Signature	Date 13-9-17
Name of Co-Author	Megan Lewis
Contribution to the Paper	Co-supervised the development of the research, and evaluated the manuscript
Signature	Date 25/9/17
Name of Co-Author	Gregory Lyle
Contribution to the Paper	Co-supervised the development of the research, assisted conceptualisation of the research and evaluated the manuscript
Signature	Date 26/9/17

Abstract

Soil, an essential component of agricultural ecosystems, has high spatial variability. Plant growth reflects this variability in complex interactions with other factors such as rainfall and temperature. In the Mediterranean-type dryland cropping region of South Australia, water is the main driver of crop growth variability. Plant Available Water-holding Capacity of soil (PAWC) is the soil property that measures the maximum amount of plant extractable water which can be held in the soil. It interacts with weather conditions, governing crop growth. Thus understanding spatial variability of PAWC is crucial for farm and regional agricultural management. However, the physical measurement of PAWC is costly and time consuming.

Crop phenology, the timing of plant growth and development, is influenced by climatic, soil, and management factors. We hypothesised that by keeping management and climate constant by focusing on a small geographic area, the dynamic response of plants is largely due to soil functions. The objective was to use remote sensing derived phenology to understand the complex climate-soil interactions. We compared phenologic metrics of annual winter-growing crops from adjacent high and low PAWC soils at two farms (Whariminda and Minnipa) in the Eyre Peninsula, South Australia. The phenologic metrics were derived for 13 seasons from time series of Moderate Resolution Imaging Spectroradiometer (MODIS) NDVI data, at 250m spatial resolution and 16 days temporal resolution. Wilcoxon signed rank tests were applied to assess differences in phenologic metrics for crops growing on low and high PAWC soils. This allowed us to rank phenologic metrics for use as indicators of soil PAWC.

The results show a significantly higher GreenUpSlope (p<0.00008) and maximum NDVI (p<0.0004) in low PAWC soils. This indicates that crop phenology derived from MODIS satellite imagery may provide useful information about soil water conditions, which would allow improvements to the spatial detail in soil maps.

Keywords*:* PAWC, Crop phenology, spatial variability, time series, spatio-temporal, satellite imagery

3.1 Introduction

Soil is an essential component of agricultural ecosystems, as the primary supplier of nutrients and water for plants. It has high spatial variability in both its physical properties and chemical composition (BenDor et al., 2008, Grunwald, 2009). Information about the spatial variability of soil properties is one of the fundamental requirements for most agro-ecosystem management activities. However, it is impractical to satisfy the increasing demand of current management systems for high resolution soil data using traditional *in-situ* sampling and physical measurement techniques (Morgan et al., 2000, Wong et al., 2006). Researchers have successfully used broad scale soil information and provided systematic approaches at the level required for landscape and regional planning (Crossman and Bryan, 2009, Bryan et al., 2011), but significant uncertainty could result when such broad scale soil datasets are upscaled to landscape and field levels (Bryan et al., 2011). In addition , broad scale regional maps were developed based on low numbers of field observations with very limited information about spatial representativeness for upscaling (Ostendorf, 2011).

The Plant Available Water-holding Capacity (PAWC) is one of the most important soil properties in many agronomic management systems. PAWC, the 'bucket size of the soil' (Dalgliesh and Foale, 1998), is defined as the total amount of water that can be stored in the soil for plant use. This soil property shows significant variability at scales lower than the farming field. In arid and semi-arid farming regions, PAWC has been reported to be the main cause of crop growth variability (Oliver et al., 2006) but there is paucity of detailed spatial information on this critical soil property.

Plants are affected by soil variability through complex interactions with climate and other factors. Remote sensing allows us to observe plant spatial and temporal variability, which in turn may expose soil properties. Based on this concept, vegetation cover has been used as a proxy in predictive soil property mapping. Remote sensing of vegetation reflectance has been used as an indicator for soil salinity (Dutkiewicz et al., 2006, Zhang et al., 2011, Setia et al., 2013). It has also been used to model other soil attributes such as soil depth and water table depth (Taylor et al., 2013). The horizon thickness of the soil has also shown high correlation with remote sensing derived vegetation cover maps (Meirik et al., 2010). Whilst these examples were successful by using single images, multi-temporal observations of vegetation reflectance can provide an additional dimension. Remotely sensed vegetation phenology has been used as an indicator for climate change (White et al., 1997, Kramer et al., 2000), to estimate agricultural productivity (Labus et al., 2002, Hill and Donald, 2003, Sakamoto et al., 2013) and regional management for crop type mapping (Brown et al., 2013, Niazmardi et al., 2013) and many more applications.

The spatio-temporal variability of crop growth and yield are main concerns for farm management (Basso et al., 2001, Abuzar et al., 2004). Precision agriculture uses this variability for matching input requirements with the actual need and expected productivity, to ensure sustainable and profitable production and minimal environmental degradation (Cook and Bramley, 1998, Zhang et al., 2002). Advancements in precision agriculture have led to requirements for soil information at increasingly fine scales (Van Alphen, 2000, Adamchuk et al., 2004, Oliver et al., 2006, Wong and Asseng, 2006, Moeller et al., 2009). Soil water information, specifically PAWC, is a critical input for agronomic models such as Agricultural Production System sIMulator (APSIM) (Keating et al., 2003, Holzworth et al., 2014). In order to use these models at broader scales, reliable spatial soil information is required (Dalgliesh et al., 2012).

Methods to estimate PAWC include proximal sensing techniques (Viscarra Rossel and McBratney, 1998, Morgan et al., 2000) and inverse yield modelling (Morgan et al., 2000). However, these techniques are location-specific and need calibration for different landscapes. The use of other readily measurable soil properties through pedotransfer functions has also been suggested (Rab et al., 2011). However these also are limited in the range of specific combinations of soil properties for which they are effective for predicting PAWC in different landscapes.

Crop stand spatial variability is a suitable indicator of soil PAWC variability, especially under low rainfall conditions (Wong and Asseng, 2006, Rab et al., 2009). Temporal crop growth variability has also been reported as a result of soil PAWC interaction with seasonal rainfall variability (Wong and Asseng, 2006). These findings suggest that vegetation vigor may provide a suitable surrogate for PAWC. The spatial and temporal dynamics of the vegetation could be adequately measured by remote sensing phenological observation, as it has temporal consistency and is capable of quantifying vegetation vigour through vegetation indices. The most popularly used index in such studies has been Normalized Difference Vegetation Index (NDVI) (eg. Huang et al., 2013, Petus et al., 2013).

Phenology reflects the complex interaction of seasonality of rainfall and the hydrological characteristics of soils (Seghieri et al., 1995, Zhang et al., 2005). Hence, understanding how growth variability is affected by rainfall seasonality and soil PAWC interactions may allow us to use remote sensing phenology derived parameter as a surrogate for soil PAWC. Research suggests that variation between locations in the shape and other parameters of the NDVI dynamic curve can reveal the site-specific factors of soil, management practices and climate that determine crop performance (Labus et al., 2002). However, application of remote sensing phenological metrics to observe the climate-soil interaction has not previously been attempted.

The objective of this study was to use remote sensing phenology to understand the complex climate-soil interaction, with the aim of identifying phenologic metrics which can be used as indicators of soil PAWC at the farm field level. We hypothesise that in keeping management and climate constant by focusing on a few controlled sites, the dynamic response of plants is largely due to soil conditions. For this study NDVI dynamics for 14 seasons were used to describe the complex relationship between the soil PAWC and rainfall seasonality and its reflection in crop phenology metrics. This methodology could support growers and land managers in farm and regional level decisions.

3.2 Materials and Methods

3.2.1 Study site

The study sites were two fields in Eyre Peninsula (EP), South Australia. The region is characterised by a Mediterranean climate, with cool wet winters and hot dry summers. The agricultural region in EP has a range of sandy to clay loam soils (Eyre Peninsula Agricultural Research Foundation 2011). The study fields are located in upper EP, near Minnipa Agricultural Research Centre, and in lower EP near Wharminda town (Figure 3.1). The sites were selected because their soil types represent wider areas of the EP region and because of their previously characterised soil samples (Eyre Peninsula Agricultural Research Foundation 2011). These fields have been studied as focus sites of the Eyre Peninsula Agricultural Research Foundation (EPARF) soils (Eyre Peninsula Agricultural Research Foundation 2011). The field at Minnipa, approximately 68 ha in area, is characterized by sandy loam to sandy clay loam soils, with the land zones of sandy rise reported to perform well in dry years and a shallow flat that rarely performs well regardless of crop or pasture choice (Latta et al., 2013). The average annual and growing season rainfall of the Minnipa field are 325mm and 242mm, respectively. The Wharminda field of approximately 75ha is characterized by siliceous sand over sodic clay soil with an uneven wetting nature at the beginning of growth seasons that results in uneven germination. The average annual and growing season rainfall in Wharminda are 320mm and 250mm, respectively. In both fields, wheat has been the most commonly sown crop followed by barley and pasture.

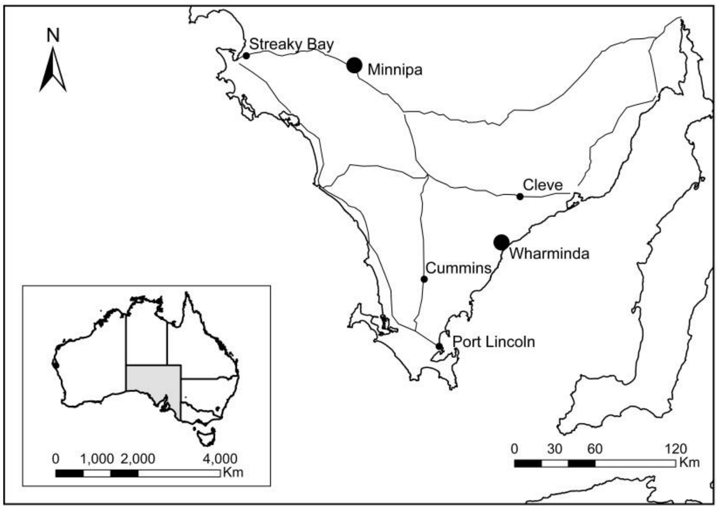

Figure 3.1. *Location of the study area*

3.2.2 Datasets

3.2.2.1 Soil data

The soil data used for this study was sourced from APSoil, a database of national and international agronomically important soils (The APSIM initiative, 2015). It contains PAWC measurements for representative agricultural soils in Australia (Burk and Dalgliesh, 2008). So far, the database holds PAWC measurement of over 800 regionally important soils with 69 of them in the South Australian agricultural region (The APSIM initiative, 2015). Each of our study sites has a pair of soil samples from this database: APSoil-353 and APSoil-354 (Minnipa) and APSoil-394 and APSoil-395 (Wharminda)(Table 3.1).

Table 3.1. *The APSoil points at the study fields, with soil type and their PAWC measurements.*

Apsoil No.	Soil type	PAWC (mm)
	Minnipa	
APSoil-354	Red light sandy clay loam	209
APSoil-353	Red sandy clay loam	57
	Wharminda	
APSoil-394	Shallow sand over clay	116
APSoil-395	Loam over rock	95

3.2.2.2 Rainfall data

The rainfall data used were daily gridded rasters with 5km resolution, provided by the Australian Government Bureau of Metrology (BOM) (Bureau of Metrology, 2015). The cumulative rainfalls were computed from the daily data for the corresponding 16 MODIS composite dates, for each pixel. The cumulative rainfall totals for each year and season were also calculated by summing the daily rainfalls.

In South Australian farming regions, time of sowing is usually determined by rainfall at the break of the season; the farmers wait for a few rainy days in autumn to start sowing (French et al., 1979). During the study period (2000-2013), the sowing date varied from May 6 (in 2009) to June 24 (in 2005) (EPARF, 2014). In this period, the highest annual rainfall was observed in 2010 (407mm) and the lowest in 2006 (244mm). The highest growing season rainfall was recorded in 2009 (342mm) and lowest in 2008 (137mm). A considerable inter-seasonal variation in rainfall was also observed, from very erratic to evenly distributed in the winter period.

3.2.2.3 MODIS NDVI data

Moderate Resolution Imaging Spectroradiometer (MODIS) provides one of the most widely used satellite images in remote sensing phenological studies (Zhang et al., 2003, Sakamoto et al., 2005, Zhang et al., 2005, Clerici et al., 2012, Yang and Zhang, 2012, Hmimina et al., 2013). Both NDVI and Enhanced Vegetation Index (EVI) from MODIS are the widely used indices of plant performance in the remote sensing literature. The saturation problem of NDVI at high biomass and the greater sensitivity of EVI to canopy variation are very well documented (Huete et al., 2002, Wardlow et al., 2007, Zhang et al., 2010). Despite this limitation, MODIS NDVI and EVI have been reported to perform similarly in crop related applications (Wardlow and Egbert, 2010). Moreover, both indices have comparable dynamic range and sensitivity for assessing spatial and temporal vegetation changes (Huete et al., 2002). As we are focusing on dynamic change in crop cover, both temporal and spatial, there should not be any difference in our observation from either NDVI or EVI, and MODIS NDVI was used throughout the study.

We used sixteen-day composites of MODIS 250m-NDVI data (MOD13Q1). The compositing technique means that the acquisition date of a pixel may record vegetation conditions of any unspecified date within the period; in fact if cloud cover persists for the entire period, the value may be filled using a historic average. Thus, the values representing the 16 day interval for each pixel may not be from the same observation dates (Solano et al., 2010, LP DAAC, 2015). Moreover, there may also be a mismatch in the location of successive observations of MODIS pixels. These grids, however, have been fitted to predefined grid cells. This mismatch between the gridding artifacts and the predefined cells may introduce bias during the compositing process and cause unavoidable influence on the spatial properties of the resulting composite image (Wolfe et al., 1998, Tan et al., 2006). Nevertheless, MODIS NDVI time series have shown considerable potential for revealing the general temporal patterns of phenology in cropping regions, despite the spatial heterogeneity within MODIS pixels (Hmimina et al., 2013).

Indeed, there could be substantial variability within a MODIS pixel that is averaged out in the NDVI time series. However, considering the inherent trade-off between the spatial and temporal resolution of remote sensing imagery, MODIS provides reliable observations of temporal changes in agricultural landscapes. In our case, pixels close to the PAWC measurement locations and within relatively homogenous soil types were taken as representative pixels.

3.2.3 Phenologic metrics derivation

A total of 319 MODIS NDVI 16 day composite images, between 18/02/2000 and 18/12/2013, were downloaded (23 images per year except 2000, which has only 20 images). The images were then reprojected using MODIS Reprojection Tools (MRT) of NASA Land Processes Distribution Active Archive Centre (LP DAAC). The NDVI values of each pixel across the 319 images were extracted and re-arranged as multi-dimensional arrays of NDVI values to represent 14 years at 16 days intervals.

We used unsmoothed original MODIS NDVI data, although the NDVI time series curves show some irregularities or noise. Several authors have used different smoothing and fitting techniques to reduce these irregularities on the NDVI time series curve, such as moving average (Reed et al., 1994, Hill and Donald, 2003), curve fitting (Zhang et al., 2003, Lu and Guo, 2008), and applying filters (Sakamoto et al., 2005). Generally, most of the smoothing and curve fitting techniques tend to follow the general trend and average the values within windows. However, smoothing and curve fitting techniques could significantly reduce peaks in the curves that are valid NDVI values (Reed et al., 1994). Consequently, we applied no smoothing and compared the raw NDVI curves from the selected two pixels.

The phenologic metrics were derived from the NDVI time series curves to indicate the timing and magnitude of NDVI responses for certain phenologic stages of the crop (Figure 3.2). The definition and interpretation of the phenologic metrics were partly adapted from previous works of Hill et al (2003) and Reed et al. (1994). Table 3.2 provides the abbreviations, names and definitions of the metrics derived.

Table 3.2. *Definitions of the phenologic metrics derived from the NDVI dynamics.*

Abbreviation	Metrics	Definition
OnsetT	Time of Onset of	The start time of high NDVI
OnsetV	Value of NDVI at the time of Onset	NDVI at OnsetT
MaxV	Maximum NDVI value	Maximum NDVI
MaxT	Time of Maximum	The time of maximum NDVI
OffsetT	Time of Offset of Greenness	The end time of high NDVI
OffsetV	NDVI value at Offset of greenness	The NDVI value at OffsetT
GreenUpSlope	Rate of NDVI increase	Slope of NDVI between OnsetT and MaxT
BrownDownSlope	Rate of NDVI decrease	Slope of NDVI between MaxT and OffsetT
TINDVI	Area under the curve	Integrated area of NDVI under the curve
TINDVIBeforeMax	Area under the curve before MaxT	Area under the curve left of MaxT
TINDVIAfterMax	Area under the curve after MaxT	Area under the curve right of MaxT
LengthGS	Length of growing	Time between OnsetT and OffsetT
Asymmetry measure	TINDVIBeforeMax - TINDVIAfterMax	Approximation of the skewness of the curve

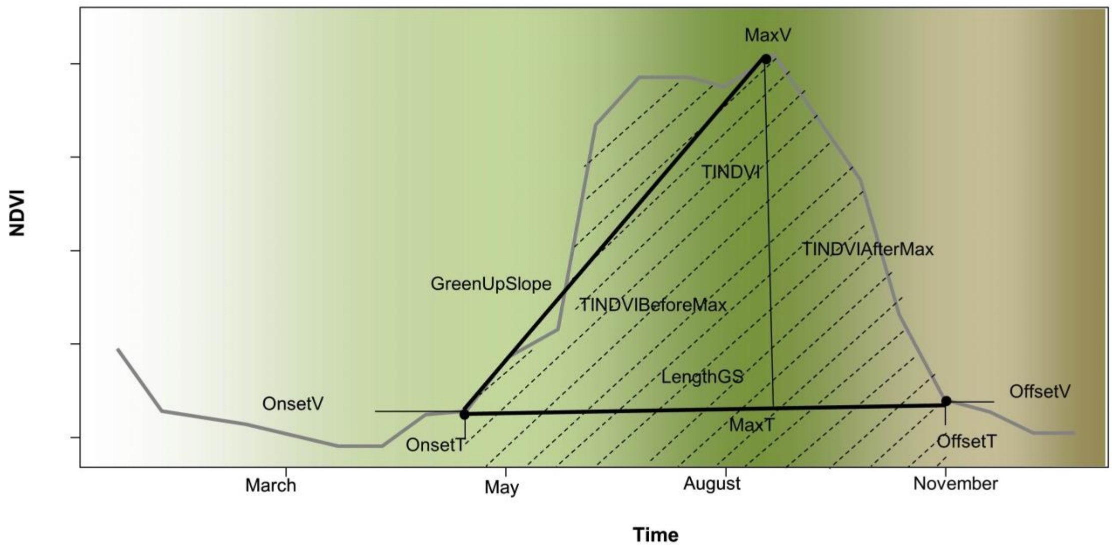

Figure 3.2. *A diagram showing phenologic metrics used. Details and abbreviations are explained in the text and in Table 2. The grey curve exemplifies NDVI from Wharminda in 2009.*

The onset of greenness is the NDVI value at the time (OnsetT) when an increase of greenness is observed at the start of the season, as the first few leaves appear above the ground. We defined it as the value at the point where the rate of increase in NDVI values is higher than the previous successive observations, during the green-up period between March and June. Likewise, the offset of greenness (OffsetV) was defined as the value at the time (OffetT) when the decline of NDVI value is high in the maturity period between October and December. At Offset, the crop reaches its physiological maturity, when most of the leaves and the grain have turned to brown. The length of growing season (LengthGS) was calculated as the difference between OffsetT and OnsetT. The highest point of the curve, the maximum NDVI (MaxV), is attained during the anthesis phenological stage of the crop, which is after all the leaves are elongated and before phenological maturity. The gradient between the OnsetT and the MaxT is defined as the rate of greenup (GreenUpSlope). Similarly, the BrownDownSlope is defined as the slope between the Offset and the MaxV. Hill et al (2003) defined the ratio of these two parameters, GreenUpSlope and BrownDownSlope, as the quality of the season, which measures the skewness of the curve. They also defined the area under the curve as 'Time Integrated NDVI" (TINDVI), which they have shown to be potentially useful as an indicator of the seasonal condition in terms of agricultural productivity. In addition to TINDVI, we have also defined TINDVIBeforeMax and TINDVAfterMax, which are the areas under the curve before MaxT and after MaxT respectively (Figure 3.2). We approximated the NDVI integrals as a sum of the 16-day NDVI values.

3.2.4 Statistical analysis

We derived phenologic metrics for each year and each observation point for 14 years, resulting in a total of 28 paired samples for each of the 9 metrics used in this study (see below in Table 3). For each metric we calculated the difference between low and high PAWC locations and tested if the average difference is different from zero using the nonparametric Wilcoxon signed-rank test.

When multiple tests performed on a single set of data, the probability of identifying at least one significant result due to chance increases as the number of tests increases. The probability of making such a type I error due to multiple tests, the familywise error rate (FWER), should be addressed. In our analysis, nine metrics were compared from a single set of data. We applied the Bonferroni-Holm's correction, which controls for the FWER by reducing the significance probability threshold alpha (Holm, 1979, Armstrong, 2014).

3.3 Results and Discussion

3.3.1 NDVI dynamics

The NDVI dynamics from the study area for the years 2000- 2013 are presented in Figure 3.3. These dynamics show vegetation growth as influenced by environmental and management factors including crop type, sawing date, and fertilizer. As water availability is the driving factor in the region, the NDVI curve largely indicates the interaction between seasonal rainfall and the soil. The crops attained their maximum NDVI during the August – September period. The NDVI gradually decreases to reach a minimum during the maturity period, around October. As the actual time of onset and offset varied from year to year, the length of growing seasons varies accordingly.

High rainfall over a short period allows a high PAWC soil to store more water than a low PAWC soil, for later use by the crop. On the other hand, a relatively regular frequency of rainfall could possibly favour low PAWC soils, as it keeps on filling the profile for timely usage by the crops. The latter case could disfavour the high PAWC soil as the water sinks deep into the 'big bucket', especially during the early growth period where the crop roots are not yet extended deeply.

The NDVI response on the two contrasting soils from both fields showed considerable variability that provides insight into soil–climate interactions. Annually, the difference between the phenologic metrics varies depending on the rainfall pattern (Figure 3.3). The effect of soil PAWC is greatest when the season starts with good rainfall which fills the soil profile and is followed by a dry period. In these years plants in the high PAWC soil benefit more than those in the low PAWC soil. In the Minnipa field, 2001 was one such year, with nearly average March - May rainfall followed by a below average July and August. In this year, the curve from the lower PAWC soil point shows a faster increase in greenness to its maximum and drops more quickly in the down slope than that of the high PAWC soil (Figure 3.3a). A similar observation was made in the Wharminda field in 2009, when the low PAWC soil (APSoil-395) reached its maximum NDVI earlier than the high PAWC soil after low rainfall in late July- August following a wet June (Figure 3.3b).

If the rainfall is evenly distributed throughout the growing season, even if not very frequent, the soil profile will be filled regularly with the rain. Thus the influence of the soil bucket size on plant growth is likely to be minimal. The 2002, 2010 and 2011 years in the Minnipa field were characterized by relatively evenly distributed rainfall during the growing season.

The Minnipa field had high growing season rainfall (300mm) in 2009. However most of the rains were during the high temperature summer; the growing season started with a dry May across the whole state. Sowing started on 5th of May (Eyre Peninsula Farming Systems, 2009). At this time there might have been water in the 'bucket' from the March rainfall, but that may have been used up quickly and the crop in the 'low bucket' soil faced water stress (Figure 3.3a).

At Minnipa, the NDVI curves from the two soils points show low NDVI around 0.3-0.4 in years with lower growing season rainfall, such as 2003, 2006, 2007 and 2008. The differences between the two curves are small compared to the other years. Similarly, in Wharminda, the minimum NDVI between 0.5-0.6 was recorded in relatively lower rainfall years during the study period such as 2006 and 2002. However the lowest maximum NDVI in Wharminda was higher than that of Minnipa.

The year 2006, the driest year on record for the state, had very low rainfall over the growing season, which caused the vegetation to onset late. The NDVI curve of the low PAWC soil at Minnipa (APSoil-353) shows a steeper increment in NDVI and attains maximum vegetation earlier than the high PAWC soil (APSoil-354). Similarly, 2008 had relatively low growing season rainfall, resulting in early onset and an early peak NDVI at the low soil point (APSoil-353). In 2004, the curves in both fields show similar onset and maximum NDVI for the low bucket soils. The year 2005, on the other hand, started with a very warm and dry March and April, resulting in very late onset. In both fields, the onset in the low PAWC soils was earlier than that of high PAWC soil; the maximum NDVI was also attained earlier than in the high PAWC soil.

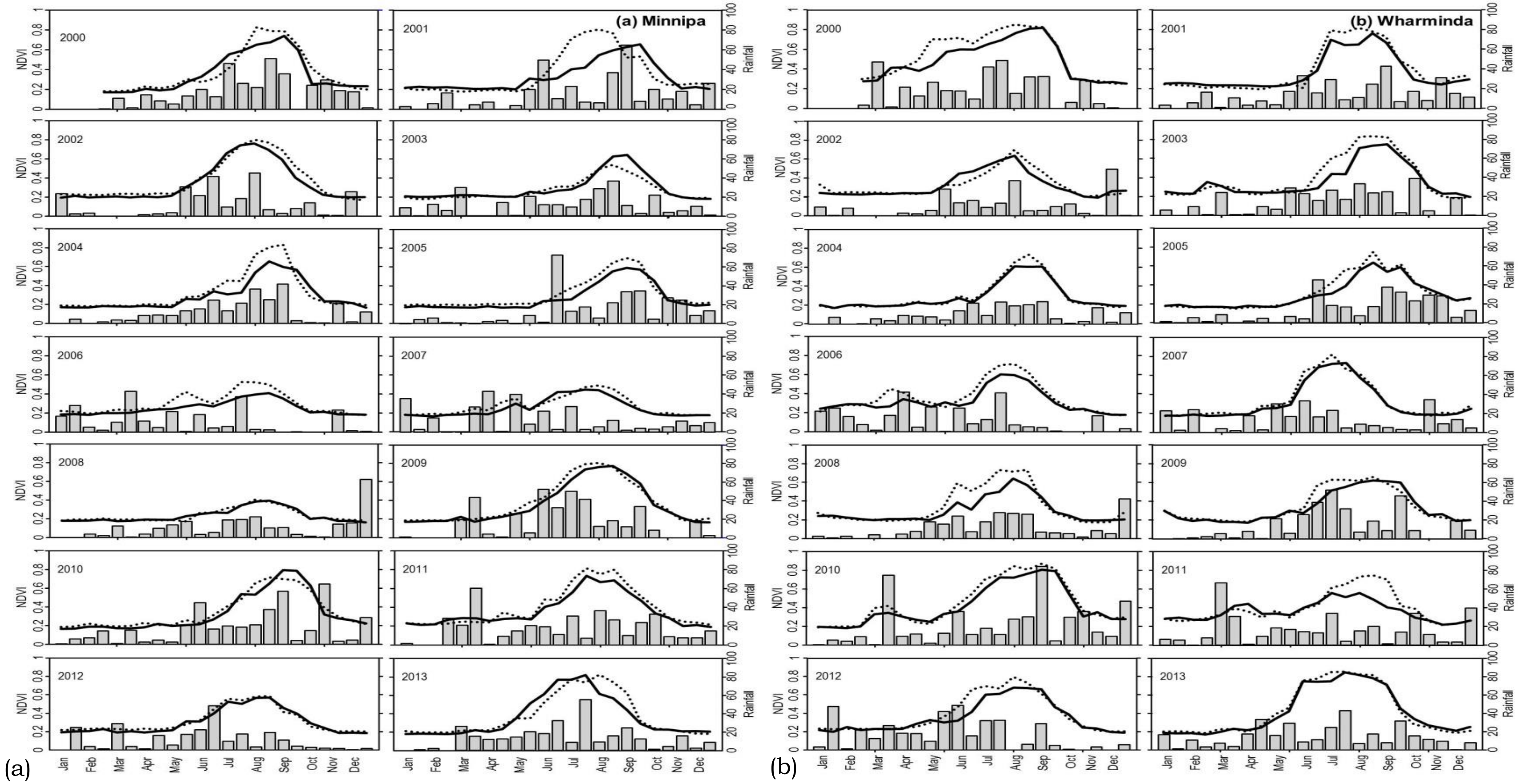

Figure 3.3. *The NDVI dynamics curves of the two soil types with 16 days cumulative rainfall for the years 2000 – 2013 in (a) Minnipa and (b) Wharminda fields Shaded bars represent 16days cumulative rainfall; solid line curve represents the higher PAWC soil in fields (APSoil-353 in Minnipa and APSoil-395 in Wharminda); dotted curve represents lower PAWC soils in both fields (APSoil-354 in Minnipa and (APSoil-394 in Wharminda).*

3.3.2 Comparison of phenologic metrics

The use of metrics makes it possible to reduce the complexity of the NDVI dynamics. The paired soil conditions (low and high PAWC) under the same management provide the basis for an objective analysis of individual metrics with respect to their strength as indicators for PAWC.

The NDVI time series show significant differences between the two soils with contrasting PAWC. We compare the average differences (n=28) of each of the phenological metric pairs and assess their statistical significance. The difference between GreenUpSlope and MaxV is significant, followed by the Asymmetry measure (Table 3.3). When considered individually, also MaxT, MaxV, and the timing of offset show a consistent effect (Table 3.3).

Table 3.3. *The Wilcoxon signed-rank test result for the metrics with Mean and standard deviation of the difference and the Bonferroni-Holm adjusted threshold values. The non-significant results are highlighted in bold.*

Metrics	Mean	Std. deviation	*p*-value	Bonferroni Holm-adjusted *p*-value
GreenUpSlope	0.0165966	0.0197046	0.0000720	0.00079
MaxV	0.0602071	0.07161184	0.0003655	0.00366
Asymmetry	**0.9141134**	**1.486209**	**0.008225**	**0.07403**
MaxT	**0.5357143**	**1.170063**	**0.01647**	**0.13176**
OffsetT	**0.3339843**	**0.8627308**	**0.04512**	**0.31584**
OfsetV	**0.1308932**	**0.7417776**	**0.05076**	**0.30456**
LengthGS	**0.4609813**	**1.330122**	**0.06281**	**0.31405**
TINDVI	**0.2261187**	**0.6961463**	**0.1042**	**0.41680**
OnsetV	**0.0043848**	**0.03316866**	**0.4652**	**1.39560**
BrownDownSlo	**0.0279674**	**0.1362654**	**0.567**	**1.13400**
OnsetT	**0.0164659**	**1.050088**	**0.6918**	**0.69180**

Below, we assess the effect of the differences in PAWC on the individual phenological metrics in detail.

Onset, Offset of NDVI and length of the growing season

The time of onset of NDVI shows high variability between the contrasting pair of soils and is weak indicators of differences in soil conditions. The difference in OnsetT between low and high PAWC soils ranged from nearly one day (2004) to 23 days (2005) in Minnipa, with an average difference of 11.4 days. In Wharminda it ranged from 4 days (2001) to 27 days (2007), with an average of 13 days without any significant differences in the statistical analyses.

The time of Offset shows difference between the two soils, in most years, the low PAWC soils reached to offset earlier than the corresponding high PAWC soil (indicated as a solid line in Figure 3.4 (a)). The difference ranges from 22.6 days (2001) to 0.21 days (2008) both in Minnipa. The Wilcoxon signed–rank test showed some effect (p=0.045), but the family-wise error rate lack of significance and hence rejecting this variable as a good indicator of soil PAWC.

The length of the greening season is less temporarily variable, the difference between soils is not strongly expressed, either (Table 3). This can be largely explained by their high dependency on seasonal weather conditions and management decisions of sowing date with little influence of soil conditions.

The NDVI values before onset and after offset of NDVI (OnsetV and OffsetV) are also highly variable and are not indicative of differences in soils.

Time of Maximum NDVI

In contrast to the timing of onset and offset, MaxT from the two contrasting soils shows marked differences, but the variability is high. In most of the years, soils with low PAWC (APSoil-353 and APSoil-395) reached their maximum NDVI value earlier than their corresponding high PAWC soils, (indicated by solid lines in Figure 3.4(b)). For example, in the Minnipa field, the difference between the MaxT from the two contrasting soils reached a maximum of 48 days in 2001. This year was characterized by a wet June and dry July and August. The higher PAWC soil had the advantage of supporting the crops using stored water from the June rainfall up to the again increasing rainfall in September; the low PAWC soil on the other hand reached MaxT just before September. A similar pattern was observed in the Wharminda field in 2009: a good June and July followed by drier August and September, resulting in early anthesis or maximum NDVI in the low PAWC soil. The distribution of the MaxT values in the two contrasting pairs of soils do not differ significantly (Bonferroni Holm adjusted p=0.143) (Table 3.3).

Maximum NDVI

The peak NDVI values (MaxV) were observed to be consistently higher in low PAWC soil in most of the years (Figure 3.4(c)). Plants on low PAWC soils predominantly reach their peak stage earlier and appear to be able to establish relatively higher leaf area than soils with a higher PAWC. Climatic conditions, particularly temperature and photoperiod during peak growth periods are different, likely causing the crop to react different. But the number of available samples was too low to empirically assess interactions of temperature and solar irradiation. The Wilcoxon signed rank test indicated that the maximum NDVI values from the low PAWC soils showed statistically significantly higher than values from high PAWC soils (Bonferroni Holms adjusted $p < 0.004$) (Table 3.3). Thus this metric could also be a good indicator for soil PAWC estimation.

Slope of NDVI during the green-up period and after peak NDVI

The rate of increase in NDVI during the green-up period from the two soils shows the most consistent differences ($p<0.0008$). In the majority of years, GreenUpSlope was higher for low PAWC soils (indicated as solid line in Figure 3.4(d)). It is also evident that the difference in the green-up slope varies amongst years. The highest effect can be seen in 2001. The region experienced heavy rainfall during June, which eased in July, followed by a dry August (see also Figure 3.3). Hence there was sufficient water for a rapid start with a high, early peak for the low PAWC soil, which later suffered from water scarcity, resulting in in a high green-up slope. The big bucket soil still has sufficient water during the later period when water becomes limited. Here, NDVI shows a late, yet relatively high peak and consequently this soil shows a lower green-up slope. On the contrary, in years like 2006, Wharminda faced very low rainfall which equally limited both soils, reflected as low difference in GreenUpSlope (Figure 3.4(d)). Similarly, in Minnipa during 2009, a more homogeneous rainfall distribution during the growing season produced less difference in GreenUpSlope between high and low PAWC soils. This provides evidence that this metric has some potential to elucidate differences in plant available water content. However, homogeneity and amount of rainfall interact with the NDVI response to differences in PAWC.

The slope of NDVI between maximum NDVI and Offset of greenness, the BrownDownSlope on the other hand doesn't show significant difference to indicate the soil PAWC. This metric is influenced by after-anthesis rainfall pattern and whether water is available for the crop. Thus we would expect some soil signal and effect of PAWC. However, there is little pattern. BrownDownSlope shows high variability across observation years because of a high dependence on seasonal rainfall patterns. Furthermore, as it is the resulting effect of both the MaxT and Offset T, parallel shifting of both of these metrics could minimize the total effect on the BrownDownSlope.

TINDVI

The time integrated NDVI (TINDVI) shows high variability between the two soils, and no significant difference was indicated in the Wilcoxon signed rank test (Table 3.3). However, consistent differences were recorded across the observation years. This indicates that climatic conditions are the main driving factors for TINDVI. TINDVI has repeatedly been reported by researchers to show a strong correlation with the annual yield or primary production (Tucker et al., 1980, Hill and Donald, 2003, Mkhabela et al., 2011). The PAWC has also been reported to explain the yield variability across the field to a large extent (Oliver et al., 2006, Armstrong et al., 2009, Moeller et al., 2009). Accordingly, one might expect a possible significant relationship between TINDVI and PAWC. However, the high influence of weather on TINDVI between years would likely conceal the effect of PAWC on yield. Unlike our study, most TINDVI – yield research has been conducted in relatively large geographic regions. Moreover, the correlations reported showed high variability across the annual precipitation of the regions, with high correlation recorded in the low rainfall regions (Mkhabela et al., 2011). Whilst TINDVI is sensitive to yield differences across years, the residual effect of soil conditions is inconsistent suggesting that this variable is not a good indicator of soil differences

Asymmetry measures (TINDVIBeforeMax and TINDVIAfterMax)

There is also a noticeable asymmetry of the NDVI curve for the contrasting soils, as expressed by differences between TINDVIBeforeMax and TINDVIAfterMax. The high PAWC soils in both fields showed positive (more area before peak NDVI) skewness in most of the years. The NDVI curves from the high PAWC soil shows higher Asymmetry measure than the low PAWC soil (indicated by a solid line in Figure 3.4 (e)). The Wilcoxon signed rank test indicated that high PAWC soil has bigger area under curve before maximum NDVI than the low PAWC soils ($p<0.01$), which is consistent with above observations, but insignificant after correcting for family-wise error (Table 3.3).

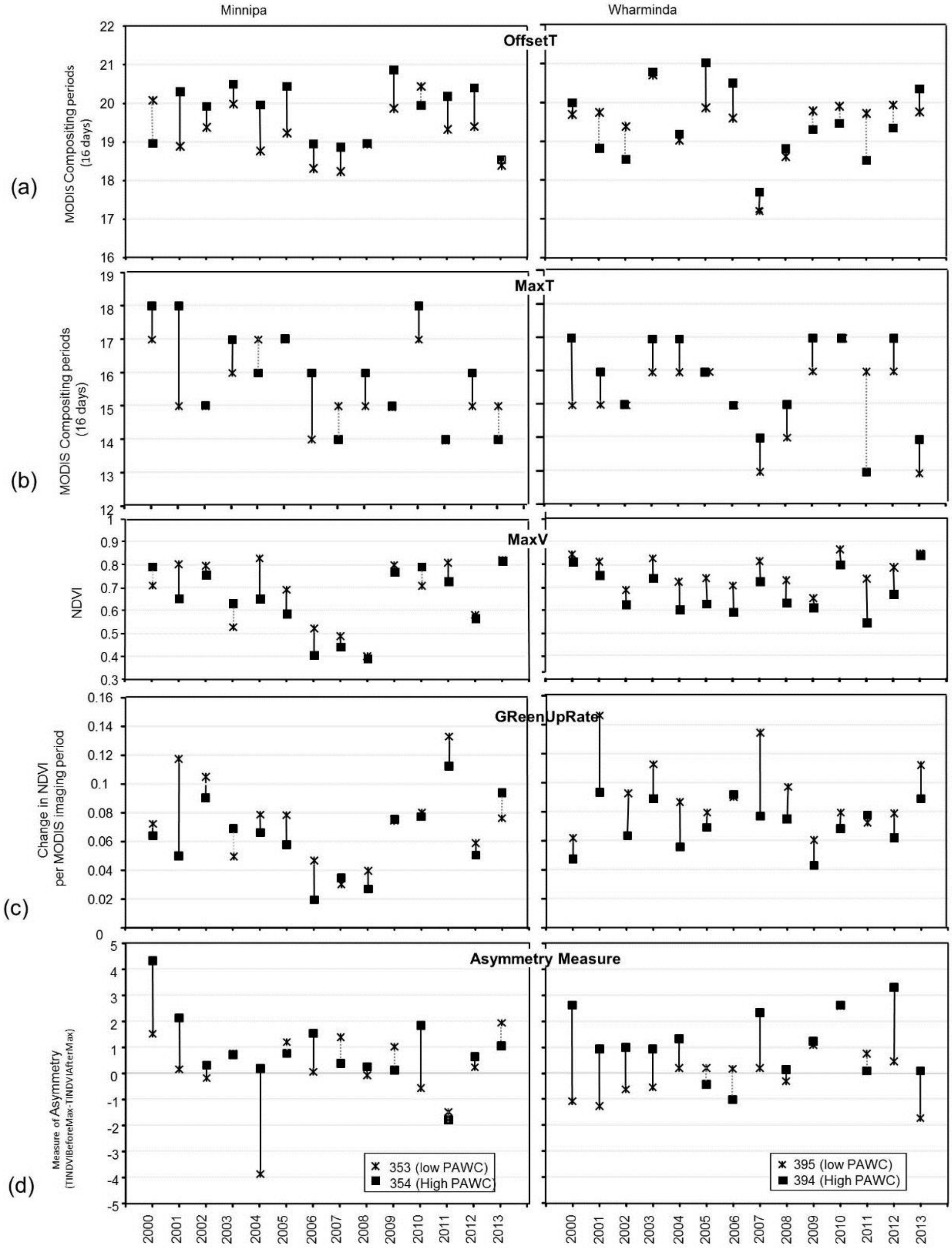

Figure 3.4. *Graphs showing individual indicators for a) OffsetT, b) MaxT, c) MaxV, d) GreenUpSlope and e) Asymmetry measure. Solid lines indicate years that follow the general trend, grey dotted lines indicate years in which the sign of the differences is inverse, indicate years with low PAWC soils attain larger difference between area before and after maximum NDVI than that of high PAWC soil.*

3.3.3 Interpretation of phenologic metrics

The higher slope of NDVI between onset and maximum NDVI (higher GreenUpSlope) in low PAWC soils than in high PAWC soils was one of the results observed in our study. As the low PAWC soil contains less water to be used by plants than the high PAWC soil, the observed effects are consequently due to the water stress. Studies on crop physiology also confirm that water plays an important role in the timing of growth stages. Robertson et al. (1994) studied wheat crops under water deficit at early, mid and late phenologic periods and found stressed crops reached anthesis stages on average 3 to 5 days earlier than non-stressed crops. The study also showed that early stress had the largest effect on developmental timing compared to mid and late stresses (Robertson and Giunta, 1994). Experiments done by McMaster et al. (2003a) also show that winter wheat and barley under half average precipitation reached anthesis and maturity phenologic stages 13 and 15 days earlier than non-stressed crops respectively. Numbers of similar experimental studies have assessed the effect of inadequate water availability at various growth stages on the growth of different crops (Angus and Moncur, 1977, McMaster and Wilhelm, 2003a, McMaster, 2005, McMaster et al., 2011). Generally, these studies indicate that the timing and duration of growth stages are highly influenced by water availability; faster crop growth to the next phenologic stage is one of the evident effects of water stress during crop growth. This fact has also been observed in our study as shorter time to reach to maximum NDVI in low PAWC soil than high PAWC soil, which results in higher slope between onset and Maximum NDVI.

The numbers of kernels and spikelets are determined during the reproductive phase of the crop, which is from emergence to anthesis, where the crops gain maximum greenness, and afterwards the spikes start turning from light green to a yellowish colour (Satorre and Slafer, 1999, Acevedo et al., 2002, Stapper, 2007, Fischer, 2011). Linking this to our NDVI dynamics curve, a slow rise to anthesis stage gives the plant enough time to develop a higher number of spikes and kernels than a quick rise. Thus the low PAWC soil, which is characterized by low production potential, has shorter time to reach to maximum NDVI than the high producing high PAWC soil. The grain-filling physiologic phase, ranging from anthesis to maturity and harvest, is the phase where the potential size and final weight of the grain is determined (Satorre and Slafer, 1999, Kouadio et al., 2012). However, previous studies report that the potential grain yield is more sensitive to the number of kernels than the kernel weight (Satorre and Slafer, 1999, Acevedo et al., 2002). This fact has also been expressed as higher A*symmetry measure* metric in high PAWC soil (more area before maximum NDVI than after Maximum NDVI) which indicates longer growth period and/or high NDVI, prior to maximum NDVI (anthesis) than after maximum NDVI.

Previous studies have successfully predicted yield from different part of the NDVI curve (area under the curve - Tucker et al., 1980, ((Eg. decreasing curve - Kouadio et al., 2012). In particular the decreasing section of the NDVI time-curve has been suggested as a predictor of crop yield (Kouadio et al., 2012). As the low PAWC soils have lower production potential than the high PAWC soils, the parameter derived from the decreasing curve (BrownDownSlope) was expected to capture this difference. However our result shows that BrownDownSlope was not a strong indicator of the soil PAWC, whereas it shows high variability across the observation years that could be indicative of weather conditions. Unlike our study, the research done by Kouadio et al. (2012) was undertaken over large geographic areas, across different years, in which the results more likely reflect climatic factors than soil differences. Moreover, our results show that the low PAWC soil is characterized by earlier Maximum NDVI and earlier Offset, which shifts both endpoints of the slope, results a very low difference in slope. This can be seen in the idealized curves (Figure 3.5) as the slope of the line connecting the maximum NDVI and Offset from the two contrasting soils have very low difference as both points are shifted.

Single-date observations of NDVI have also been popularly used as an indicator for yield. Studies have reported high correlations between NDVI and crop yield during anthesis and grain filling periods (Labus et al., 2002, Mkhabela et al., 2011). Accordingly, Ren et al. (Ren et al., 2008) suggested the most accurate crop yield prediction to be 40 days before harvest; likewise Mkhabela et al (2011) reported the optimal time for prediction as one to two months prior to harvest. Labus et al. (2002) also report a strong relationship in late July and August. A similar observation was made by Lyle and Ostendorf (Lyle and Ostendorf) in South Australian agricultural regions, with high correlation of yield and NDVI in early September. Our study supports these findings; in the late anthesis –grain filling stage NDVI on the High PAWC soil appears higher than that of the low PAWC soil. This is indicated in the idealized curve (Figure 3.5) as the high PAWC soil attains high NDVI on part of the curve after Maximum NDVI.

Labus et al. (2002) reported a strong relationship between time-integrated NDVI and yield at both regional and farm scales. They reported variation in the curves among locations, such as high amplitude/short length or low amplitude/long length, which might produce the same integrated NDVI values. These variations can be due to site-specific factors such as plant cultivar used or other farm management practices, soil and climate.. Moreover they suggested that the shape and timing of the growth profile might reveal more about the yield as it conceals the site specific factors. Our results support this idea that the earlier part of the curve such as maximum NDVI and parameters derived from the increasing curve could be good indicators of site specific conditions, particularly soil water conditions at locations were water is the driving force for crop growth.

3.3.4 Summary of phenological indicators for PAWC

Generally, the maximum NDVI value, and Greenup slope are the two metrics found to be good indicators of the soil PAWC. Higher Maximum NDVI (MaxV) and higher GreenUpSlope (GreenUpSlope) was generally associated with the low PAWC soils as compared with the high PAWC soil. The other metrics compared: Time of Onset (OnsetT), NDVI at onset (OnsetV), time of Maximum NDVI (MaxT), Area under the curve (TINDVI), measure of asymmetry (Asymmetry measure), NDVI at offset (Offset V), time of Offset of greenness (OffsetT), the slope between maximum NDVI and offset (BrownDownSlope), and length of the growth season (LengthGS) were found to be not good indicators for the soil PAWC.

Even though the above mentioned metrics difference, between high and low PAWC, is more observable during the years with good early season rainfall followed by a drier growing season, the low PAWC soils showed quicker growth in the earlier phenologic stages. Figure 3.5 shows the idealised dynamics of the high and low PAWC soils. Generally, the NDVI dynamics curve reflects the interaction of the soil PAWC with seasonal rainfall, which naturally has high variability. Under identical weather and management we would expect two soils with different PAWC to exhibit consistently different growth patterns. Low PAWC soils show faster growth with a higher peak but insufficient water to produce good yield. Moreover the water stress hastens the plant growth rate, shorting growth stages and reaching high NDVI point quicker. Our results also show a high PAWC soil mostly got larger area under the curve before maximum NDVI than after maximum NDVI.

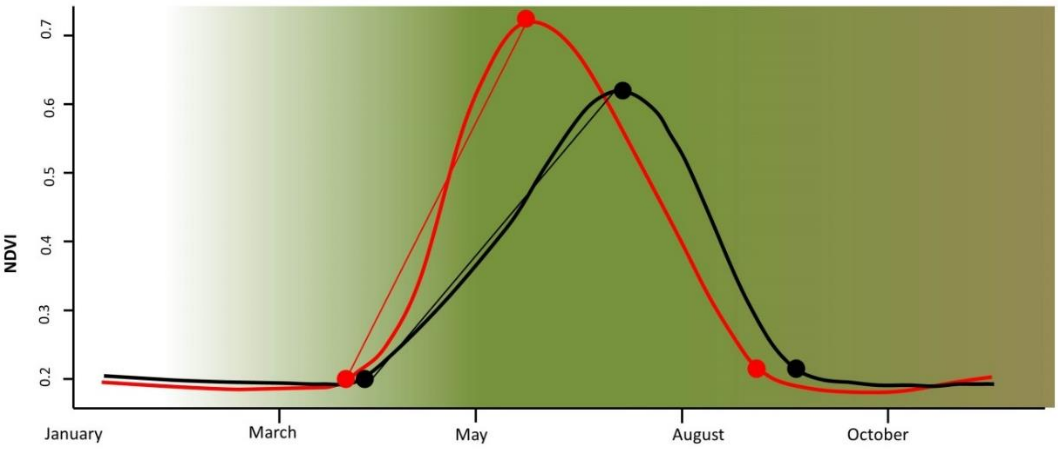

Figure 3.5. *The idealized NDVI curves of vegetation from high and low PAWC soils: red – low PAWC soil and Black – high PAWC soil. Low PAWC soils showed higher maximum NDVI, steeper green-up slopes, and a higher time-integrated NDVI.*

3.4 Conclusion

Our study demonstrates the potential of remote sensing derived phenologic metrics for understanding soil PAWC variability. The results indicate that there are clear differences in two phenologic metrics between high and low PAWC soils, with higher maximum NDVI and green-up slope in low PAWC soils. Plants growing on 'big-bucket' soils tend to be able to better budget their available water throughout the season, producing higher yields, whilst plants growing on soils with limited water holding capacity seem to grow faster initially and then run out of water sooner. Although there is substantial variability in the phenologic metrics, the differences between the two soils are apparent irrespective of a wide range of climatic conditions and management during the study period.

The results presented here have implications for the structure of future PAWC models based on NDVI dynamics. Inverse models of PAWC using a combination of the NDVI metrics identified here seem possible. There are, however, some factors that may obscure the PAWC signal in the NDVI time series. The most prominent of these may be the effect of management (i.e. different crop types and varieties, fertiliser and herbicide applications) and more research is needed. Furthermore, localised soil variability may be obscured in the relatively coarse 250m pixel size of the MODIS sensor, and higher resolution imagery, once available, may give better results.

The analysis in this study is unique in that it is long-term and that the soils selected for comparison are under the same climatic conditions and management (i.e. within a field), so the influence of other factors is minimised. As NDVI dynamics can be used as an indicator for PAWC, we are able to identify relative differences in PAWC within fields from publicly available satellite remote sensing of vegetation.

3.5 Acknowledgements

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Chapter 4

Remote Sensing Derived Phenological Metrics to Assess the Spatio-Temporal growth variability in cropping fields

This chapter is published.

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Principal Author

Name of Principal Author (Candidate)	Sofanit Araya		
Contribution to the Paper	Development conceptualization and realisation of the research, collected and organized data, undertaken analysis and interpreted results, wrote manuscript.		
Overall percentage (%)	85		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	5-10-17

Co-Author Contributions

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

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

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

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

Name of Co-Author	Assoc. Prof. Bertram Ostendorf		
Contribution to the Paper	Supervised research development and conceptualisation, assisted statistical analysis and interpretation, and evaluated manuscript		
Signature		Date	13-9-17
Name of Co-Author	Prof. Megan Lewis		
Contribution to the Paper	Co-supervised research development and conceptualisation, and evaluated manuscript		
Signature		Date	25/9/17
Name of Co-Author	Dr. Gregory Lyle		
Contribution to the Paper	Co-supervised research development and conceptualisation, assisted interpretation of the result and evaluated manuscript		
Signature		Date	26/9/17.

Abstract

Precision Agriculture (PA) recognizes and manages intra-field spatial variability to increase profitability and reduced environmental impact. Site Specific Crop Management (SSCM), a form of PA, subdivides a cropping field into uniformly manageable zones, based on quantitative measurement of yield limiting factors. In Mediterranean environments, the spatial and temporal yield variability of rain-fed cropping system is strongly influenced by the spatial variability of Plant Available Water-holding Capacity (PAWC) and its strong interaction with temporally variable seasonal rainfall. The successful adoption of SSCM depends on the understanding of both spatial and temporal variabilities in cropping fields. Remote sensing phenological metrics provide information about the biophysical growth conditions of crops across fields. In this paper, we examine the potential of phenological metrics to assess the spatial and temporal crop yield variability across a cropping field. The study was conducted in a wheat cropping field at Minnipa, South Australia. The field was classified into three management zones using prolonged observations including soil assessment and multiple year yield data. The main analytical steps followed in this study were: calculation of the phenological metrics using time series NDVI data from Moderate Resolution Imaging Spectroradiometer (MODIS) for 15 years (2001-2015); producing spatial trend and temporal variability maps of phenological metrics; and finally, assessment of association between the spatial patterns and temporal variability of the metrics with management zones of the cropping field. The spatial trend of the seasonal peak NDVI metric showed significant association with the management zone pattern. In terms of temporal variability, Time-integrated NDVI (TINDVI) showed higher variability in the "good" zone compared with the "poor" zone. This indicates that the magnitude of the seasonal peak is more sensitive to soil related factors across the field, whereas TINDVI is more sensitive to seasonal variability. The interpretation of the association between phenological metrics and the management zone site conditions was discussed in relation to soil-climate interaction. The results demonstrate the potential of the phenological metrics to assess the spatial and temporal growth variability across cropping fields and to understand the soil-climate interaction. The approach presented in this paper provides a pathway to utilize phenological metrics for precision agricultural management application.

Key words: Remote sensing, crop phenology, multi-temporal images, NDVI, precision agriculture, spatio-temporal variability

4.1 Introduction

Precision agriculture (PA) recognizes and manages intra-field spatial variability with the desired outcome of increasing profitability and reduced environmental impact (Bramley, 2009). Site Specific Crop Management (SSCM) is a form of PA that focuses on managing Spatial crop yield variability through matching agricultural inputs with the site potential. SSCM subdivides a cropping field into uniformly manageable zones, based on quantitative measurement of yield limiting factors (Chang et al., 2003, Mzuku et al., 2005, Xiang et al., 2007).

Spatial variability in crop yield is the result of complex interaction of factors influencing crop growth that include soil (such as nutrients, soil water availability), topographical factors (such as elevation) and climatic factors (such as rainfall and temperature) (Corwin, 2013). In addition to their spatial variability, some of these factors such as climate have temporal variability, which causes the spatial pattern of crop yield to vary from season to season. The optimal choice of PA over uniform farm management requires a sound understanding of such temporal variability, and is well framed by Whelan et al. (Whelan and McBratney, 2000) as a "null hypothesis" for precision agriculture i.e. "Given the large temporal variation evident in crop yield relative to the scale of a single field, then the optimal risk aversion strategy is uniform management". The degree of variability, and whether PA can be technically and economically beneficial to manage the variability, are the most important issues to be considered (Jochinke et al., 2007). Hence, SSCM requires a comprehensive understanding of both spatial and temporal variability in crop growth.

In Mediterranean environments like South Australia, yield variability of rain-fed crops is often controlled by soil water availability. The soil property Plant Available Water-holding Capacity (PAWC) explains a high degree of intra-field spatial variability (Oliver et al., 2006, Oliver et al., 2009, Rab et al., 2009). Hence, it is suggested as a basis for management zone delineation (Oliver et al., 2006). However, the impact of PAWC on crop yield is highly determined by the seasonal rainfall. For example, high PAWC soils in dry seasons may have small differences in yield compared with low PAWC soils, as they rarely filled to their capacity. On the other hand in years with good opening rains, but with decreasing water availability during the growing season, large differences in yield may occur between high and low PAWC soils. In such way, soil PAWC interacts with the seasonal rainfall and controls the spatial and temporal crop yield variability.

While delineation of agricultural management zones vary in terms of the information used, it is generally based on soil and other yield determining factors (Corwin, 2013), with crop yield data often the primary source of information. However, interpreting the temporally variable pattern of multi-year yield maps and making use of them for PA purpose is a challenging task for farmers. Researchers have developed a number of different approaches to analyse multiple year yield data. The use of spatial and temporal variograms, where the semi variance is a function of spatial lag and temporal lag (McBratney et al., 2007, Florin et al., 2009), and development of spatial trend and temporal stability maps (Blackmore et al., 2003, Gunzenhauser and Shanahan, 2011) are two examples of approaches for interpretation of multiyear yield data. However, the availability of multiple year yield data, representing variable climatic conditions, has also been identified as a limitation (Kaspar et al., 2003, Kaspar et al., 2004, Gunzenhauser and Shanahan, 2011). As an alternative approach, a few studies have used remote sensing technology to observe spatial crop yield variability (Abuzar et al., 2004, Anwar et al., 2009).

Remote sensing vegetation indices have potential to assess crop growth variability by quantifying relative growth and health condition of the crop. The Normalized Difference Vegetation Index (NDVI) is one of the most widely used indices to quantify vegetation vigour from the spectral reflectance of vegetation. NDVI has been used for many crop-monitoring applications (Smith et al., 1995, Abuzar et al., 2004, Mkhabela et al., 2011, Lyle et al., 2013). In precision agriculture, NDVI has been used as a surrogate for crop yield for SSCM zone delineation (Basso et al., 2001, Abuzar et al., 2004, Buttafuoco et al., 2015). While single images are useful for yield estimation, the inter-annual growth variability resulting from soil-climate interaction can produce spurious results depending on the image date selection (Maynard and Levi, 2017). Multi-temporal NDVI, on the other hand, provides an additional temporal dimension to uncover the vegetation dynamics. Remote sensing phenology estimates phenological growth stages including the start of season and end of season from multi-temporal vegetation index data (Reed et al., 2009, Araya et al., 2016). The derived metrics may not necessarily correspond directly to conventional, ground-based phenological events, but they provide important information about the vegetation growth dynamics that can be associated with environmental factors such as soil properties [e.g. (Araya et al., 2016, Maynard and Levi, 2017).

The aim of this paper is to explore the potential of remote sensing derived phenological metrics for assessing spatio-temporal growth variability in cropping fields and to understand the soil-climate interactions that strongly influence crop yield. The specific objective of the project was to examine the relationship between spatial and temporal trend of phenological metrics and predefined management zones, in a South Australian cropping field where intra-field variability is strongly attributed to soil PAWC. The approach presented in this paper provides a pathway for future studies in utilizing phenological metrics for management zone delineation.

4.2 Materials and Methods

4.2.1 Study area

The study was conducted in the rain-fed cropping region of South Australia. The region experiences a Mediterranean climate, with hot summers and wet winters with average annual rainfall of approximately 325 mm and average growing season (April-October) rainfall of approximately 241 mm (Bureau of Meteorology, 2017). In this region, sowing starts in late March to May, following sufficient rainfall for seeding. Following seeding, the crop germinates, grows and progressively increases in cover to reach peak greenness in September. The crops ripen and reach senescence in October and harvested in November.

The study site was a field close to Minnipa town, in Upper Eyre Peninsula (Figure 4.1). The field is approximately 65 ha in area, predominantly cultivated for wheat interspersed with some years of barley and pastures. This field was chosen for its soil types, which are representative of those across the wider region. It has also been studied as a focus site for Eyre Peninsula Agricultural Research Foundation (EPARF), where numbers of agricultural research and developmental trials have been undertaken (EPARF, 2014). The field is characterized by sandy loam to sandy clay loam soils, with the land zones of sandy rises reported to perform well in dry years, and shallow flats, which rarely perform well regardless of crop or pasture choice (Latta et al., 2013).

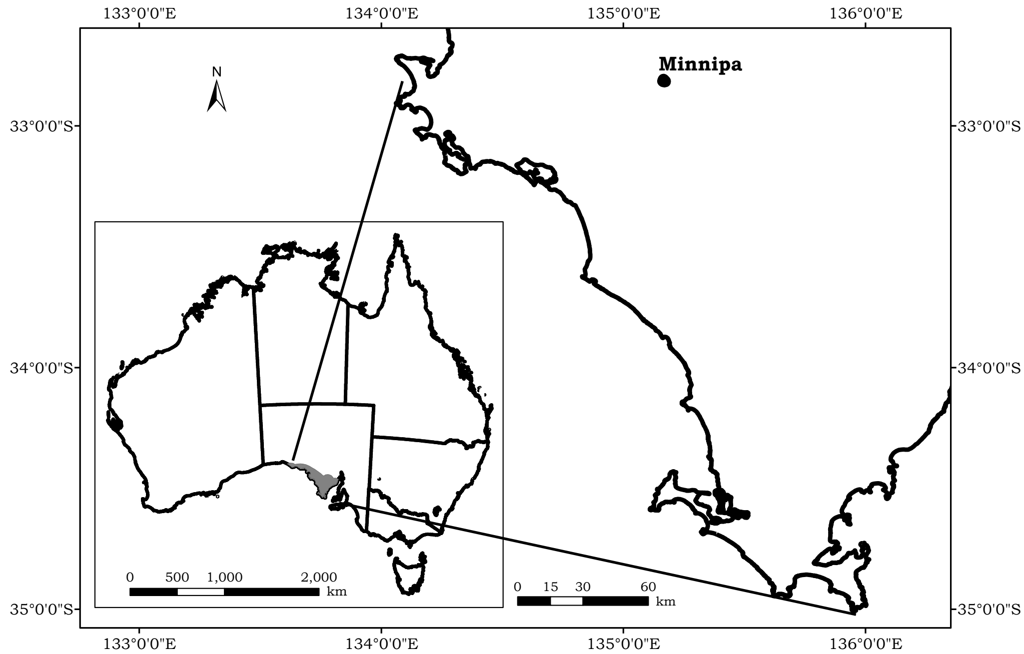

Figure 4.1. *Location map of the study area on Eyre Peninsula, South Australia (Source: Geoscience Australia, 2001)*

4.2.2 Data

4.2.2.1 NDVI

Derivation of crop phenological information from remote sensing imagery requires a high temporal frequency of images. Moderate Resolution Imaging Spectroradiometer (MODIS) is one of the widely used sensors for phenological studies. For this study, we used the 16 days composite NDVI image product (MOD13Q1), which has 250m spatial resolution. The MOD13Q1 product is derived from daily NDVI data using the Constrained View Angle Maximum Value Composite algorithm which extracts the maximum NDVI value for each pixel within each 16 day interval to create a cloud-free composite image (Huete et al., 2002, Vermote et al., 2002, Solano et al., 2010). A total of 345 images between 01/01/2001 and 18/12/2015 were downloaded from NASA Land Processes Distributed Active Archive Center (LP DAAC) website.

Overlaying the farm boundary on the MODIS NDVI image, using ArcGIS 10.2.1 software (ESRI, 2014), the area intersects 17 pixels to varying degrees. In order to minimize signal contamination, only the six pixels with more than 75% of the pixel area lying within the field boundary were considered (Figure 4.2b).

4.2.2.2 Management Zone map

The farm at Minnipa has long been a focus site for research on low rainfall cereal crops (EPARF, 2014). Management zones in this field are well understood and have been delineated on the basis of a long record of scientific observations. The field has been subdivided into three management zones: good, medium and poor, using historic yield data, soil Electro Magnetic survey (EM38) and elevation maps (Latta et al., 2013) (Figure 4.2a). The good zone is characterized by red light sandy clay loam with maximum rooting depth of 80 cm and PAWC of 108 mm. The soil type in the medium zone is red loam with a constrained maximum rooting depth of 60 cm and PAWC of 74 mm. The poor zone, in contrast, has only 40 cm maximum rooting depth with soil type of red sandy clay loam (Minnipa heavy) and PAWC of 57 mm (Latta et al., 2013, The APSIM Initiative, 2017).

Intersecting the MODIS pixel grids with the management zone map, the pixels were assigned management zone values based on their relative area coverage in the zone map, into continuous ranks between 1 (poor zone) and 3 (good zone). For example, a pixel covered 50% by good and 50% by medium zones was assigned the zone value of 2.5, (50/100*3+50/100*2). The resulting management zone values for the pixels range from 2.4 to 1.43. These values do not represent any quantification of management values, rather they intent to rank the relative performance. Figure 4.2b shows the selected six pixels. The management ranks for these pixels are presented in Table 4.1.

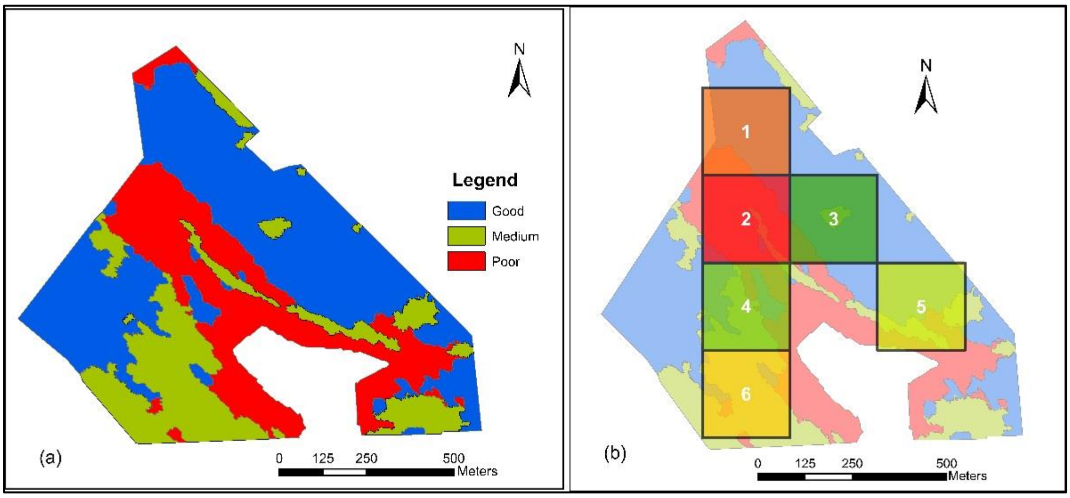

Figure 4.2. *Minnipa farm (a) management zone map (Latta et al., 2013) (b) the 6 selected pixels overlaying the management zone map.*

4.2.3 Analysis

4.2.3.1 Overview of the approach

Figure 4.3 summarizes the steps followed in our analysis. Firstly, the phenological metrics were derived from the MODIS NDVI data, their standard scores were calculated, and then the temporal mean and temporal variance of the metrics were calculated. Finally, the correlation between the management zone values and the spatial trend (temporal mean) and temporal variability (temporal variance) of each of the metrics were assessed.

Table 4.1. *The selected MODIS pixels with the proportion of good, medium and poor zones and their calculated zone values*

	% Good	% Medium	% poor	Zone Value
Pixel 1	53.2	0	25.9	1.86
Pixel 2	16.7	9.9	73.2	1.43
Pixel 3	67.3	9.7	23.0	2.44
Pixel 4	40.1	50.3	9.4	2.30
Pixel 5	45.7	15.9	26.5	1.96
Pixel 6	10.3	79.8	4.1	1.95

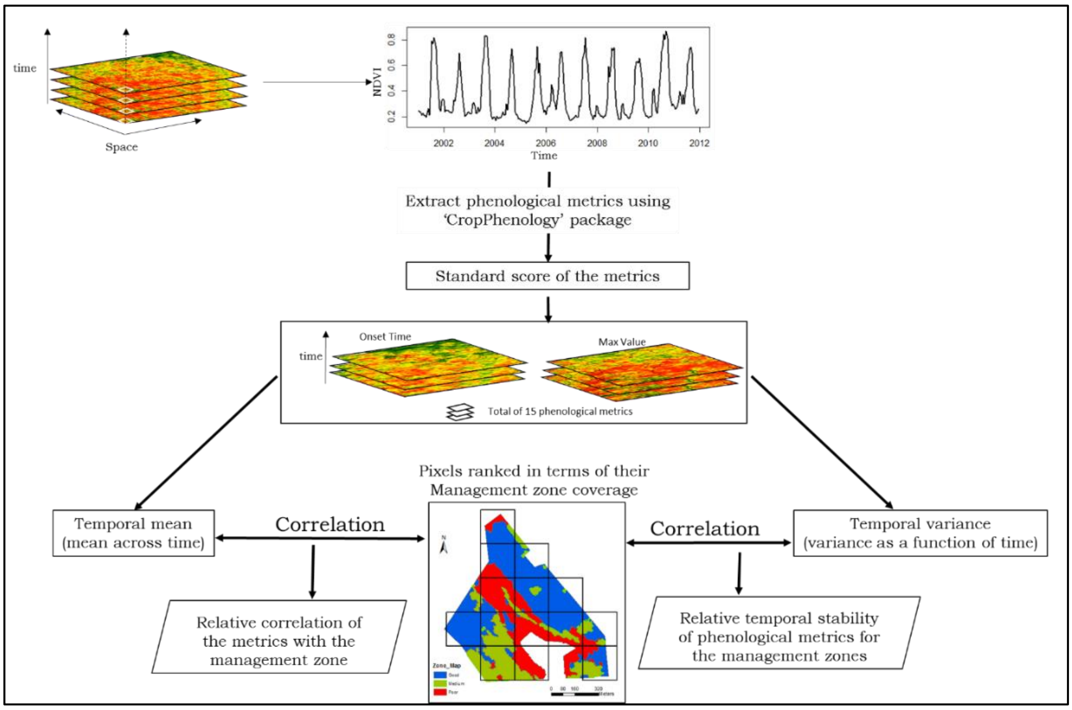

Figure 4.3. *Conceptual workflow of the analysis*

4.2.3.2 Extraction of phenological metrics

The phenological metrics were extracted using 'CropPhenology' package (Araya et al., 2017), in the R software environment (The R core team, 2015). Figure 4.4 shows how the phenological metrics are defined on the NDVI growth dynamic curve. The inferred physiological descriptions of the defined metrics are summarized in Table 4.2. The PhenoMetrics function of the CropPhenology package takes the time series of MODIS NDVI imagery and the boundary shape file of the study area and provides outputs of 15 phenological metrics in raster file format.

Table 4.2. *Description of phenologic metrics and their relation to yield*

Metrics	Definition on NDVI curve and Physiological description
OnsetT	The NDVI value at the start of the growth, seedling
OnsetV	The time when Onset is achieved
MaxV	The maximum NDVI value in the season
MaxT	The time when the MaxV attained, anthesis growth stage
OffsetV	The NDVI value at the end of the season
OffsetT	The time when Offset attained, senescence growth stage
LengthGS	The length of growing season
BeforeMaxT	The length of time between Onset and MaxV
AfterMaxT	The length of time between MaxV and Offset
GreenUpSlope	The rate of increase in NDVI value between Onset and MaxV
BrownDownSlope	The rate of decrease in NDVI value between MaxV and Offset
TINDVI	The area under the NDVI curve between Onset and Offset
TINDVIBeforeMax	The area under the NDVI curve between Onset and MaxV
TINDVIAfterMax	The area under the NDVI curve between MaxV and Offset
Asymmetry	The difference between BeforeMaxTINDVI and AfterMaxTINDVI

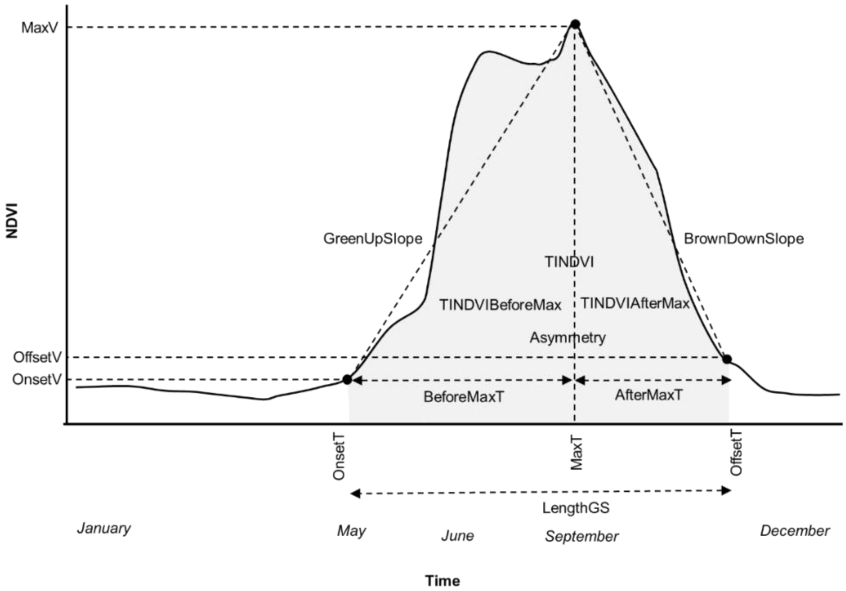

Figure 4.4. *Illustration of NDVI dynamics and phenological metrics*

For the relative values at a given pixel to be comparable across time, we normalized the values relative to the mean of the field, using the standard score (Equation (4.1)). The standard score value at the given pixel indicates how the pixel value deviates from the field mean in the measure of the standard deviation. Accordingly, we calculated the pixel's standard score for each phenological metrics. Blackmore et al. (2000) have used similar standardization to compare the relative yields among different crops.

The standard score of the metric values for each pixel was calculated as follows:

$$\text{Standard score}_{ijk} = \frac{(\text{Value}_{ijk} - \text{mean}_{jk})}{\text{sd}_{jk}} \quad \text{.................... (Equation 4.1)}$$

Where Standard score_{ijk} is a standard score value of metric K, at pixel i for year j, Value_{ijk} is the value of metric k at pixel i for a year j, mean_{jk} and sd_{jk} is the mean and standard deviation of the metric k across all pixels of year j.

4.2.3.3 Spatial trend and temporal variability of phenological metrics

Spatial trend map

The temporal mean was calculated as the average metric value, at a pixel, over the year of interest (Equation (4.2)). It is adapted from Blackmore (2003), who used it for spatial yield trend mapping. The spatial trend map of a metric shows the spatial variability of the average value of the metric across observation years. A total of 15 spatial trend map were created for the 15 metrics.

The temporal mean of a pixel is calculated as:

$$\text{Temporal mean}_{ik} = \frac{\sum_{j=2015}^{j=2001}(standard\ score\ _{ijk})}{n} \quad \text{................} \quad \text{(Equation 4.2)}$$

Where Temporal Mean_{ik} is the mean value of phenological metric k for the pixel i, standard Score_{ijk} is the standard score value for phenological metric k at of pixel i on year j, and n is the total number of observation year.

Temporal variability map

The temporal variability map was created using the temporal variance over the observation years, adopted from (Blackmore et al., 2003). Temporal variability is classified into two categories: inter-year variability and relative temporal variability (Blackmore et al., 2003). Inter-year variability is the temporal variability caused by the change in annual rainfall, which affects the overall productivity of the field. The second category described how each part of the field behaved relative to the other parts from year to year. In this analysis, we are interested in second category, which assess the relative variability of growth at particular pixel, over the study period. This relative temporal variability was calculated using a temporal variance, a modified variance measured in a function of time (Whelan and McBratney, 2000, Blackmore et al., 2003) (Equation 4.3). The temporal variance of all metrics was calculated for each pixel across years, to form 15 temporal variability maps, for the 15 metrics. The temporal variance of each metric across the season revealed the temporal variability of the growth conditions at the various phenological stages. The calculated temporal variance has low values if the pixel is stable over time and often has values close to the mean of the observation seasons. On the other hand, if the metric is temporally unstable, with high values in some years and low values in others, its temporal variance will be high.

The temporal variance was calculated as

$$\text{Temporal variance}_{ik} = \frac{\sum_{j=2001}^{j=2015}(standard\ score\ _{ijk} - Temporal\ mean_{i})}{n-1} \quad \text{.....(Equation 4.3)}$$

Where Temporal Variance_{ik} is the temporal variance at pixel i of metric k, standard score_{ijk} is the standard score of metric k at pixel i for year j, temporal mean_{i} is the temporal mean of for pixel i and n is the number of observation year.

4.2.3.4 *Relationship between management zone and trends of phenological metrics*

In this study, the monotonic relationship between the management zone values and the trends of the 15 phenological metrics were assessed. Spearman rank correlation was used to test the relative direction and strength of the relationship between the management zone pixel values and phenological metrics, in R computing environment. Spearman correlation ranks the variables and provides the correlation coefficient, rho (ρ) that indicates the strength of the correlation (Wilcox, 2009).

4.3 Results and Discussion

4.3.1 *Relationship between management zone and spatial trend of phenologic metrics*

The Spearman rank correlations between management zone and the spatial trend of phenological metrics are shown in Table 4.3. In this analysis, we have undertaken multiple tests on a single dataset. This can introduce the probability of making type I errors, family wise error rate (FWER). To address this problem, we used the Bonferroni correction that adjusts the significance level (*p*-value) (Armstrong, 2014), by dividing the *p*-value by the number of comparisons made, which results a new *p*-value of 0.0333.

The results indicate that the spatial trend of Max Value is significantly correlated with the management zone values ($\rho(13) = 0.82$, $p\text{-value} = 0.024$). Although the associations are not significant, the GreenUpSlope and MaxT showed high correlation coefficients, with different directions of association. The Asymmetry, TINDVIBeforeMax and BeforeMaxT metrics also showed moderate association with the management zone values.

Table 4.3. Spearman correlation coefficient and statistical significance (p value) of the relationship between temporal mean of phenologic metrics and the management zone

Metrics	rho (ρ)	*p*-value
OnsetV	-0.214	0.662
OnsetT	-0.365	0.236
MaxV	0.821	0.024
MaxT	0.763	0.2357
OffsetV	-0.143	0.783
OffsetT	0.286	0.556
LengthGS	0.364	0.139
BeforeMaxT	0.569	0.109
AfterMaxT	0.036	0.964
GreenUpSlope	-0.763	0.2357
BrownDownSlope	-0.179	0.7131
TINDVI	0.346	0.139
TINDVIBeforeMax	0.587	0.134
TINDVIAfterMax	0.036	0.964
Asymmetry	0.607	0.167

This result corroborates previous observations that have recognized the ability of NDVI to estimate crop yield (Tucker et al., 1980, Quarmby et al., 1993, Doraiswamy et al., 2005). Although strong associations between NDVI and yield have been reported at differing stages during the growth period, these dates are mostly around heading and flowering stages (Smith et al., 1995, Shanahan et al., 2001, Abuzar et al., 2004, Schut et al., 2009, Mkhabela et al., 2011, Tagarakis et al., 2012, Lyle et al., 2013, Peralta et al., 2016). As crops often attain their maximum NDVI close to heading and flowering stages (Sakamoto et al., 2005), the high association of MaxValue with the management zone can be directly linked to these observations.

The results also show trends of increasing Max Time and decreasing of GreenUpSlope, moving from the poor to good management zone. As the soil PAWC strongly relates with yield potential in South Australia, the observed relationship is likely be related with water availability. Numbers of researchers reported that water stress has a strong influence on crop growth stages with evident observation of faster growth to the next growth stages in water stressed crops. Under similar climatic conditions, plants in low PAWC soils will likely to face water stress between rainfall events, as there is less water stored in the soil profile compared with the high PAWC soils. The early Maximum (low MaxT) can then be related to the hasten growth of the crop to anthesis due to water stress in the poor zone (Angus and Moncur, 1977, McMaster et al., 2005, Araya et al., 2013, Araya et al., 2016). This is also reflected as faster rate of greenness, higher GreenUpSlope, in low PAWC soil.

Similar observations of low Max Time and high GreenUpSlope were observed in our previous study (Araya et al., 2016). Unlike our current approach of averaging values across the years, the previous study considered paired comparison of pixels across number of years. The pared comparison study showed higher Max Values in low PAWC soils than the high PAWC soils. Such pattern of paired comparison observed in the previous study may average out thorough the observation years, in the current study, to reflect average higher Max Value for higher PAWC soils.

The positive moderate association of Asymmetry, TINDVIBeforeMax and BeforeMaxT metrics, indicated that the good zones have higher values of these metrics than the poor zone. Generally, this observation shows that the good zone experienced longer time before the NDVI peak, higher area under the curve between the Onset and Maximum NDVI, and higher difference between TINDVIBeforeMax and TINDVIAfetrMax than poor zone. These differences are related with the high and late NDVI peak in the good zone than the poor zone, which is explained above. Furthermore, the trend of TINDVIBeforeMax in our analysis agrees with previous field studies that confirm the strong association of pre-anthesis growth with yield potential, as it is the time when the number of grains are determined (Poole and Hunt, 2014).

4.3.2 Relationship between Management Zone and Temporal Variability of Phenological Metrics

The seasons considered in this study, 2001 – 2015, were characterized by variable rainfall amount and seasonality. The temporal variance of the phenological metrics measures the relative variability of the metrics across the variable rainfall. The Spearman correlation analysis assessed the trend of temporal variability of phenological metrics across management zones (Table 4.4).

Table 4.4 Spearman correlation coefficients and statistical significance (p value) of the relationship between temporal variability of phenologic metrics and the management zone.

Metrics	rho (ρ)	*p*-value
OnsetV	0	1
OnsetT	0.143	0.783
MaxV	0.214	0.662
MaxT	-0.214	0.662
OffsetV	-0.357	0.44
OffsetT	-0.786	0.048
LengthGS	0.393	0.396
BeforeMaxT	-0.286	0.556
AfterMaxT	-0.321	0.498
GreenUpSlope	-0.25	0.595
BrownDownSlope	-0.286	0.556
TINDVI	0.857	0.018
TINDVIBeforeMax	0.071	0.906
TINDVIAfterMax	0.071	0.906
Asymmetry	-0.214	0.662

The results indicate that the temporal variability of TINDVI has a significant positive correlation with the management zone, indicating an increase of temporal variability from poor to good management zones. This variability demonstrates the interaction of the spatial soil variability with the temporal rainfall seasonality. In good seasons, the spatial variability of soil PAWC becomes significant, as the high PAWC soils store more water than the low PAWC soils. However, in dry seasons there will be less difference in stored water between the contrasting soils. This results in larger spatial variability in good seasons compared with dry seasons(Oliver et al., 2006, Wong and Asseng, 2006). Temporally, the good zone with high PAWC soil will have higher variability across variable seasons than the poor zone with low PAWC soils (Wong and Asseng, 2006).

Previous research has reported that TINDVI can be a good indicator for crop production (Tucker et al., 1980, Hill and Donald, 2003, Mkhabela et al., 2011). However, the sensitivity of TINDVI for crop production depends on rainfall seasonality; it can be a good indicator for crop production when water is the limiting factor for crop growth (Hill and Donald, 2003). Considering the profound correlation between TINDVI and yield in cropping fields, the high temporal variability in TINDVI in good zone than in poor zone coincide well with the yield data observation in the study area. Yield data from EPARF research shows higher difference in good zone (3.1t/ha) between the dry year 2008 and the wet year 2010 than the poor zone (2.13t/ha) (Paterson et al., 2011, Latta et al., 2013).

The relationship between the temporal variability of MaxV and the management zone showed weak correlation. We have observed in the previous section that the spatial trend (temporal mean) of this metrics showed a strong correlation with ranks. The low correlation of temporal variability with the management zone can be interpreted as both the good and poor zones are variable to a similar degree with the higher mean values from good zone than the poor zone. Thus, the MaxV metrics is sensitive to spatial yield variability than temporal variability; on the other hand, TINDVI better reflects the temporal yield variability.

4.3.3 Summary of Indicative Phenological Metrics for Crop Field Management

Generally, our analysis demonstrates the potential of phenological metrics to recognize the intra-field crop growth variability and to provide a comprehensive understanding of soil-climate interactions. Single vegetation index images have been successfully utilized to recognize yield variability across a crop field (eg . Abuzar et al., 2004). However, the single image approach has been criticized for lacking information on intra-seasonal growth dynamics (Maynard and Levi, 2017). On the other hand, multi-temporal images and the derived phenological metrics uncover the intra-annual biophysical properties of the crop across the field, as driven by soil-climate interaction. This potentially provides a better understanding of both inter-annual and intra-annual variability, which is a key factor to improve management practices.

Furthermore, the method presented in this analysis show the efficacy of phenological metrics to recognize crop growth variability without demanding accumulated multi-year yield data. Considering the increasing availability of remote sensing imagery, the spatio-temporal variability estimation using phenological metrics can provide valuable information for PA suitability assessment in areas where there is limited availability of yield data.

Currently, MODIS is the most appropriate imagery for such analysis due to its high temporal resolution. However, its coarse spatial resolution limits the application of this method to broad acre cropping. The technology of integrating the higher spatial resolution of sensors such as Landsat or Sentinel with the temporal resolution of MODIS to generate high temporal/high spatial resolution datasets (Gao et al., 2017) may allow future application for smaller fields. Whilst these fused spatio-temporal datasets are presently not available to the public at broad extents, once available, may be utilized at a scale typical for yield mapping in precision agriculture today. In such a way, this paper provides a basis for further analysis to utilize phenological metrics for crop management support systems.

4.4 Conclusions

In this study, the spatial and temporal variability of crop growth was assessed using remote sensing phenological metrics in relation to the relative yield potential of sites in the field. Phenological metrics provide information about the temporal and spatial variability of plant growth across cropping fields. Our study demonstrates the potential of satellite based phenological metrics to provide information about site conditions relevant for management zone delineation. The results of our analysis show that Time-integrated NDVI reflects seasonal effect on crop growth, whereas the magnitude of NDVI peak strongly reflects the soil quality and showed spatial variability of long-term site conditions across the field.

Crop yield response to PAWC is strongly influenced by the amount and seasonal distribution of rainfall, which is temporally variable. The effect is stronger when there is sufficient rainfall to fill the soil profile at the start of the season and the plants are dependent on deep stored soil-water as the season progresses. Phenological metrics provide comprehensive insight of the spatio-temporal crop growth variability across the variable seasons, which advances our understanding of soil-climate interaction across the cropping field.

The method presented here provides a pathway towards better estimation of spatio-temporal variability, which is vital for PA success. It can be used to develop future, more detailed studies to fully utilize the potential of phenological indicators for site characterization through unravelling the complex spatio- temporal soil-climate interactions.

4.5 Acknowledgements

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Chapter 5

Spatial Estimation of Plant Available Water-holding Capacity using phenological indicators

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Principal Author

Name of Principal Author (Candidate)	Sofanit Araya		
Contribution to the Paper	Development and conceptualisation and realisation of the research, collected and organized data, undertaken analysis and interpreted results, wrote manuscript.		
Overall percentage (%)	85		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	5-10-17.

Co-Author Contributions

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

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

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

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

Name of Co-Author	Bertram Ostendorf		
Contribution to the Paper	Supervised development of the research, assisted statistical analysis and interpretation and evaluated manuscript.		
Signature		Date	13-9-17
Name of Co-Author	Megan Lewis		
Contribution to the Paper	Co-supervised development of the research and evaluated manuscript		
Signature		Date	25/9/17
Name of Co-Author	Gregory Lyle		
Contribution to the Paper	Co-supervised development of the research, assisted interpretation of the result and evaluated manuscript		
Signature		Date	26/9/17.

Abstract

Plant Available Water-holding Capacity (PAWC), the measurement of the maximum amount of water that can be stored in the soil for plant use, is one of the key factors influencing crop growth in Mediterranean rain-fed farming systems. The conventional PAWC measurement method is expensive and time-consuming and hence, is impractical to satisfy the increasing demand for high-resolution PAWC spatial data using the conventional methods. To overcome this problem digital soil mapping techniques use surrogates and pedotransfer functions to predict PAWC. However, these methods are limited in their ability to map PAWC variability within the mapping units. Moreover, high uncertainty has been reported due to poor sampling density. This study addresses the need for an alternative approach to create detailed spatial estimations of PAWC.

Remote sensing imagery is commonly used in digital soil mapping to infer soil properties. Soil PAWC has strong interaction with temporally variable climatic factors to change vegetation response both spatially and temporally. Hence multi-temporal vegetation indices that quantify inter-annual and intra-annual vegetation change may be better suited to infer this indicator. Phenological metrics derived from multi-temporal vegetation indices have been widely used as effective summaries of vegetation response to climate. In this study, the suitability of phenological metrics for spatial estimation of soil PAWC is assessed. The study was conducted in the South Australian Agricultural region, which is typified by Mediterranean climate.

Firstly, phenological metrics were extracted from Moderate Resolution Imaging Spectroradiometer (MODIS) NDVI data, at 250m spatial resolution and 16 days temporal resolution, for 15 seasons (2001 – 2015). And then, a linear mixed effect model was developed to assess the relationship between the phenological metrics and PAWC measurements, at point locations dispersed across the study area. The model was tested for spatial prediction of PAWC across the study area. Then, the predicted PAWC map was verified by assessing its correspondence with the broad scale soil-landscape PAWC map. The phenological metrics Maximum NDVI, Time of Maximum NDVI, and Offset Value were strongly correlated with PAWC. The model predicted PAWC map showed good agreement in spatial pattern with fair correspondence in values with the soil-landscape PAWC map, with overall accuracy of 52%. The predicted map shows distinct variability within soil map units, which is impossible to assess from soil sampling or through soil-landscape mapping. Most importantly, the pattern in the predicted map is not influenced by agricultural management boundaries. This study demonstrates the strong potential of remote sensing derived phenological metrics as spatial indicator for soil PAWC and provides unprecedented spatial detail for digital soil mapping at broader spatial scales. Thus, it narrows the gap between regional modelling and farm based management models.

Keywords: PAWC, Phenological metrics, remote sensing, Digital Soil Mapping, MODIS, NDVI

Highlights:

- Remote sensing derived phenological metrics are potential indicators of soil PAWC.
- Spatial estimation of PAWC using phenological metrics is a promising approach.

5.1 Introduction

Regions with Mediterranean climate produce about 10% of the world's grain production (Acevedo et al., 1999). This climate is defined by its low, winter dominant rainfall and plant growth is strongly dependant on water stored in the soil (Arnfield, 2016). Rain-fed cropping in these regions are susceptible to climate change and future climate variability is a major cause of concern (Huang et al., 2016, Yang et al., 2016, Schlaepfer et al., 2017). Plant Available Water-holding Capacity (PAWC) of the soil is a critical indicator for plant growth in water limiting climates as it determines the maximum water that can be readily extracted by plants. In rain-fed cropping systems, differences in PAWC can explain a large proportion of yield variability (Oliver et al., 2006, Wong and Asseng, 2006). PAWC is a key indicator influencing the complex crop responses to climate (Wong and Asseng, 2006, Lawes et al., 2009, Wang et al., 2009). As such, maps of soil conditions are essential variables in spatially explicit climate impact studies for sustainable agricultural practices (Wang et al., 2009, Yang et al., 2014, Yang et al., 2016).

Adequately mapping the distribution of soil properties is a difficult task because of their high spatial variability and the challenge of choosing a representative field sample for soil analysis. (McBratney et al., 2003, Grunwald et al., 2011). This has led to the use of surrogates or pedotransfer functions (Hong et al., 2013, Ugbaje and Reuter, 2013) to assess the spatial pattern of soil conditions. In particular, PAWC is difficult to assess because it involves drying and rewetting of soil samples (Burk and Dalgliesh, 2013). At a field scale, spatial yield data has improved models of PAWC (Florin et al., 2010). At the regional scale, mapping of PAWC could be enhanced by including topographical variables (Malone et al., 2009, Poggio et al., 2010, Padarian et al., 2014). However, these regional approaches have used existing soil maps and have had low success in mapping PAWC spatial variability within the mapping units (Hong et al., 2013, Grundy et al., 2015, Viscarra Rossel et al., 2015). High uncertainty was also reported because of limited sampling density (Padarian et al., 2014). Although there is increasing need for spatial data of PAWC is becoming increasingly more important, reliable spatial information of this critical soil indicator for plant growth processes is lacking.

Remote sensing methods have been employed to directly infer soil characteristics from surface reflectance of multispectral imagery (Metternicht and Zinck, 2003, Boettinger et al., 2008), thermal imagery (Yang et al., 2015) and hyperspectral imagery (Summers et al., 2011). These methods are limited to small spatial extents. Furthermore, the surface conditions may not be indicative of soil conditions throughout the soil profile (Rossel et al., 2010). In particular, PAWC is a soil property that integrates over the entire rooting depth of plants. Hence indirect methods that assess vegetation conditions may be better suited to infer this indicator.

Remote sensing has long been used to quantify vegetation condition using vegetation indices such as the Normalized Difference Vegetation Index (NDVI) (Tucker et al., 1980). Single images of remote sensing vegetation indices are commonly used in digital soil mapping (Sharma et al., 2006, Kim et al., 2012, Levi and Rasmussen, 2014) . However, mapping soil properties like PAWC that interact with climate demands multiple observations to understand soil modulation of vegetation response to climate variability. Hence, multi-temporal vegetation index data can potentially quantify inter-annual and intra-annual vegetation changes from which such soil properties may be inferred.

Multi-temporal vegetation indices have been used to derive phenological indices as effective summaries of vegetation response to climate (Reed et al., 2009, Henebry and de Beurs, 2013). Sensors that provide vegetation indices at sufficient temporal resolution to evaluate phenological changes include Advanced Very High Resolution Radiometer (AVHRR) (Reed et al., 1994, Hermance et al., 2007, Colditz et al., 2008), and Moderate Resolution Imaging Spectrometer (MODIS) (Zhang et al., 2003, Sakamoto et al., 2005, Hmimina et al., 2013, Ma et al., 2013).

The time series of vegetation indices plotted across time creates a curve that summarizes the growth dynamics of the plant. The curve can be systematically analysed to extract metrics that indicate growth dynamics at the particular season. Some of these metrics are: *onset of greenness; offset of greenness; maximum NDVI;* and *time of maximum NDVI*. Although these metrics may not be directly comparable to the ground-based phenological events, they provide a very important indication of growth factors (Reed et al., 2009, Araya et al., 2016). Remote sensing derived phenological metrics have been widely used in many crop related studies including estimation of biomass (Hill and Donald, 2003), crop yield forecast (Bolton and Friedl, 2013), crop type mapping (Zhong et al., 2011, Foerster et al., 2012). In soil studies, remote sensing phenology has been used for detection of soil salinity (Zhang et al., 2015) and soil capability mapping (Li et al., 2012). Remote sensing phenology has also been used for estimation of soil texture (Maynard and Levi, 2017) and PAWC (Araya et al., 2016) at field level.

The aim of this study was to evaluate the suitability of phenological metrics as an indicator for spatial prediction of soil PAWC across broad spatial scales. The objectives were to define the empirical association of remote sensing derived phenological metrics with existing PAWC estimates in the agricultural region of South Australia. The specific objectives were to:

(1) develop a regression model to evaluate the relationship between PAWC and remote sensing phenological metrics at locations where there are PAWC measurements; and

(2) estimate the spatial pattern of PAWC at the broad scale and corroborate the estimates with landscape-scale soil maps.

5.2 Materials and Methods

5.2.1 Study area

The study was conducted in the cropping region of South Australia (Figure 5.1). This region is characterized by dry hot summers, wet cold winters, and variable rainfall (Lennartson, 2005). The average minimum and maximum rainfalls are 205 mm and 625 mm, respectively (Bureau of Meteorology, 2017). Wheat and barley are the predominant grains growing in the region (PIRSA, 2017).

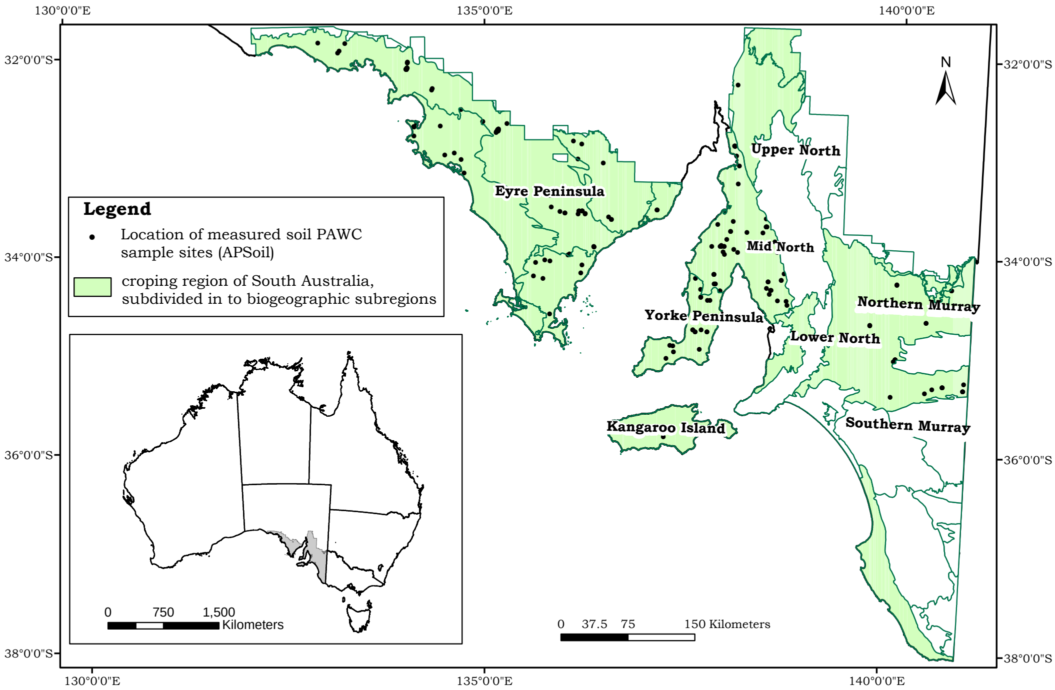

Figure 5.1. *Map of the extent of the South Australian agricultural region with biogeographic subregions and major cropping district names. The locations of measured soil PAWC sample sites are also shown across the region.*

5.2.2 Overview of the approach

The workflow of the study is illustrated in Figure 5.2. Firstly, the maps of phenological metrics were extracted from MODIS NDVI images using CropPhenology R package (Araya et al., 2017). Secondly, the regression model was developed to estimate PAWC using the derived phenological metrics, rainfall data and soil PAWC measurement points. Thirdly, the spatial PAWC map of the study area was estimated. The model was visually and quantitatively verified by comparing the predicted PAWC map with the landscape-scale PAWC map of the study area. In order to assess the degree of agreement between the predicted PAWC map and the existing landscape-scale map, the uncertainty between the landscape-scale PAWC map and the soil data used for calibrating our model was assessed.

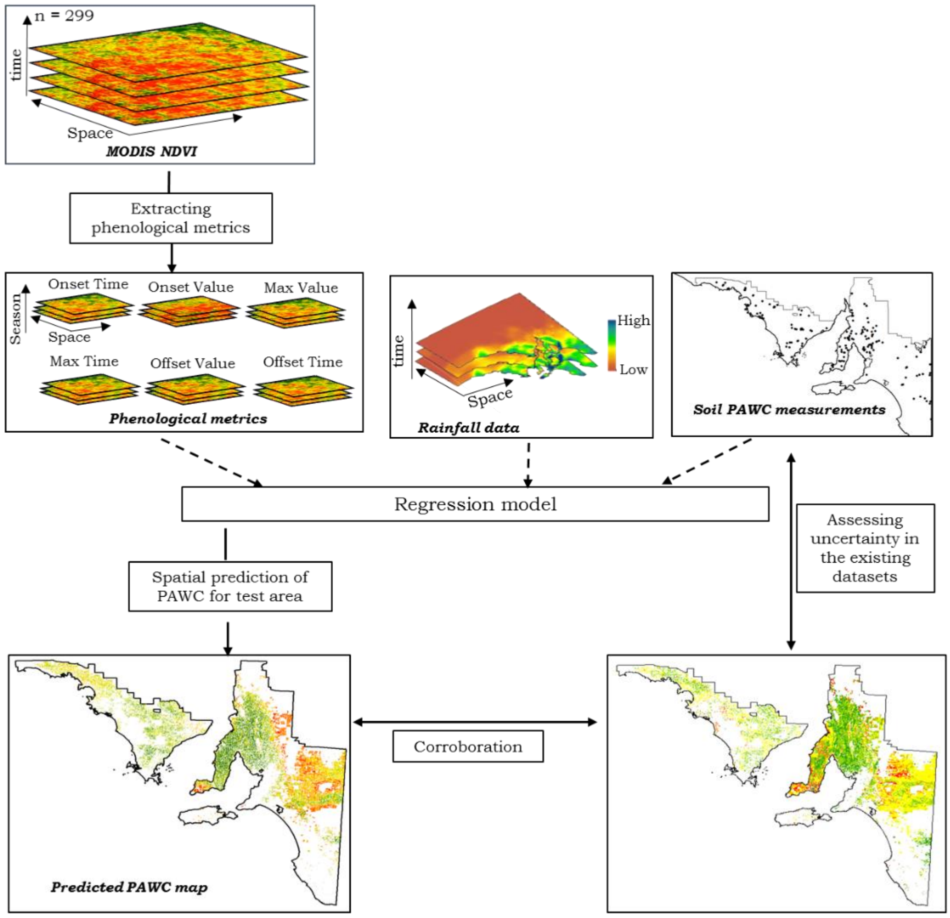

Figure 5.2. *Overview of the approach taken in this study: dashed arrow show inputs, solid arrows show direction of the analysis, and double arrows show comparisons.*

5.2.3 Data

5.2.3.1 Soils

APSoil PAWC measurements

APSoil is a point-based dataset of soil PAWC measurement for representative soil profiles (Dalgliesh et al., 2012). The APSoil database is accessible as a standalone product from the Agricultural Production Systems sIMulator (APSIM) website (The APSIM initiative, 2015) or from Australian Soil Resource Information System (ASRIS) website (CSIRO Land and Water, 2013). PAWC is defined in the APSoil database as the maximum soil water available to be extracted by plants and is calculated from field measurement or laboratory soil analysis. The practical information and the methodologies of field PAWC measurement are well documented by Burk et al. (2013).

APSoil allows the user to create modified soil profiles from the existing database to fit local conditions. However, local knowledge and soil-landscape information are required to identify the appropriate soil type from the database (Dalgliesh et al., 2012, Verburg et al., 2015) and spatial extrapolation to the area of interest from dispersed point measurements cannot give reliable results. For our analysis, we used the 232 available PAWC measurements from APSoil database, located sparsely across the study area and with values ranging between 14 and 282 mm (Figure 5.1).

Soil Landscape Map of South Australia

In South Australia, the most comprehensive documentation of spatial soil information is the Soil Landscape Map of South Australia, presented at the scale of 1:100,000 (Hall et al., 2009). It shows the distribution of 40 soil attributes including surface soil texture, Available Water Holding Capacity (AWHC), and soil type. Although this soil data has a wide range of soil attribute information to provide a strong foundation for regional-level resource management and decision-making, it has been criticized for its inadequate resolution for farm-scale management decisions (Summers et al., 2011).

The AWHC attribute was calculated on a regional basis using the available water holding capacity estimated for different soil texture classes adapted from previous studies (Dent, 1981). The total AWHC is defined as the sum of the capacity of each layer in the profile and is therefore directly comparable with the PAWC estimates in the APSIM database. Based on this calculation, the South Australian agricultural region was classified into five AWHC classes: Class 1 (more than 100 mm); Class 2 (70-100 mm); Class 3 (40-70 mm); Class 4 (20-40 mm); and Class 5(less than 20 mm). The South Australian agricultural region is largely covered by Class 2 and Class 3 soil landscape units. Class 5 and Class 4 appear mainly in the western Eyre Peninsula and lower Yorke Peninsula regions, whereas Class 1 occurs in the central north and lower east parts of the region. The soil-landscape map for attribute AWHC was used in this analysis and is referred to as landscape-scale PAWC map throughout this paper.

5.2.3.2 Rainfall

The daily rainfall data were downloaded as raster images of 5 km spatial resolution (Bureau of Meteorology, 2017). The cumulative growing season rainfall for the period between April and October was extracted for each of the APSoil measurement locations across the South Australian agricultural region. Across the APSoil locations, the lowest growing season rainfall was around 100 mm, reported in 2006 and 2012, and the highest was around 450 mm, reported in 2013.

5.2.3.3 Agricultural farm boundary data

To distinguish cropping fields from native vegetation, a farm boundary and detailed land cover map of the region was needed. However, this did not exist at the regional scale. We used the generalized land use map of the region, which is publicly available through the 'Data SA' portal (South Australian Government, 2017). This land use spatial layer is derived from property cadastre and land use data of the state (Department of Planning Transport and Infrastructure, 2016). For this analysis, we extracted only the agricultural fields and masked out the non-cropping and native vegetation regions.

5.2.3.4 Biogeographic subregion boundary data

The Interim Biogeographic Regionalisation for Australia (IBRA) classifies the land surface of Australia based on combination of major environmental factors that influence vegetation growth (Thackway and Cresswell, 1995, Environment Australia, 2000). In this project we used the subregion boundaries from the IBRA dataset to classify the soil PAWC measurement sites into regions of similar climatic and geographic regions. The data was downloaded from Australian Government, Department of Environment and Energy web site http://www.environment.gov.au/. Using the biogeographic subregions of IBRA we subdivided our study area into eleven subregions, with variable number of PAWC soil sample sites in each (Figure 5.1)

5.2.3.5 Phenological metrics derived from MODIS NDVI

We used the 16 days MODIS NDVI composite (MOD13Q1) for phenologic metric calculation. The 16 days NDVI composite (MOD13Q1) is one of the MODIS vegetation products computed from the daily NDVI data using algorithms to choose the best pixel value from all the acquisitions during the 16 days period to avoid cloud, heavy aerosols and water effects (Didan and Huete, 2006, Didan, 2015). This product has a spatial resolution of 250 m and is freely available for download from the National Aeronautics and Space Administration website (NASA, 2017). We downloaded 345 MODIS NDVI images of the region for the period 2001- 2015. The images were then reprojected to the South Australian Lambert projection using MODIS Reprojection Tool (USGS, 2011).

The phenologic metrics were extracted for APSoil PAWC measurement locations, using the 'CropPhenology' package (Araya et al., 2017) in R software environment (The R core team, 2015). The CropPhenology package produces 15 phenological metrics per season. Note that some of the phenological metrics are defined on the basis of the other primary metrics. For example, the length of growing season (LengthGS) is defined as the difference between the Offset Time and Onset Time. Such derived metrics will have linear associations with the metrics defining them and may bias the statistical analysis (Zuur et al., 2010) so, to avoid such collinearity among the variables, the derived metrics were excluded from the model. Hence, only six metrics, Onset Time, Onset Value, Max Value, Max Time, Offset Value, Offset Time, were included in the model (Table 5.1). Figure 5.3 illustrates the NDVI growth dynamics and the major phenological metrics.

Table 5.1. Summary of the six phenological metrics, of CropPhenology package, used in the analysis.

Phenological metric	Description
Onset Value	NDVI value measured at the start of the growth. It is inferred to the seedling growth stage of the crop
Onset Time	MODIS Image acquisition date for Onset Value
Max Value	Maximum NDVI value achieved during the season.
Max Time	MODIS Image acquisition date for Max Value. It is inferred to anthesis physiological growth of the crop
Offset Value	NDVI value measured at the senesce of the crop
Offset Time	MODIS Image acquisition date for Offset value. It is inferred to the maturity physiological stage of the crop

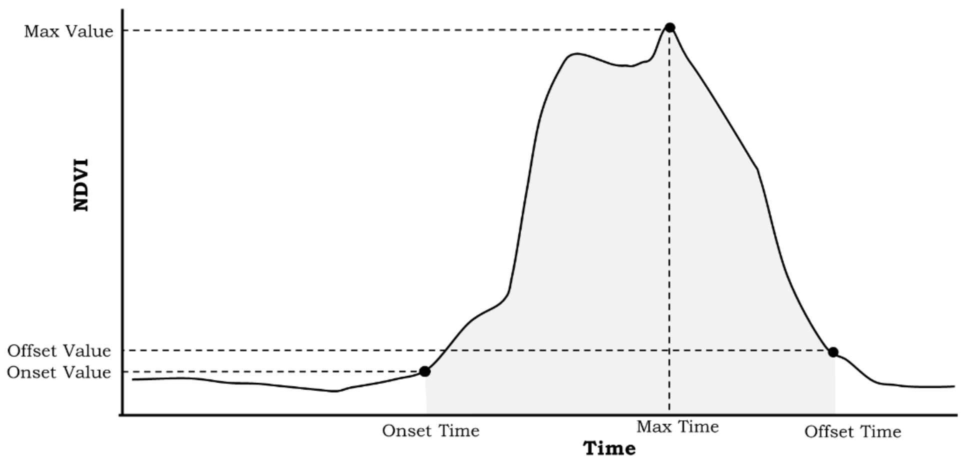

Figure 5.3. *NDVI dynamics curve with major phenological metrics*

5.2.4 Modelling the relationship between soil PAWC and phenological metrics

To assess the relationship between the phenological metrics and the soil PAWC, a multiple linear regression model was developed in R software environment. The model used the six phenological metrics, growing season rainfall, biogeographic subregion and year as explanatory variables, with PAWC as a dependent variable. Firstly, the distributions of the variables were checked for normality using the histogram and normal Q-Q plot. Subsequently, the appropriate transformations were applied to the skewed variables using the ladder of power approach, i.e. going up the ladder to square or cube for left skewed variables; and down the ladder to square root and cube root for right skewed variables (Tukey, 1977). The variables PAWC and Max Value were skewed to the right and left, respectively. Accordingly, PAWC and Max Value were transformed using a cube root and cube transformation, respectively. Secondly, the dependent variables were tested for collinearity using the 'Variance Inflation Factor' (VIF) function from 'Companion to Applied Regression' ('CAR') package (Fox and Weisberg, 2011) in R environment. The 'VIF' values for all the variables were below 3, verifying negligible collinearity among them (Zuur et al., 2010).

Soil has inherent spatial trend resulting from the influence of the soil forming environmental and climatic conditions (McBratney et al., 2003). Typically, soils in high rainfall regions develop to have deeper rooting depth than those in the low rainfall regions. Such spatial correlation may bias the complete spatial randomness assumption of statistical analysis, and hence needed to be addressed (Bivand et al., 2008). Accordingly, the biogeographic subregion were included in the model to address the spatial autocorrelation effect. The soil PAWC sample sites were classified into 11 subregions which were defined based on the regional climate, geology, landform and other environmental factors (Environment Australia, 2000). The spatial autocorrelation of the soil PAWC values under each subregion was tested using Moran's I test (Paradis, 2017) and found to be insignificant ($p>0.05$).

This analysis relates multiple year phenological metrics from the entire time series with a single PAWC observation. This may cause deviation from the independent observations assumption of statistical analysis and result in temporal autocorrelation effects (Waller, 2004). To control the temporal autocorrelation effects, the year was added as a random variable. Thus, the model was redesigned to be a linear mixed effect model with PAWC as the dependent variable and *Onset Time*, *Onset Value*, *Offset Time*, *Offset Value*, *Max Time*, *Max Value,* and *Growing season rainfall* as the fixed factor independent variables and *Year* and *Subregion* as a random factor independent variable. The model was implemented using 'Linear Mixed-Effects Models using 'Eigen' and S4' ('lme4') package (Bates et al., 2015).

To select the best fit model, we used an automated model selection function, 'dredge', from 'Multi-Model Inference' ('MuMIN') package (Barton, 2016) in R software. The 'dredge' function generates a set of models with combinations of variables from the global model and ranks them with the selected information criteria. We ran the 'dredge' function with the global model including all the independent variables and ranking the models using the corrected Akaike Information Criterion (AIC) (Akaike, 1981, Venables and Ripley, 2002, Montgomery et al., 2013). Accordingly, the best model (lowest AIC) included only *Max Value*, *Max Time*, and *Offset Value* variables.

The resulting linear mixed effect model is represented in the Equation 5.1, where j represents a specific APSoil PAWC measurement point, GSRF represents growing season rainfall, Max Value, Offset Value and Max Time representing the phenological metrics derived location j at a *Year* (eg. 2001 – 2015), S representing a dummy variable for 11 subregions and β and a represent the fixed and random effects regression coefficients, respectively and Ɛ represents the error term in the model. The relative effects of the predictor variables to the change in the response variable (PAWC) were assessed by the effects plot using the 'Effects' package (Fox, 2003) in R environment.

$$PAWC_{j}^{\frac{1}{3}} = \beta_0 + \beta_1(Max\,Value_j)^3 + \beta_2\left(Offset\,Value_j\right) + \beta_3\left(Max\,Time_j\right) + \beta_4(GSRF) + a_1(Year) + a_2(S) + \varepsilon_j \quad \text{(Equation. 5.1)}$$

In addition to the mixed effects model, we also used a linear regression model with interaction term to assess the interaction of growing season rainfall and phenological metrics for variable PAWC values.

5.2.5 Spatial estimation of PAWC

The linear mixed effects model (Equation 5.1) was tested for spatial PAWC prediction across the cropping zone of South Australia (approximately 58,000 km^2) at 250m spatial resolution. Seasonal phenological metrics for the cropping region from the MODIS NDVI data for 2001-2015 using CropPhenology package. The growing season rainfall classes were calculated from rainfall data. Then, a predicted PAWC map was created using these datasets as inputs for the model.

5.2.6 Corroboration

The model prediction was corroborated by testing the correspondence between the predicted PAWC map and the landscape-scale PAWC map. Importantly, when interpreting the results of the corroboration we need to consider both the map uncertainty of the landscape-scale map, as well as the difficulty in obtaining spatially representative APSoil field measurements. Firstly, an exploratory statistical analysis was done to assess the level of discrepancy between APSoil PAWC measurements and landscape-scale PAWC map units. Secondly, the correspondence between the predicted PAWC map and the landscape-scale PAWC map was assessed.

We generated an error matrix of all pixels in the mapped area (total population) to calculate indices of the mapping success: overall accuracy, producer's accuracy, user's accuracy, and kappa. The overall accuracy measures the percentage of pixels which have predicted PAWC values that correspond with the landscape-scale PAWC values. The producer's accuracy measures how well the classes in the landscape-scale PAWC map are identified as the similar class in the predicted PAWC map. And user accuracy measures how well the pixels in the given classes of the predicted PAWC map corresponds with the similar class in the landscape-scale PAWC map. The kappa value indicates how well the predicted map agreed with the landscape-scale PAWC map, taking into account the possibility of an agreement by chance (Landis and Koch, 1977, Congalton and Green, 2008).

Equally important is the visual interpretation. It is widely acknowledged that management strongly influences plant growth and hence NDVI. Spatial patterns in NDVI, therefore, often show differences across paddock boundaries unlike soil pattern that vary consistently regardless of paddock boundaries. Hence, we expect to see a spatial pattern that is unrelated to management.

5.3 Results

5.3.1 Relationship between PAWC and phenological metrics

The parameters of the linear mixed effects model (Equation 5.1) are summarized in Table 2. The results indicate that the relationships between PAWC and all the phenological metrics are statistically significant (p<0.05).

Table 5.2. *Coefficients of the linear mixed effects model showing the relationship between the phenological metrics and soil PAWC*

Determinants	Estimate	Standard error	P value
Intercept	3.18	0.54	0.000
Max Value	1.76	0.29	0.000
Offset Value	-4.91	1.54	0.002
Max Time	0.08	0.03	0.005
GSRF	0.00	0.74	0.458

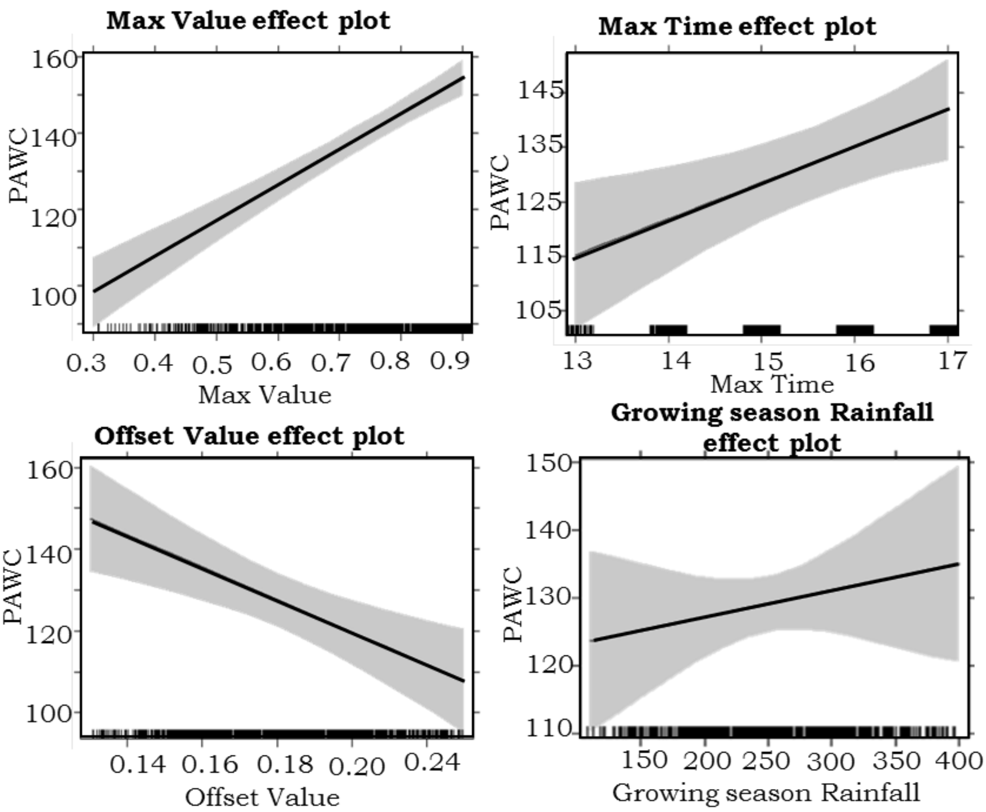

Figure 5.4. *Effect plots for PAWC determinants in South Australia based on the Soil PAWC measurments from APSoil database and phenological metrics for 2001 – 2015. The shaded bands show 0.95 confidence limits for the effects.*

The effect plots for the model, illustrate that Max Value and Max Time have strong positive relationships with PAWC whereas Offset Value has negative relationship with PAWC (Figure 5.4). The confidence band in the plot show the uncertainty of the relationship. The linear regression model with interaction terms of phenological metrics and growing season rainfall shows the effects of changes in growing season rainfall in the phenological metrics response for variable PAWC soils (Figure 5.5).

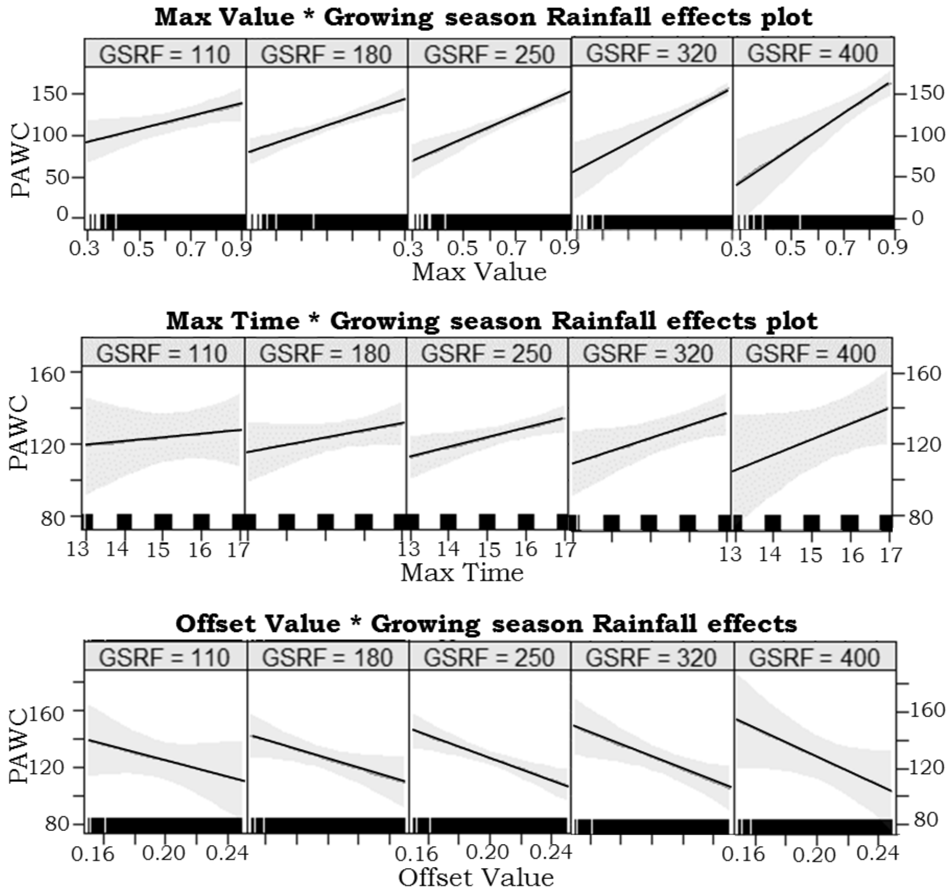

Figure 5.5. *Effects plot of the model with interaction variables of phenological metrics and rainfall*

Figure 5.6 illustrates the difference between the NDVI dynamics of the top and bottom quintiles of the APSoil PAWC measurements in the South Australian agricultural region. Plants from the higher PAWC soils (upper quintile) attain higher maximum NDVI, than that on low PAWC soils. Additionally, the maximum NDVI of the plants on the low PAWC soils occurs earlier than plants on high PAWC soils.

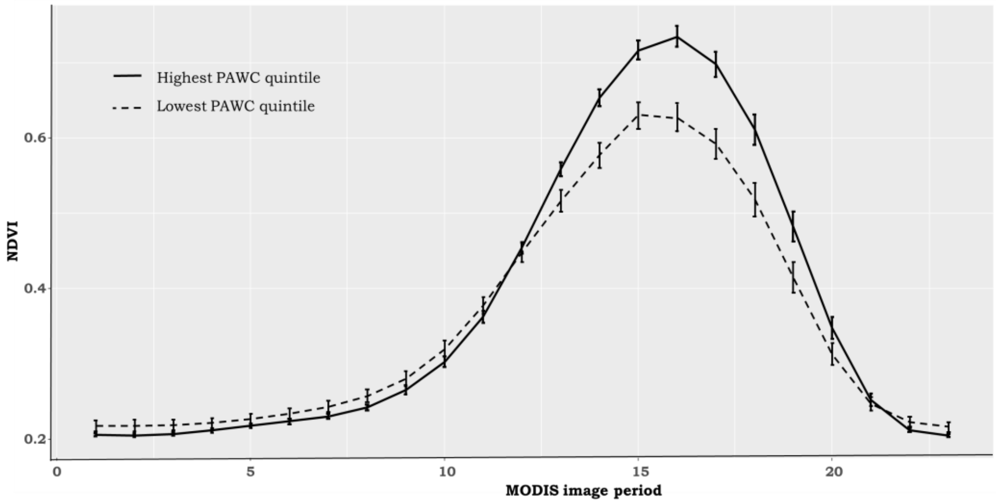

Figure 5.6. *Comparison of the NDVI temporal curves from the highest and lowest PAWC soils*

The diagnostic information of the mixed effects model shows that the model presented a reasonably good fit. The histogram of the residuals presented a smooth shape (Figure 5.7). The Q-Q plot shows that the measured and estimated values follow similar distribution. The response versus fitted values are rather scattered, but the plot shows a general trend. The spatial dependency of the residuals of the mixed effects model was tested using Moran's I test and the result indicates no spatial autocorrelation was observed (sd=0.02, *P*-value=0.87).

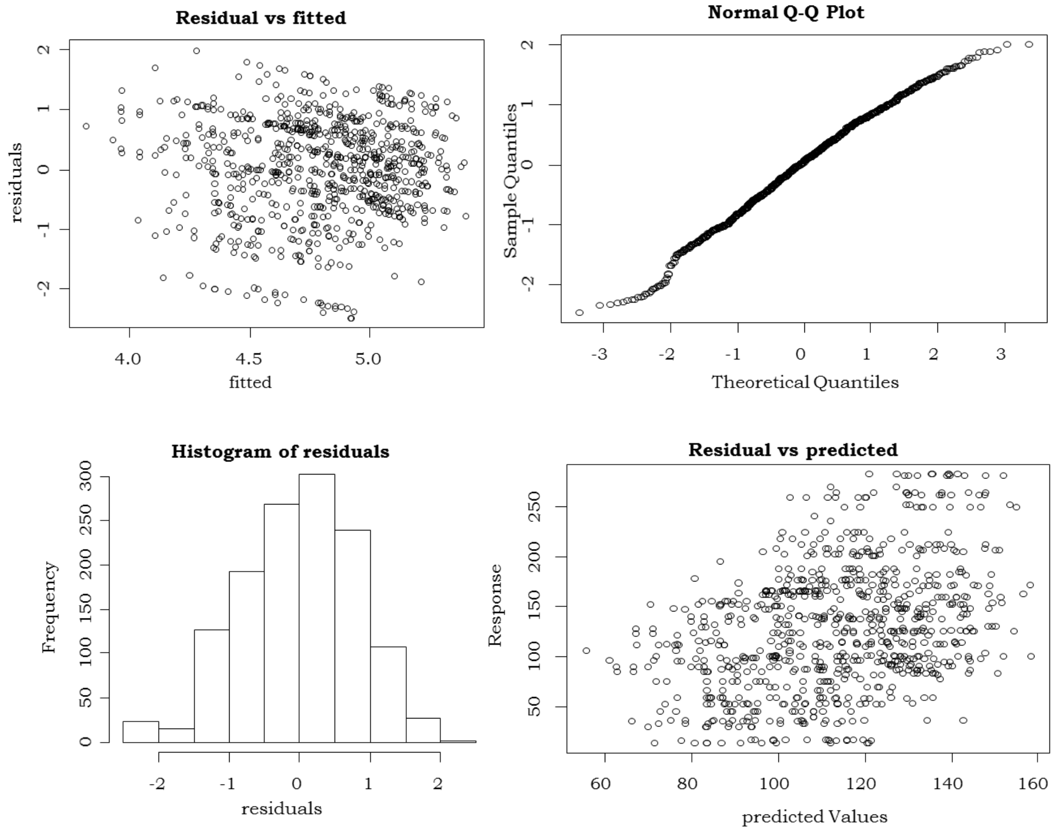

Figure 5.7. *Diagnostic plots of the model*

5.3.2 Corroboration

The comparison of the existing PAWC estimates from soil cores of APSoil database and landscape-scale PAWC map is summarized in the boxplot showing the variability of APSoil PAWC values within the landscape-scale PAWC map categories (Figure 5.8). It indicates a good correspondence of magnitudes between them, illustrated with correlated mean and median values. However, there is very high variability within the mapped soil landscape units, with highest variability in Class 1 (>100 mm) and Class 2 (70 – 100 mm). The degree of agreement between the APSoil PAWC and the landscape-scale PAWC map is relatively low, with Kappa coefficient of 0.13.

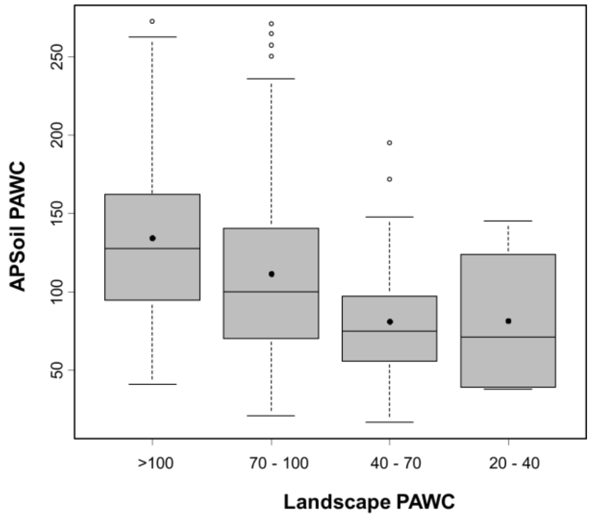

Figure 5.8. *A box plot comparing PAWC from the APSoil database and the landscape-scale PAWC map, with means represented as a black dots.*

Visually, the predicted PAWC map shows a reasonable correspondence of spatial pattern with the landscape-scale PAWC map. In both maps, high PAWC values were mapped in the Mid North and northern parts of Yorke Peninsula, and intermediate values dominating in Northern Murray and some parts of Western Eyre Peninsula with low value patches at the lower part of Yorke Peninsula and Northern Murray (Figure 5.9 a). Moreover, the predicted map shows detailed pattern within the landscape-scale PAWC map units and consistently maintain this variability across farm boundaries. Figure 5.10 shows an enlargement of predicted PAWC map of a landscape in the Eyre Peninsula with the cropping field boundaries. The PAWC pattern persists crossing the fields. This indicates that the model predictions do not correspond to differences in management but depict long-term spatial differences.

The modelled PAWC values corresponds fairly well with the broad landscape-scale PAWC map (Table 5.3). Fifty two percent of the pixels in the predicted map corresponded to the correct AWHC classes in the landscape-scale PAWC map. The difference in the User's accuracy among the classes indicates that the degree of agreement between the two maps varies from class to class. Classes 2 and 3 have slightly higher User accuracies, indicating relatively higher number of pixels in these classes were estimated to have similar range of values. and Generally, the 31% Kappa coefficient value shows that the predicted map corresponds with the landscape-scale map with 31% better probability than a random agreement by chance.

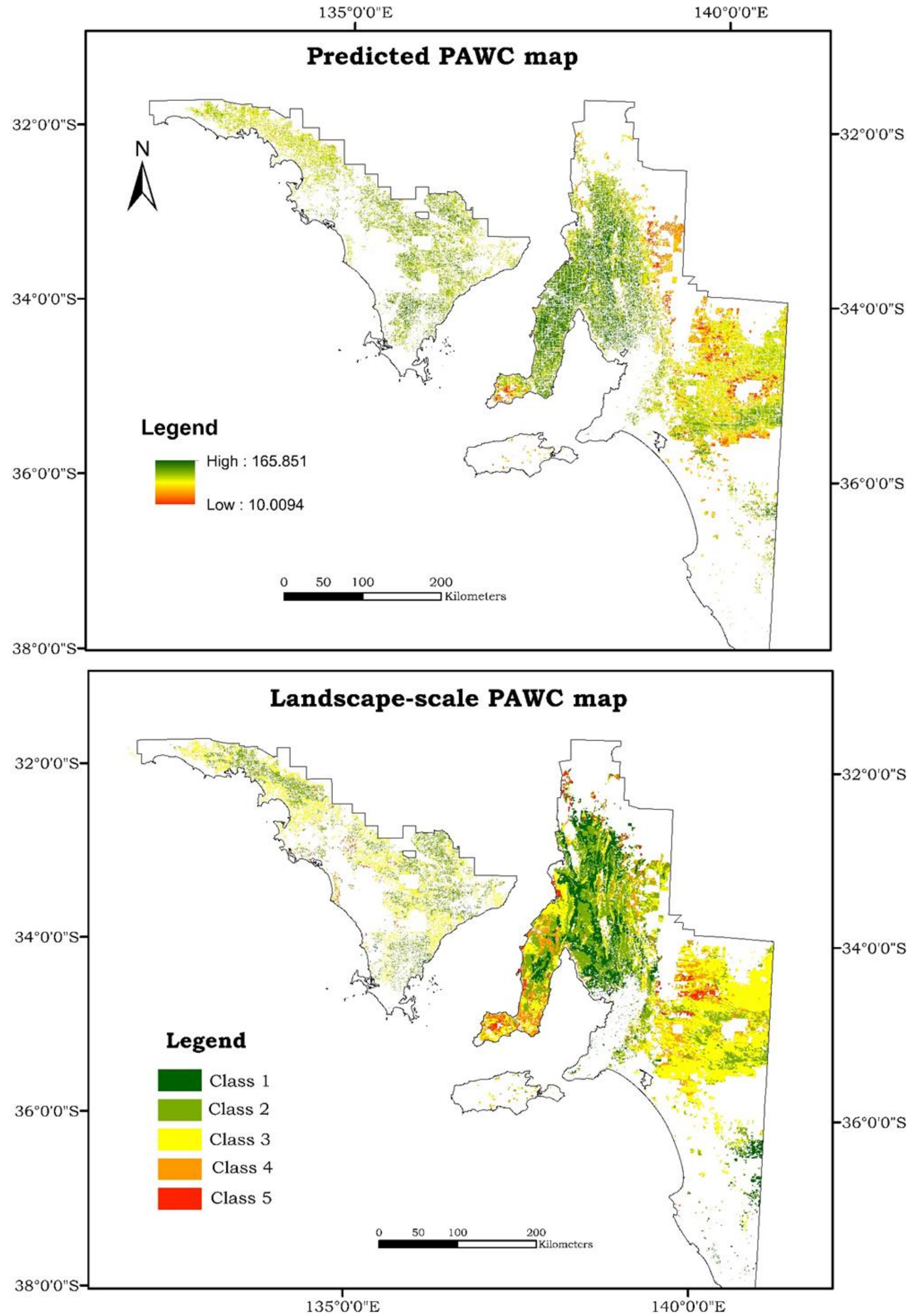

Figure 5.9. *Comparison of the model estimation (a) model predicted PAWC map (b) the landscape-scale PAWC map of the cropping farms in SA agricultural region.*

Table 5.3. *Error matrix and Kappa statistic for correspondence between predicted PAWC map and landscape-scale PAWC map, using pixel counts of the entire area.*

Landscape-scale PAWC map	**Predicted PAWC map**					
	< 20 (Class 5)	**20 – 40 (Class 4)**	**40 – 70 (Class 3)**	**70 – 100 (Class 2)**	**>100 (Class 1)**	**Producer accuracy (%)**
< 20 (Class 5)	1,517	2,161	6,011	4,541	2,752	*8%*
20 – 40 (Class 4)	1,686	6,240	13,362	19,897	18,669	*10%*
40 – 70 (Class 3)	3,031	7,351	116,772	98,947	30,220	*46%*
70–100 (Class 2)	1,095	2,570	50,257	158,573	49,815	*60%*
>100 (Class 1)	1,200	467	2,239	13,402	70,357	*80%*
User accuracy (%)	18%	*33%*	*62%*	*54%*	41%	*Kappa =0.31* *OA= 52%*

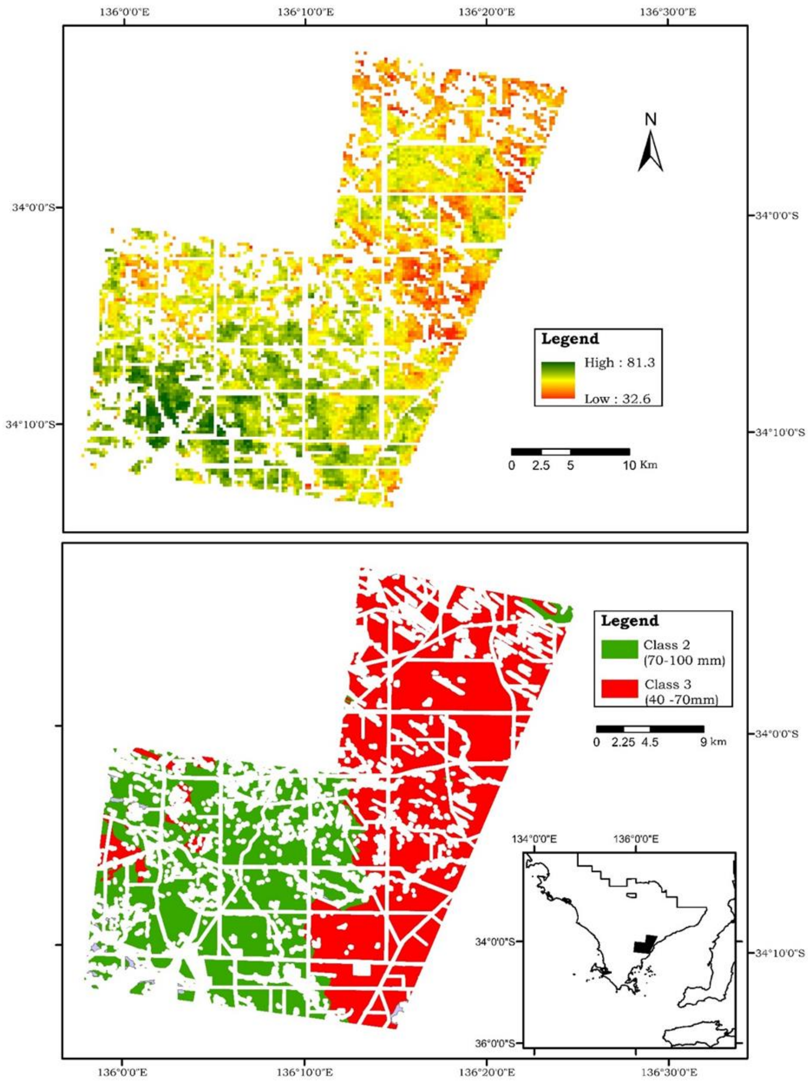

Figure 5.10. *Predicted PAWC map of the landscape in Eyre Peninsula*

5.4 Discussion

5.4.1 Relationship between PAWC and phenological metrics

Results from this study show that the phenological metrics Offset Value, Max Time and Max Value have significant relationships with measured soil PAWC. The effect plots of our mixed model (Figure 5.4) indicate that high PAWC soils attain higher and later NDVI peak than low PAWC soils. This result coincides with reports from earlier research in crop phenology about the strong influence of soil moisture on crop growth, with observations of faster crop growth to the next phenologic stage in crops under water stress (McMaster et al., 2011). Numerous experimental studies have shown that crops under water stress reach anthesis and maturity stages earlier than non-stressed plants by 3-15 days (Angus and Moncur, 1977, Robertson and Giunta, 1994, McMaster et al., 2005, McMaster et al., 2008). Soil PAWC controls soil water availability. Plants on low PAWC soil are likely to face greater water scarcity than those of high PAWC due to soils' high capacity to hold water. Early maximum NDVI for low PAWC was also observed in our previous study, using MODIS NDVI based phenological analysis (Araya et al., 2016).

One aspect of our earlier study (Araya et al., 2016) differs from this study. Our earlier research compared contrasting soils from two farms on Eyre Peninsula under identical management. In contrast, at the spatial scale studied in this paper, it is impossible to obtain information management at the field scale. Therefore many aspects that influence plant growth, remain uncontrolled factors in the analysis. At the broad scale, we can expect that farming practices such as fertilizer rates and crop varieties are adapted to local soil conditions. In our previous study (Araya et al., 2016) we found that under identical management NDVI peaks earlier and higher on low PAWC soils. In the current study, we find higher NDVI peaks in higher PAWC soils, reflecting a generally higher plant leaf cover.

The effects plot of the linear regression model with interaction variables of phenological metrics and growing season rainfall shows that the response of the phenological metrics to difference in PAWC varies with variable growing season rainfall (Figure 5.5). The relationships between the phenological metrics and PAWC are weak in lower growing season rainfall (GSRF=110) and get stronger as the growing season rainfall increases (GSRF = 320 and GSRF=400). This observation reflects the strong dependence of the vegetation – PAWC response on rainfall amount (Lawes et al., 2009, Oliver et al., 2009, Rab et al., 2009). In low rainfall seasons the spatial variability of crop growth across variable PAWC soils is low as both high and low PAWC soils would not get adequate water to support crops. In high rainfall seasons, on the other hand, the high PAWC soils respond with higher crop growth than the low PAWC soils, as they are able to store more water for supporting the crop. As the result of such interactions, spatial growth variability increases with increase in growing season rainfall and larger temporal variability occurs in high PAWC soils compare with low PAWC soils (Wong and Asseng, 2006).

The interactions between rainfall, spatial soil PAWC variability, and crop growth can be more intricate than consideration of only the growing season rainfall amount. Previous studies suggested that the crop growth response to differences in PAWC is directly influenced not only by growing season rainfall amount but also by the seasonal distribution of rainfall. The impact of PAWC on crop growth reduces in seasons with late rainfall, and the impact increases with high opening rainfall that reduces late in the growing season (Oliver et al., 2006, Lawes et al., 2009). Hence including a wide range of intra-annual rainfall distributions in the analysis is important. In our case, the study period was limited to the availability of MODIS imagery. Although our mixed effects model accounts for this intra-annual variability over 15 seasons (2001-2015), it is obvious that increasing the time series length can improve the results. However, this is currently only possible by compromising on spatial resolution. AVHRR offers the potential to increase the length of the time-series, with a rather low spatial resolution of 1km. Whilst potentially increasing the time series, the soil variability at the small scale will be averaged out, which restricts the method to homogeneous regions. Although MODIS imagery provides soil pattern at unprecedented detail, even the 250 m pixel size may have a limitation in areas with topographic undulations and variability of soil-forming processes. Image fusion and advanced sensor inter-calibration techniques may combine the benefits of high spatial resolution with the temporal frequency of different sensors (Feng et al., 2006, Fu et al., 2013) and hence increase the spatial resolution for both MODIS and AVHRR-based analysis. In spite of the limitations of this study in space and time, the results show that analysis of temporal dynamics of NDVI is a promising step in the development of high-resolution spatial indicators of soil variability, substantially increasing the spatial detail that is currently possible.

Besides the amount of rainfall, the seasonal distribution of rainfall also plays an important role in determining the crop growth response to PAWC. A marked effect of PAWC on crop growth is observed when the season is defined by high pre-anthesis rainfall, which fills the soil profile to its capacity, followed by below average late rainfall. In such seasons, the crops depend on the additional soil stored water for the rest of growth period. On the other hand, high late rainfall minimizes the effect of soil PAWC on crop growth. For future studies, considering intra-seasonal rainfall pattern in the model can provide better insight of the crop-soil interaction and may replace the random variables used in this study to account for spatio-temporal rainfall pattern.

5.4.2 Corroboration

The issue of corroboration in digital soil mapping at broad spatial scales is challenging. Relating soil laboratory analysis with broad-scale observations at the landscape-scale is inherently difficult because the spatial heterogeneity of soils within the landscape units remains uncertain. The choice of soil sampling locations is often subjective and the representativeness of point data in space is generally unknown (Ostendorf, 2011). This is evidenced by our comparison of two highly useful, but different sources of spatial soil data: the soil landscape map of SA and the APSoil database. The method used for mapping the soil PAWC in these two datasets were different. The APSoil measurements were collected using field and laboratory analysis of soil samples (Dalgliesh and Foale, 1998). On the other hand, the soil landscape units were defined based on local knowledge and experience using terrain and air photo interpretation (Maschmedt, 2000). Comparing the two soil data sources showed a significant but highly variable relationship between PAWC measurement and the landscape-scale PAWC estimates, which reveals the uncertainty of the homogenous landscape unit as well as the representativeness of the APSoil data point. Note that soil polygons depict broad classes and the heterogeneity within soil units is unknown. In addition, the boundaries of the soil polygons that represent changes in the soil property are uncertain due to subtle soil property change.

In spite of these difficulties, a comparison between the landscape-scale PAWC map and our model predictions shows substantial agreement (Table 5.3). Although, there exist differences in the degree of agreement among the soil PAWC classes, 52% of the classes were classified into similar categories, with 31% more probability than would have happened by chance.

More importantly, our predicted map shows distinct variability within soil map units, which is impossible to assess from soil sampling or through soil-landscape mapping. Whilst direct quantitative validation is impossible because information about true values at the landscape-scale does not exist, it is notable that the predicted soil pattern does not reflect farm management boundaries (Figure 5.10). Different varieties, seeding time or fertilization are factors that influence crop growth and field boundaries can be readily observed in many raw single-time images (Ji, 1996, Turker and Kok, 2013). The mapped results, however, show consistent pattern irrespective of a wide variety of factors that vary amongst fields. The predicted PAWC pattern from our model is consistent across management boundaries as would be expected from soil pattern, providing additional qualitative evidence that phenology can be used as a spatial indicator for soil mapping at higher detail than currently existing datasets.

5.4.3 Phenological indicators for spatial prediction of PAWC

The method presented in this paper shows the potential of remote sensing derived phenological indicators for soil PAWC prediction. The study demonstrates the ability of phenological metrics to provide detailed soil PAWC pattern at the broad spatial scale. This can potentially provide a pathway toward addressing the demands of high spatial resolution soil information. This will benefit many agronomic model applications by providing spatially explicit soil information for agronomic management decisions which would otherwise use extrapolated soil information from the available databases. Furthermore, it highlights a step towards a high resolution spatial modelling of climate-change responses that account for soil variability.

The method presented here shows the potential of remote sensing phenological indicators to predict soil PAWC in the Mediterranean climate of the South Australian agricultural region, where plant growth strongly influenced by soil PAWC. This approach can be used in similar environments, however, the model needs calibration using measured soil PAWC points across the area of interest. To use remote sensing phenological indicators for spatial mapping of other soil properties, the relationship between the particular soil property and the phenological growth properties of the plants that can be identified by remote sensing spectral responses needs to be comprehensively considered.

5.5 Conclusion

In this study, we have assessed the relationship between field measured PAWC and phenological metrics derived from remote sensing data, across the South Australian agricultural region. The results showed that the maximum NDVI (the greenness at anthesis), the time of maximum NDVI (the time of anthesis) and the NDVI value at Offset (the greenness at maturity) have strong relationships to soil PAWC. Generally, the high PAWC soils showed higher and later Maximum NDVI, and lower Onset and Offset NDVI than the low PAWC soils.

Furthermore, the study provided further evidence that the crop growth response to differences in soil PAWC depends on the amount of growing season rainfall. The results from our analysis shows that the relationship between phenological metrics Max Value, Max Time and Offset Value showed certain trends with increasing of the growing season rainfall. In dry years, with low growing season rainfall, the crop growth response to difference in PAWC is weaker as compared to wet season where the crop growth response shows high correlation with soil PAWC.

Our study demonstrates strong potential of remote sensing derived phenological metrics as indicators for soil conditions, providing unprecedented spatial detail for digital soil mapping at broad spatial scales. This study has shown that there is a consistent PAWC signal in the NDVI dynamics that can be utilized to develop indicators of soil condition. Hence, it provides an alternative approach for the future broad scale high-resolution soil mapping and narrows the gap in spatial detail between regional modelling and farm based management models. Whilst this paper used MODIS imagery at 250m pixel size, an increasing availability of fine-resolution satellite imagery and the technological advancement of image fusion techniques provides an encouraging future for advancing soil indicator development and digital soil mapping.

5.6 Acknowledgements

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Chapter 6

Conclusions

6.1 Overview of the research

In water limited Mediterranean climates, information on the spatial distribution of soil Plant Available Water-holding Capacity (PAWC) is very important for many agricultural activities. It explains a large portion of yield variability across cropping fields. However, the field measurement of soil PAWC is very difficult and time consuming. Hence, improved digital soil mapping techniques are required.

This thesis developed a methodological framework to estimate PAWC at improved spatial resolution using a remote sensing based approach. To achieve this, the research examined the potential of multi-temporal remote sensing vegetation index data to understand soil-climate interactions and to estimate soil PAWC at improved spatial resolution compared to existing landscape-scale maps. The objectives of this research were: (1) to design an easy to use tool to analyse the vegetation dynamics from multi-temporal remote sensing imagery; (2) to assess the use of vegetation dynamics for understanding the soil-crop response to differences in soil PAWC across the variable seasonal rainfall and to identify indicative parameters from crop growth dynamics for soil PAWC; (3) to assess the efficiency of phenological metrics to assess the spatio-temporal growth variability in cropping fields for agricultural management purposes; and (4) to assess the potential of multi-temporal vegetation index data for high resolution broad scale spatial estimation of soil PAWC.

These objectives have been addressed in the papers that comprise this thesis. The major findings and contributions of this research are summarised here.

6.2 Major research contributions

6.2.1 'CropPhenology': An easy to use, new software package for phenological metric extraction from vegetation index images

The present research provides a new software package, CropPhenology that was designed to extract phenological metrics from time series vegetation index data in the R statistical software environment. CropPhenology extracts 15 phenological metrics directly from downloaded remotely sensed images with minor pre-processing steps. It also provides hypothetical inferences to the corresponding crop growth stages, for ease of interpretation. The output metrics of the package are presented in raster format for easy integration with other spatial data. The package also offers a function called "MultiPointsPlot" to allow plotting of time series vegetation index values from different locations for comparison of the growth dynamics.

The package developed, 'CropPhenology', and several worked examples from South Australian cropping regions were presented in Chapter 2 of this thesis. Most importantly, it was used as a tool for analyzing data for all subsequent stages of this research.

The source code for CropPhenology package is available on Github repository at https://github.com/SofanitAraya/CropPhenology. The documentation and brief descriptions on how to use the package are provided in Appendix A and B.

With growing availability of archive remote sensing data, application of multi-temporal vegetation index data is increasingly being applied in many environmental studies. The package CropPhenology can be easily accessed, installed and adopted to be used as a tool for such applications including crop type detection, regional crop yield estimation, detection of spatio-temporal phenological pattern and similar crop related studies. Moreover, CropPhenology minimizes the technical difficulties involved in data pre-processing and processing stages and allow adaptation to new users and those who are less technically proficient. Being in an increasingly popular R environment, CropPhenology can be easily integrate into a pipeline of processing. For example, CropPhenology can take input from automatic downloading and pre-processing packages such as MODIStsp (Busetto and Ranghetti, 2016b) and feed the output raster metrics as an input to a remote sensing processing tools such as RStoolbox (Leutner and Horning, 2017) for post processing such as image classification. As such CropPhenology is an easy-to-use tool for future crop related studies.

6.2.2 A new approach to improve understanding of soil – climate interaction and to identify potential indicators for soil PAWC

In cropping regions, one of the most evident indicators of differences in PAWC is temporal and spatial crop growth variability resulting from its strong interaction with rainfall seasonality. Multi-temporal vegetation index data allow synoptic observation and quantification of these temporal and spatial variabilities.

The present research assessed the use of multi-temporal vegetation index data to gain an improved understanding of the soil-crop response to rainfall variability and to infer about soil PAWC. This approach was tested in two grain cropping fields in South Australia and presented in Chapter 3. To achieve this, phenologic metrics from time series of MODIS NDVI data (from 2000 – 2013) were examined for crops grown in soils of contrasting PAWC values. In order to exclude the agricultural management effects paired soils from the same cropping field were considered. The results demonstrated that the vegetation dynamics can provide improved understanding of the soil-crop response for variable rainfall. Empirical assessment of the phenological metrics from the contrasting soils indicated that the phenological metrics, peak NDVI (Max Value), the time of peak NDVI (Max Time), and the rate of NDVI increase from onset to peak NDVI (GreenUpSlope) were significantly related with soil PAWC.

The study demonstrated the existence of a signal in multi-temporal vegetation index data, which can be used to infer soil PAWC. These metrics are suggested as indicators of soil PAWC across rain-fed cropping fields. This highlighted the potential of the approach for future spatial soil PAWC prediction studies. Furthermore, the approach presented may assist future studies involving soil-crop-climate interaction, through the use of multi-temporal vegetation index data to observe inter-annual and intra-annual crop growth variability with variable climatic conditions.

6.2.3 An alternative approach for understanding spatio-temporal growth variability in cropping fields to improve crop management system

Understanding of the spatial and temporal variability in crop yield is an essential step for advanced crop management systems. Site specific crop management technique uses yield data from previous years to subdivide fields into regions of similar production that can be managed uniformly and more precisely.

Chapter 4 of the thesis tested the effectiveness of the remote sensing derived phenological metrics to assess the spatial and temporal variability in crop growth across the agricultural management zones. The associations between the phenological metrics and the predefined agricultural management zones, in a cropping field in the South Australian agricultural region were empirically assessed. The ranked correlation between the management zone and the temporal mean and variance were analysed to characterize the phenological metrics in terms of their capability to indicate temporal and spatial variabilities. The results demonstrated that the phenological metric TINDVI (area under the NDVI temporal curve) indicates temporal variability in crop growth that is sensitive to change in climatic conditions, whereas the metric Max Value (Maximum NDVI Value of the season) shows high sensitivity to spatial crop growth variability that may relate to soil condition.

The method outlined in this chapter presents a pathway towards better recognition of spatio-temporal variability in crop growth across the agricultural management zones using remote sensing vegetation index data. This alternative approach will provide valuable information to support precision agriculture practices, especially in areas where adoption of the technology is in its infancy.

6.2.4 A new approach for spatial estimation of soil PAWC

In Chapter 3, this thesis shows that the phenological metrics derived from multi-temporal vegetation index data are indicators of soil PAWC, under controlled climatic and management effects. The present study assessed the potential of the phenological metrics for spatial estimation of soil PAWC. The method was tested in the South Australian agricultural region and it is presented in Chapter 5.

In this part of the research, phenological metrics were calculated from MODIS NDVI data (MOD13Q1) for 15 years (from 2001-2015) using the CropPhenology package, developed in Chapter 2. The association between the measured PAWC values and phenological metrics and seasonal rainfall was modeled using a linear mixed effects model. The model was then tested for spatial prediction of PAWC across the entire extent of the South Australian rain-fed agricultural region. The model prediction was corroborated by assessing the correspondence between the model predicted PAWC map and the landscape-scale PAWC map. In spite of the differences between the model predicted PAWC map and the landscape-scale PAWC map in spatial scale and method of soil PAWC assessment, they corresponds fairly well with an overall accuracy of 52% and a Kappa coefficient value of 0.31. More importantly, the predicted map showed distinct spatial variability within soil map units, which has been impossible to assess from discrete soil sampling or through soil-landscape mapping.

Whilst direct quantitative validation of the predicted PAWC map is not possible because field measurement of soil PAWC at the landscape-scale does not exist, the predicted broad soil patterns were similar with those shown by the landscape-scale PAWC map. It is notable that the pattern of PAWC is consistent across agricultural management boundaries and that the approach effectively removes the dominating spatial pattern of paddocks in the satellite imagery, representing PAWC spatial information at previously unachievable spatial detail.

This study presented a new method for spatial mapping of soil PAWC. It has shown that there is a consistent PAWC signal in the NDVI dynamics that can be utilized to develop broad-scale high-resolution indicators of soil condition. Thus, it narrows the gap in spatial detail between regional modelling and farm based management models.

The results from the this study have demonstrated that multi-temporal vegetation index data can improve the digital soil mapping efforts for soil PAWC and possibly other soil properties after additional research. In such a way, the approach in this research paves a way for additional research to estimate other soil properties adopting similar methods.

6.3 Recommendation for future research

This thesis presented and implemented remote sensing based approaches to estimate soil PAWC at improved spatial resolution. The study further indicates the prospects of future research, as outlined here.

6.3.1 Improvement on CropPhenology package

The CropPhenology package has been used successfully as a tool for the all components in this research. However, it may have limitations that need to be considered for future work. One limitation is that the package is unable to automatically handle double or triple cropping systems. Although it is possible to use the package by manually separating the input image sequences in to multiple growing seasons, modification of CropPhenology is required for automated application in environments with multiple growing seasons.

6.3.2 Improved spatial scale

The approach presented in this research demanded high temporal resolution vegetation index data to monitor the vegetation dynamics across the growth season of annual crops. Equally important, high spatial resolution vegetation index data is required to capture the variable nature of soil across cropping fields. However, remote sensing data often comes with a trade-off between spatial and temporal resolutions. In this research the MODIS vegetation product (MOD13Q1), with temporal resolution of 16 days was used for monitoring crop growth across the growing season. Although the use of MODIS vegetation index product was successful in providing improved resolution of soil information, its coarse spatial resolution limits its application to broadacre cropping. Advancement in image fusion provides a promising future for integrating high spatial resolution images with high temporal resolution images (Fu et al., 2013, Gao et al., 2017). New research has demonstrated the potential of using image fusion algorithms to obtain a dataset with the high temporal resolution of MODIS and higher spatial resolution of Landsat for crop growth monitoring applications (Dong et al., 2016). Future research is recommended to explore the method presented in this thesis using such fused images for estimation with high spatial resolution that may provide ideal soil maps for field scale agricultural management.

6.3.3 Adoption of the approach

This thesis presented the use of remote sensing derived crop phenological metrics to estimate soil PAWC, implemented in the South Australian agricultural region, which is characterized by a Mediterranean climate. In general terms, crop variability is strongly related to soil physical properties. Considering such strong crop-soil relationship, the method used in this research may be used to estimate other soil properties. However, the efficacy of multi-temporal vegetation index data for assessing other soil properties depends on the influence of the desired soil property on vegetation growth. Further research is recommended to test the use of multi-temporal vegetation index data for prediction of other soil properties.

A key to adoption is the availability of a vegetation indicator at high spatial and temporal scale. The approach is not limited to MODIS, but currently this sensor provides an excellent temporal resolution and extent, compromising on the spatial scale. Other satellite imagery is available at similar spatial spatial and revisit frequency (MERIS) and could be used. Different spectral bands may be more suitable in other parts of the world and further testing may be desirable. The key to a successful adoption is a) a proven definition of an imaging sensor to discriminate vegetation condition, b) the spatial resolution to match vegetation pattern in the region of interest, c) the temporal resolution of available imagery. There is a variety of different sensors available that fore or less fulfil individual criteria. In different regions of the world different sensors may have different suitability to fulfil the criteria (e.g. satellite radar in areas of high cloud cover).

Considering the inherent relationship between soil-stored water and plant phenological growth stages, there is no foreseen limitation to adopt the methodology to other climatic regions as long as spatio-tmporal imagery and suitable vegetation indices are available. The method presented in this thesis was implemented and tested in Mediterranean climate of South Australian agricultural region. However, further research is recommended to test the observed relationship between the phenological metrics and soil PAWC in the region.

6.3.4 *Improvement in estimation accuracy*

Soil property estimation using remote sensing vegetation index data requires the inclusion of variable seasonal conditions, to maximize the vegetation response variability (Maynard and Levi, 2017). Whilst this study has incorporated sufficient observations for assessment of temporal variability, the number of years was limited to fifteen due to the availability of MODIS vegetation index data. Application of this method with additional years, as the MODIS archive continues to grow, would potentially improve results as it allows consideration of more climatic variability. Future research is recommended to test the accuracy possibly gained from increasing the climatic ranges through increasing number of years.

6.4 Conclusion

This thesis contributes to the development of an innovative method for the understanding of soil-climate-vegetation interactions and improved estimation of soil PAWC, in rain-fed cropping regions. The method is tested in the Mediterranean climatic setting of South Australia where water is the limiting factor for the plant growth.

Developing a comprehensive method to assess the vegetation change for differences in soil PAWC using multi-temporal vegetation index data, is the core of this research. The approach outlined in this thesis involved extraction of phenological metrics from the time-series vegetation index data to obtain summarized information that indicate soil properties. Design and implementation of a new software package, "CropPhenology", for extracting phenological metrics from time series vegetation index data is one of the significant contributions of this thesis. The package is built with minimal requirements for pre- and post-processing steps.

This research successfully demonstrates the use of multi-temporal vegetation index data for improved understanding of the soil-climate-vegetation interaction and for identification of differences in PAWC. The research also investigated the efficiency of phenological metrics for assessing the spatio-temporal growth variability in cropping fields, for precision agricultural management purposes. The method presented in this part of the research provides a pathway towards a better assessment of spatio-temporal growth variability in cropping fields, which is a vital contribution to the success of precision agricultural practices. Furthermore, the research presented remote sensing based approach for spatial estimation of soil PAWC, using phenological metrics derived from multi-temporal vegetation index data and rainfall data. This approach was implemented and tested in South Australian agricultural region. The result presents a considerable achievement of this research and demonstrates the strong potential of remote sensing derived phenological metrics as spatial indicators for soil PAWC, providing unprecedented detail for digital soil mapping at broader spatial scales. The knowledge presented in this thesis contributes for future improvement of digital soil mapping efforts which provide high resolution soil information for regional and local decision makers.

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Appendices

Appendix A

Package Documentation

Package ‘CropPhenology’*

September 18, 2017

Type Package

Title Extract phenologic metrics from timeseries vegetation index data

Version 0.1.0

Author Sofanit Araya

Maintainer Sofanit Araya <sofanitgirma.araya@adelaide.edu.au>

Description CropPhenology-package

License GPL (>=2)

Encoding UTF-8

URL https://github.com/SofanitAraya/CropPhenology,
http://cropphenology.wix.com/package

Repository github

Depends foreign, raster, sp (>= 1.0-13), maptools, shapefiles,
rgdal,Rcpp, rgdal, rgeos

SystemRequirments R (> 3.0)

LazyLoad true

LazyData true

RoxygenNote 6.0.1

R topics documented:

* This package documentation is also available at:
https://github.com/SofanitAraya/CropPhenology/wiki/CropPhenology-Package

Description

Extract phenological metrics from time series vegetation index data

Details

Introduction

Multi-temporal vegetation index data can be used to get information on seasonal vegetation growth dynamics. This information indicates vegetation phenological growth stages and conditions of environmental factors influencing the vegetation growth. In cropping regions the crop growth dynamics observed from multi-temporal vegetation index data has been used in applications such as crop type detection (Zhong et.al. 2011, Roerink et.al. 2011), regional crop yield estimation (Hill et.al. 2003) and many more related studies. Moreover, the long term vegetation dynamics can provide information about influential environmental factors such as soil property mapping (Araya et,al. 2016). Plotting a time series of vegetation index values across time creates a curve that summarises the vegetation dynamics (Figure 1).

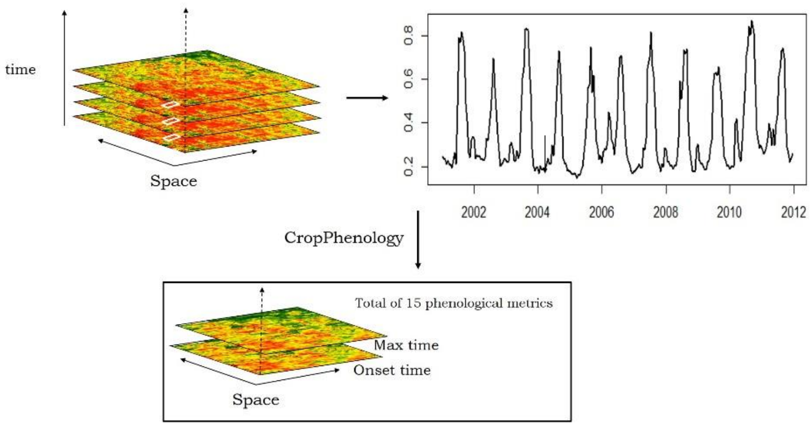

Figure 1 – Illustration for vegetation dynamics derived from multi temporal vegetation index data, and phenological metrics derived from vegetation dynamics using CropPhenology package

Extraction of seasonal parameters is an essential step for analysing such vegetation dynamics curve. CropPhenology package has been developed to extract phenological parameters from time series vegetation index data in cropping regions.

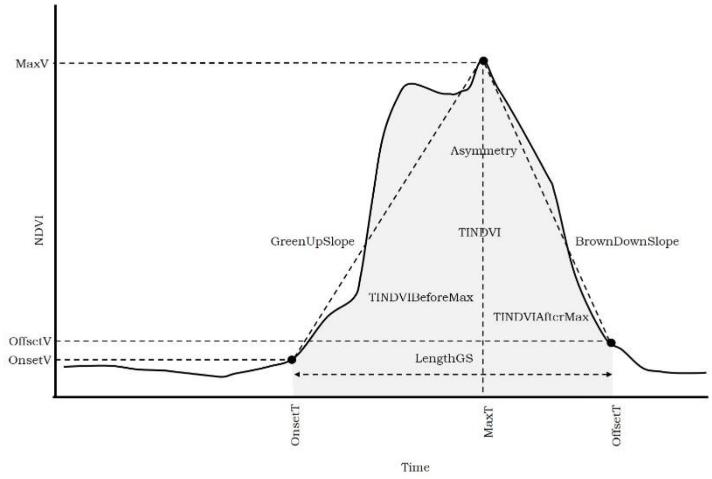

Figure 2 Illustration for the CropPhenology defined phenological metrics in NDVI dynamics curve.

Metrics	Definition on the NDVI curve, Formula, and description
OnsetV (in NDVI value)	NDVI value measured at the start of continuous positive slope over a threshold between successive NDVI values. The threshold is defined as user defined percentage above the minimum NDVI value before the Maximum value.
OnsetT (in MODIS image period)	MODIS acquisition time when OnsetV is derived.
MaxV (in NDVI value)	Maximum NDVI value achieved during the season MaxV= Maximum (NDVI1 : NDVI23)
MaxT (in MODIS imaging period)	MODIS acquisition time when MaxV is derived.
OffsetV (in NDVI value)	NDVI value measured at the lowest slope below a threshold between successive NDVI values. The threshold is defined as the user defined percentage of the minimum NDVI value after maximum. Values are higher than 0.2.
OffsetT (in MODIS imaging period)	MODIS acquisition period when OffsetV is derived.
LengthGS (in MODIS imaging period)	The duration of time that the crop takes to go through all the stages of crop growth $LengthGS = OffsetT - OnsetT$
BeforeMaxT (in MODIS image period)	The length of time from OnsetT to the MaxT $BeforeMaxT = MaxT - OnsetT$
AfterMaxT (in MODIS image period)	The length of time from MaxT and OffsetT $AfterMaxT = OffsetT - MaxT$
GreenUpSlope	The rate at which NDVI increases from the OnsetV to MaxV over the time difference between MaxT and OnsetT $GreenUpSlope = \frac{(MaxV - OnsetV)}{(MaxT - OnsetT)}$
BrownDownSlope	The rate at which NDVI decreases from MaxV to OffsetV over the difference between OffsetT and MaxT. $\mathrm{BrownDownSlope} = \frac{(\mathrm{MaxV} - \mathrm{OffsetV})}{(\mathrm{OffsetT} - \mathrm{MaxT})}$
TINDVI (Accumulated NDVI value)	Area under the NDVI curve between OnsetT and OffsetT. TINDVI is estimated using trapezoidal numerical integration.
TINDVIBeforeMax (Accumulated NDVI value)	Numerical integration of NDVI between OnsetT and MaxT. This metric indicates the pre-anthesis crop growth.
TINDVIAfterMax (Accumulated NDVI value)	Numerical integration of NDVI between MaxT and OffsetT. This metric indicates the post-anthesis growth.
Asymmetry (in NDVI value)	The symmetry of the NDVI curve. It measures which part of the growing season attain relatively higher accumulated NDVI values. $Asymmetry = TINDVIBeforeMax - TINDVIAfterMax$

Table 1 – summary of descriptions of the phenological metrics defined in CropPhenology

Overview of data processing

CropPhenology has two functions: PhenoMetrics and MultiPointsPlots.

PhenoMetrics:- takes the path for the time series vegetation index data and the vector file that defines the Area of Interest (AOI). It extracts fifteen phenological metrics (Figure 2) which represent the seasonal growth condition of the crop at each pixel for the season (Table1) . The output is presented as a raster stack of phenological metrics or a table of phenological metrics for point AOI.

MultiPointsPlots:- provides the user with the ability to visualise the NDVI curve by plotting the temporal sequences of NDVI values of user selected raster pixels (maximum of five). This allows the user to observe the spatial and temporal differences in relative dynamics of the vegetation index for the selected points (Figure 3).

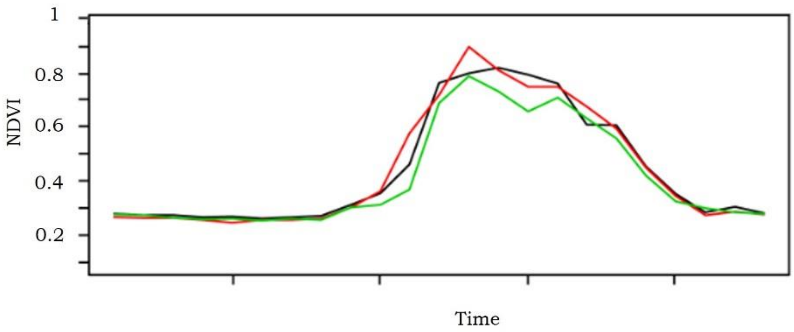

Figure 3 – Illustration for NDVI dynamics from 3 locations ploted together using MultiPointsPlots

Author(s) Sofanit Araya, Bertram Ostendorf, Megan Lewis and Greg Lyle

References

Araya, S., Lyle, G., Lewis, M., and Ostendorf, B. 2016. Phenologic metrics derived from MODIS NDVI as indicators for Plant Available Water-holding Capacity. *Ecological Indicators* **60:1263- 1272.** http://dx.doi.org/10.1016/j.ecolind.2015.09.012

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Zhong, L., Hawkins, T., Biging, G., Gong, P., 2011. A phenology-based approach to map crop types in the San Joaquin Valley, California. *International Journal of Remote Sensing*, **32, 7777-7804**.

MultiPointsPlot Time series curves for Multiple points in the Region of Interest

Description

MultiPointsPlot function takes the ID for the pixels within the region of interst and returns, the timeseries curves from these points, ploted together. The Id numbers can be obtained from the txt file (AllPixels.txt) outputs.

Usage

MultiPointsPlot (path, N, Id1, Id2, Id3, Id4, Id5)

Arguments

path - the path whee AllPixel.txt saved
N - number of intersted points
Id1 - ID number for point 1
Id2 - Id number for point 2
Id3 - ID number for point 3
Id4 - ID number for point 4
Id5 - ID number for point 5

Details

This function allows plotting time series curves from multiple points together in a single plot which helps understanding the growth variability across the field. This information allow observation of the spatial and temporal crop growth variability across the growth seasons, which provide important information about the environmental factors influencing crop growth and thus potential opportunities for influencing crop management (eg . Araya et al., 2016)
The maximum number of pixels allowed plotting together are 5 points.

Value
Multiple time series curves together at the plot panel

See Also
PhenoMetrics()

PhenoMetrics Phenologic metrics from time series vegetation index data

---

Description

This function extracts 15 phenologic metrics from time series vegetaion index data, as raster and Ascii files. The function takes path of the vegetation index data and the boolean Value for BolAOI (True- if there is AOI polygon, FALSE- if the parameters are calculated for the whole region).

Usage

PhenoMetrics (Path, BolAOI, Percentage, Smoothing)

Arguments

Path - Text value - the path where the time series images saved

BolAOI - Logical value - if there is any area of intererst or not

Percentage - Optional Numeric Vlaue - percentage of minimum NDVI value at which the Onset and Offset is defined. The 'Percentage' paramenter is optional; if not provided, a Default value of 10 will be taken.
Smoothing - Optional logical value - if the user chooses to use smoothed curve or row/unsmoothed curve. If "Smoothing' is set to TRUE, the moving avegare filter will be applied to the vegetation index curve. The default value, if not provided, is FALSE, then the unsmoothed row data be used for the analysis.

Value

Phenostack.img - a raster stack of 15 images of phenological metrics OnsetV, OnsetT, MaxV, MaxT, OffsetV, OffsetT, LengthGS, BeforeMaxT, AfterMaxT, GreenUpSlope, BrownDownSlope, TINDVI, TINDVIBeforwMax, TINDVIAfterMax, Asymmetry in the specified order

See Also

MultiPointsPlot (Path, N,Id1, Id2...IdN)

Examples

```
# EXAMPLE – 1
PhenoMetrics(system.file("extdata/data1", package="CropPhenology"), FALSE, 15, TRUE)
# EXAMPLE - 2
PhenoMetrics(system.file("extdata/data2", package="CropPhenology"), TRUE)
```

Index

Appendix B

Practical guide of CropPhenology package

This appendix provide steps and few example scripts on how to use the CropPhenology package.

1- How to install CropPhenology package

In order to install packages from GitHub repository, the package 'Devtools' is required to be in the R library.

```
> install.packages("Devtools")
> library (Devtools)
> install_github("SofanitAraya/CropPhenology")
> library(CropPhenology)
```

2- How to ran PhenoMetrics function

Two example datasets are embedded in the package. Two examples are shown here with and without Area of Interest (AOI).

(a) Without AOI

```
> PhenoMetrics("E://Data1", FALSE, 15, FALSE)
```

Where the path where the Vegetation index image files are saved at `"E:/Data1"`, the required threshold level for Onset and Offset definition is 15%, and no AOI and smoothing required.

The result is saved under `E://Data1//Matrics`

- `PhenoStack.img` – the raster stack of 15 phenological metrics images.
- `AllPixels.csv` – the time series vegetation index values for all pixels

(b) With AOI

```
> PhenoMetrics("E://Data2", TRUE, 15, TRUE)
```

Where the path where the Vegetation index image files and the boundary of the AOI are saved at `"E:/Data2"`, the required threshold level for Onset and Offset definition is 15%, and smoothing required.

The results are saved under `E:/Data2/Matrics/`

- `PhenoStack.img` – the raster stack of 15 phenological metrics images.
- `AllPixels.csv` – the time series NDVI values for all pixels

3- How to ran MultiPointsPlots function

```
> MultiPointsPlots("E://Data2//Metrics",3,13,5,7)
```

Where the csv file for the time series data is located at `"E://Data2//Metrics"`.

The result plots curves from 3 points with id 13, 5 and 7.

Appendix C

Paper presented at 20th International Congress on Modelling and Simulation, Adelaide, Australia, 1–6 December 2013, www.mssanz.org.au/modsim2013 (p1896 -1902)
http://www.mssanz.org.au/modsim2013/H15/araya.pdf

Statement of Authorship

Title of Paper	"Crop phenology based on MODIS satellite imagery as an indicator of plant available water content"
Publication Status	☑ Published ☐ Accepted for Publication ☐ Submitted for Publication ☐ Unpublished and Unsubmitted work written in manuscript style
Publication Details	Araya, S., Ostendorf, B., Lyle, G., and Lewis, M. (2013), "Crop phenology based on MODIS satellite imagery as an indicator of plant available water content." In MODSIM 2013, 20th International Congress on Modelling and Simulation. December 2013, pp. 1896–1902. ISBN: 978-0-9872143-3-1

Principal Author

Name of Principal Author (Candidate)	Sofanit Araya
Contribution to the Paper	Development, conceptualization and realisation of the research, wrote the manuscript
Overall percentage (%)	85
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.
Signature	Date 5-10-17

Co-Author Contributions

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

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

Name of Co-Author	Bertram Ostendorf
Contribution to the Paper	Supervised development of the research, assisted in analysis and evaluated manuscript
Signature	Date 13-9-17
Name of Co-Author	Megan Lewis
Contribution to the Paper	Co-Supervised the development of the research and evaluated the manuscript
Signature	Date 25/9/17
Name of Co-Author	Gregory Lyle
Contribution to the Paper	Co-supervised development of the research, assisted analysis and evaluated manuscript
Signature	Date 26/9/17.

Crop phenology based on MODIS satellite imagery as an indicator of plant available water content

Sofanit Araya [a], Bertram Ostendorf [a], Gregory Lyle [a], Megan Lewis [a]
[a] Spatial Information Group, School of Earth and Environmental Sciences, University of Adelaide
Email: SofanitGirma.Araya@adelaide.edu.au

Abstract

Maintaining agricultural productivity into the future is one of the most important goals of our society. The world's vast grain production areas in arid environments have a high sensitivity to climate change, thus demanding accurate future predictions. Management and decision making depends on an understanding of complex spatial and temporal interactions between rainfall, temperature and soils, but detailed soil information is extremely costly and generally unavailable.

Crop phenology, the timing of plant growth and developmental stages, is the combined response to environmental factors such as soil, water and temperature. Crop phenology plays an important role in crop growth models and agronomic management. In Mediterranean environments like South Australia, water is the driving factor for crop growth. In these rain-fed farming systems, water availability largely depends on rainfall amount and seasonality and the capacity of the soil to retain rainfall inputs and hence make water available for crops. Plant Available Water Capacity of soil (PAWC) is an important measure of the spatial and temporal variability of crop growth and yield, but there is a paucity of detailed maps at a management relevant spatial resolution and extent.

In this study, different phenological metrics derived from MODIS NDVI imagery were assessed over sites of known PAWC and cropping history. We used the metrics:

- NDVI at the onset of greenness (Onset) and time of Onset (OnsetT)
- NDVI at peak greenness (MaxV) and time of maximum greenness (MaxT) The length of the growing season (WidthGS)
- Rate of greenup (GURate)

The green up rate of the curve (GU-rate) showed the most consistent difference between soils of different PAWC. The Rate of Green up is higher for the soil points with relatively low PAWC. Some of the variability in the difference between sites with low and high PAWC can be explained with rainfall amount and seasonality but the relationship is complex. The results indicate that the crop phenology derived from MODIS satellite imagery is consistently different and may therefore provide useful information about site conditions, which would allow improvements to the spatial detail in soil maps.

Keywords: *Digital Soil Mapping (DSM), remote sensing, satellite imagery, spatio-temporal*

1. INTRODUCTION

Soil information is very important information for policy making and various environmental practices. Most global and regional environmental models need soil information as one of the input parameters (Asseng et al., 1998, Henderson et al., 2005). Missing this information at the global or local scale leads to uncertainty in the basic sustainability decision makings (FAO et al., 2009).

Field measurements of plant available water capacity (PAWC) are expensive and time consuming (Morgan et al., 2000) and there is the need to estimate PAWC through relatively easily measurable soil properties (Mullins, 1981, Morgan et al., 2000, Jiang et al., 2008). Seasonal variability of the crop growth is theoretically related to PAWC variability but it is difficult to extract this information because of the number of factors that influence dynamics of water availability and crop growth.

Vegetation condition and crop growth timing is strongly influenced by underlying soil conditions. The spatial variability of soil PAWC and its interaction with the rainfall seasonality is considered a major cause of the growth variability (McDonald, 2006, Oliver et al., 2006, Wong et al., 2006a, Wong et al., 2006b). In turn, improved understanding of the growth dynamics may allow inferences about the soil’s water condition.

Vegetation phenology, the timing and seasonality of the plant growth stages, could be a useful indicator of different environmental factors including soil (Reed et al., 1994, Zhang et al., 2003). In non-irrigated agricultural area, phenological phenomena reflect how plants respond to short term weather events (Reed et al., 1994).

The Normalized Difference Vegetation Index (NDVI) has been used in many vegetation phenologic studies, including global land cover classification (Lloyd, 1990, DeFries et al., 1995), crop classification (Wardlow et al., 2007, Wardlow et al., 2008, Sun et al., 2012), and agricultural productivity estimation (Hill et al., 2003, Kouadio et al., 2012). Moderate Resolution Imaging Spectroscopy (MODIS), mounted on the NASA Earth Observation System’s Terra Spacecraft, provides vegetation indices with the resolution of 250m – 1km. The NDVI data from MODIS is one of the most widely used satellite images for time series analysis (Rodrigues et al., 2011). Despite the usefulness of MODIS NDVI for understanding of the plant and environmental conditions, little evidence exists if NDVI dynamics can be used as a spatial indicator for environmental factors that control the plant growth such as soil conditions.

In this paper we assess plant dynamics within two cropping paddocks in different climate zones that have marked differences in PAWC and area sufficiently large to be used with MODIS imagery. We have derived phenological metrics from the time series MODIS NDVI images are used to explore the seasonal variation of vegetation and its interaction with the climatic conditions to examine the response of the soil PAWC to different rainfall amount and seasonality.

2. MATERIALS AND METHODS

The study was carried out on two paddocks around Wharminda and Minnipa towns in the upper Eyre Peninsula, South Australia. The sites were selected for their setting with the soil types which may represent wider area coverage of the Eyre Peninsula region (Eyre Peninsula Farming Systems, 2009). Both of these farms have been studied as the focus site of the Eyre Peninsula Agricultural Research Foundation (EPARF) (Eyre Peninsula Agricultural Research Foundation 2011). Average annual and growing season rainfall is 325mm and 242mm, respectively.

The paddock around Wharminda (Wharminda Paddock) is situated at 33°9'30"S, 136°19'47"E. It is characterized by siliceous sand over sodic clay soil, which approximately represent 455,000 ha area of the Eyre Peninsula (Eyre Peninsula Agricultural Research Foundation 2011). These sands are reported to be a challenge for the farmers due to their uneven wetting nature at the beginning of the growth seasons. This uneven wetting is worse in the deep sand soils. It results in uneven germination at the beginning of the growing season (Eyre Peninsula Farming Systems, 2009). The Minnipa Paddock, N1 at Minnipa Agricultural Center (MAC) is located at 32°48'47"S, 135°9'55"E.

3. DATASETS

MODIS NDVI data (MOD13Q1 16 days composites) was used to estimate phenological indices. The imagery is available from NASA's Earth Observing System (EOS), with ground resolution of 250m. These composites were calculated using Constrained View angle – Maximum Value Composite (CV-MVC) and Maximum Value Composite (MVC) techniques (Solano et al., 2010). The MODIS NDVI data is available since 2000. Thus we will have 273 images (23 images per year except 2000 at which only 20 images available).

Rainfall data (daily gridded data with 5km resolution) was provided by the Australian Government Bureau of Metrology (BOM).
Soil data from APSoil was used in this study. The APSoil was developed for regional use with the Agricultural Production Systems Simulator (APSIM) (The APSIM initiative). The APSoil database is a point based soil characterization. There are around 69 points in the South Australian Agricultural region. The points used in this study are #394 and #395 from Wharminda and #354 and #353 from Minnipa stations, respectively.

The paddocks were zoned based on yield and Electro Magnetic Survey (EM38) surveys (Eyre Peninsula Agricultural Research Foundation 2011) . The representative soil points were taken from the zones of both paddocks. Table 1 shows the PAWC measurement of these soil points and the soil type at the location. The closest pixels to these soil points were chosen and the NDVI time series data were extracted for those pixels. The chosen pixels are within the representing zones and are the closest possible pixels for the soil points. Moreover, the pair soil points are within the same paddock, which means that the compared MODIS time series are under the same management with constant seeding and fertilser rates.

Table 1. Soil points at the study sites

Paddock at Wharminda		
Apsoil ID	PAWC	Soil Type
394	166mm	Shallow sand over clay
395	95mm	Loam over roack
Paddock at Minnipa		
353	57mm	Red Sandy Clay Loam
	209mm	Red Light Sandy Clay Loam

3.1. Phenological metrics

We evaluated five different phenological metrics that may be used as indicators for biophysical conditions (Figure1): Onset of greenness, time of Onset of greenness, Maximum greenness, time of maximum greenness, offset of greenness, and time of offset of greenness.
In this study, the onset of greenness was defined as the point where the highest slope observed between two consecutive NDVI values, on the period of March – June. The maximum greenness is the highest NDVI value and loosely correlated with the phenologic period of Anthesis. The offset of greenness (Offset) and time of offset (OffsetT) are defined as a point at which the crop loses its greenness and gets ready for harvest. This point

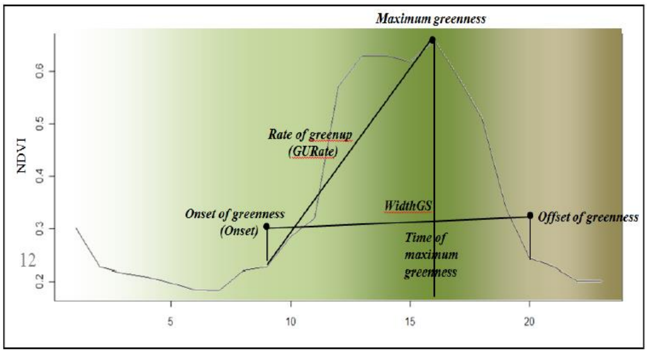

Figure 1. Phenological metrics used in this study

is defined as the point where lowest slope observed in the time series curve. This phenologic event loosely corresponds to the Maturity phenologic stage. Similarly, the time of offset is defined as the time when the offset of greenness is recorded. The length of the growing season (LengthGS) is defined as the duration of the period between the Onset of greenness and offset of greenness. The rate of greenup (GURate) is defined as the rate at which the NDVI increased from onset to the maximum greenness. It is calculated as the slop of the straight line between the onset of greenness and the maximum NDVI i.e (Maximum NDVI-Onset of greenness)/ (time of maximum greenness-time of onset).

4. RESULTS

A comparison of time series of NDVI of twelve years (2000 – 2011) at the soil sites in both stations shows noticeable differences (Figure 2). In Wharminda paddock, the MaxV for all the years from Pixel 395 (low PAWC) was higher than that of Pixel 394. Maximum NDVI was also observed to appear 15 – 30 days earlier than that of 394. Similarly the OnsetT also showed marked differences. In most of the years both Onset of greenness and maximum NDVI were earlier at low PAWC. However the difference is not consistent in all the years.

Similarly, in Minnipa paddock, the region with low PAWC (Pixel 353) was characterized by a higher maximum in most of the years. Onset of greenness and maximum NDVI was also observed to be earlier at low PAWC.

The Rate of Greenness (GURate) depends on the onset of greenness and the timing and magnitude of the maximum NDVI. The soil points with relatively lower PAWC, Pixel 395 (Wharminda Paddock) and Pixel 353 (Minnipa paddock), have a higher GURate compared with their corresponding points. However, GURate differed markedly between years, possibly related to rainfall amount and seasonality.

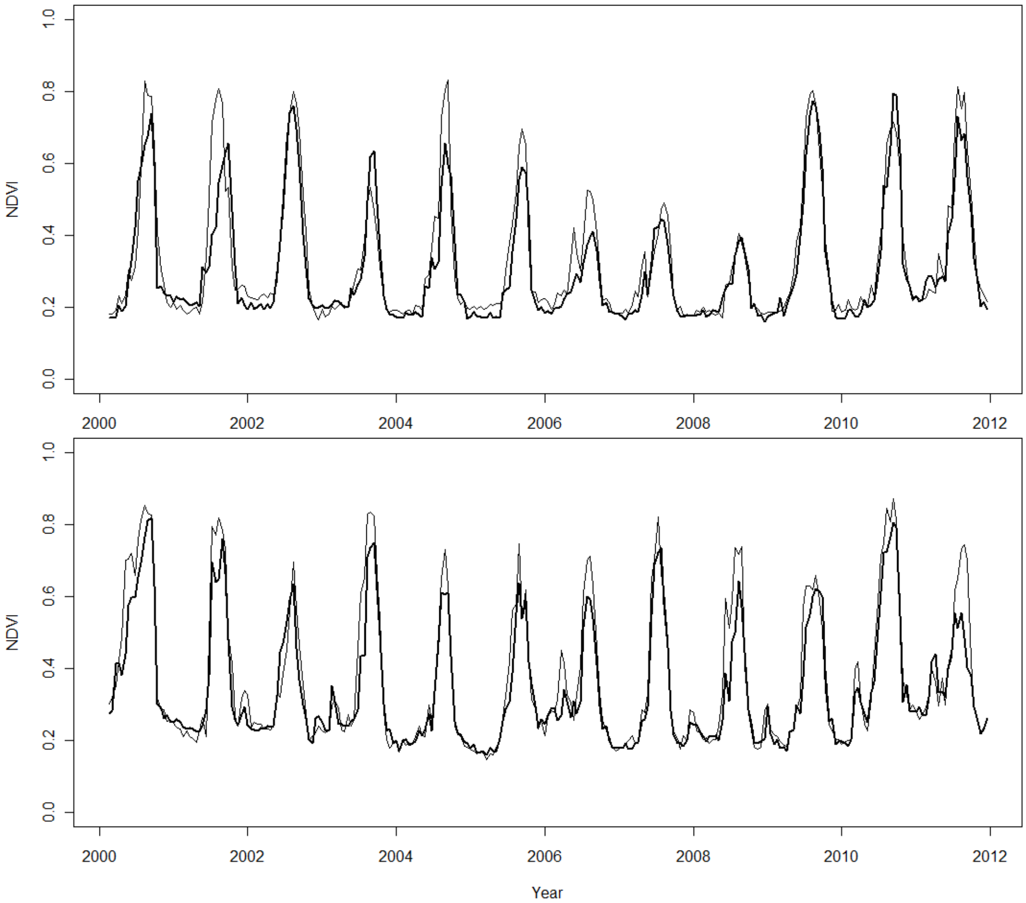

Figure 2 Time series of NDVI at (a) Minnipa and (b) Wharminda. The darker lines show NDVI of pixels with high PAWC.

4.1. Relationship between Phenologic metrics and rainfall amount and seasonality

The rainfall seasonality interacting with PAWC reflects differences in the vegetation growth. This is exemplified for Wharminda in Figure 3. The illustration compares 16 days cumulative rainfall variability with the difference of the rate of vegetation growth between the two representing pixels. Reflecting rainfall seasonality and amount, NDVI around the soil points showed substantial variability. On both paddocks, locations with lower PAWC (Pixel 395 of Wharminda and Pixel 353 of Minnipa) show a faster increase of NDVI compared to locations with higher PAWC.

NDVI of Pixel 395 generally peaks earlier than that of Pixel 394 (Figure 3). In some years (e.g. 2006 and 2007), the rainfall was more dominant in the earlier seasons. Early rainfall filled the soil profile to support the vegetation growth during the low rainfall season. The greater water holding capacity of the sandy soil supports faster plant growth than the loam over clay soil.

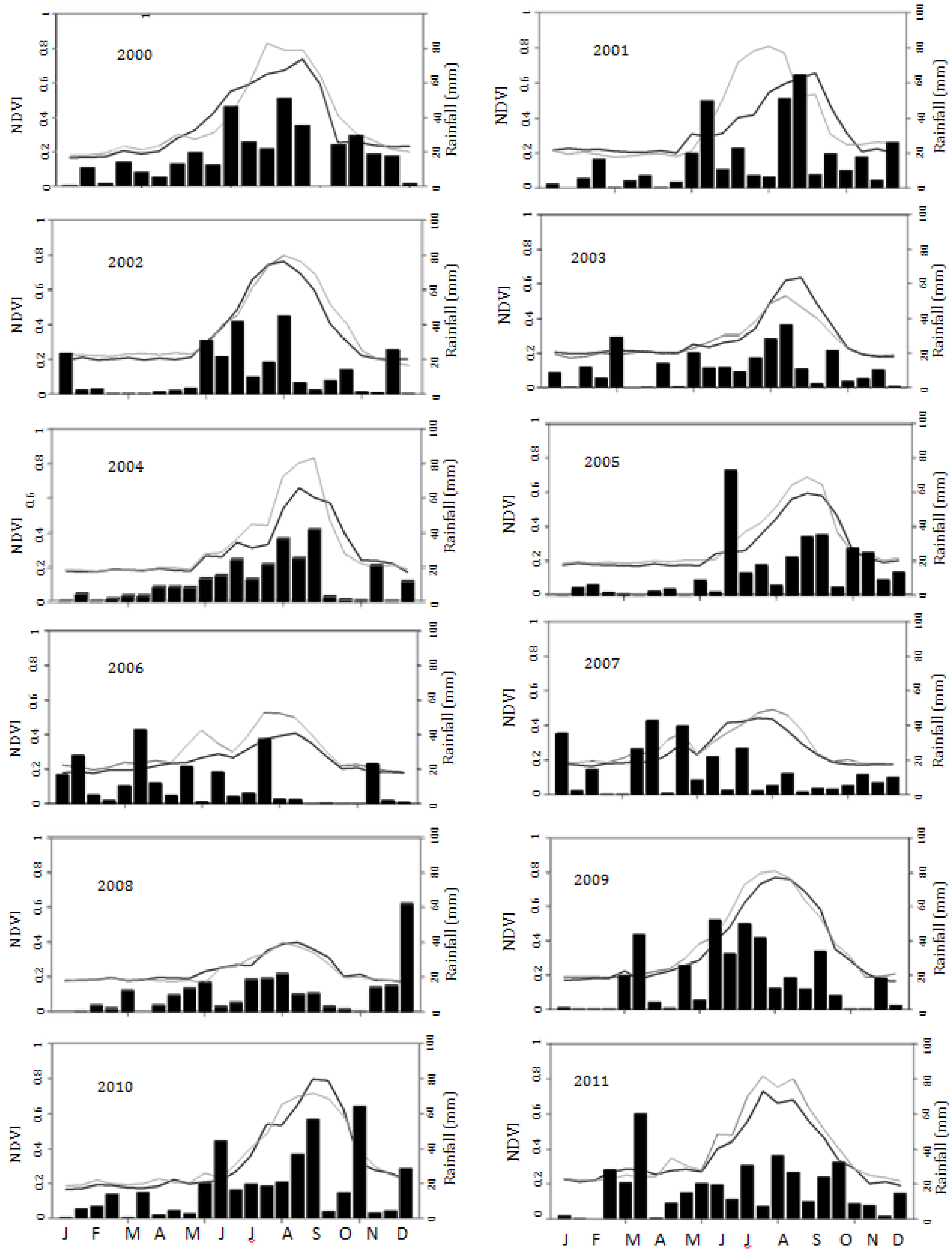

Figure 3 Time series of NDVI and rainfall at Wharminda. The darker lines show NDVI of pixels with high PAWC.

In the year 2006, rainfall was dominated towards the warmest summer seasons, which may be lost through evaporation due to the high temperature during the summer season. The April-May rainfall was low, following the fair rainfall in the beginning of May. The NDVI of Pixel 395 sets to onsets before the vegetation at Pixel 394. The year 2007 was also with very low rainfall throughout the growing season. The vegetation in both soil type reached to Onset at a similar time, followed by steep NDVI increment in the loam soil as a result of low June and July rainfall. The years 2008 and 2009 were characterized with lower early rainfall in April and May, results early onset and maximum greenness for the vegetation from Loam soil (Figure 3).

5. DISCUSSION AND CONCLUSIONS

The PAWC is a controlling factor for vegetation growth in dryland agriculture, especially in arid and semiarid farming area like South Australia and determines phenological events. Understanding how growth variability is affected by rainfall seasonality and soil PAWC interactions may allow us to work towards inverse modeling schemes that infer about soil conditions based on the spatio-temporal differences in satellite imagery. Growth dynamics can be quantified as variability of the phenological stages including the time of maximum NDVI (MaxT), time of Onset (OnsetT) and combined effect on the rate of growth (GURate).

The GURate was observed to be higher in low PAWC corresponding with an earlier onset and higher maximum NDVI than the relatively higher PAWC soils. This corresponds with observations by Robertson etal., (1994) who studied wheat crop under water deficit during early, mid and late phenologic periods and found that the timing of heading phenologic stage is highly affected by the water deficit. The stressed crop (Robertson et al., 1994) reached heading and anthesis stages approximately 5 and 3 days earlier than the nonstressed crops. Moreover, the study showed that the early stress had the largest effect on developmental timing comparing to the mid and late stresses (Robertson et al., 1994). Numbers of similar experimental research works have been done to assess the effect of inadequate water availability, at various growth stages, on the growth of different crops. These research projects indicate that the timing of growth stages and duration are highly influenced by water availability. Faster crop growth rate is one of the evident effects of water stress during crop growth (McMaster et al., 2003, McMASTER, 2005, McMaster et al., 2011).

The low PAWC soils in both paddocks meant that these soils stored less water and at the time of water scarcity, the soil with higher storage capacity could sustain plant growth compared to low PAWC soils. Thus the vegetation on low PAWC soil faces water stress earlier than the high PAWC soils, which cause the vegetation to accelerate growth to the next growth stages. This can be seen a fast raising curve in the NDVI time series curve, which is measured as GURate for the lower PAWC soils.

Comparing the differences in the growth stages, the maximum is observed at the time maximum NDVI (MaxT). These agreed with the observation made by previous researchers (Angus et al., 1977, Robertson et al., 1994, McMaster et al., 2003, Brisson et al., 2005, McMaster et al., 2008) on the fact that the water deficit affected the anthesis phenological stage, which could loosely correspond to the maximum NDVI (MaxV and MaxT), is more than the other stages. At Wharminda we also observe a higher nutrient concentration in the shallow loam, producing a higher establishment rate and higher initial biomass without yield improvement (Eyre Peninsula Farming Systems, 2009). Potential improvements in inverse modeling of yield may come from focusing on the later part of the season to distinguish bucket size from other growth factors that influence leaf area development. NDVI during the earlier part of the season may be more strongly influenced by moisture content and nutrient concentrations in the upper soil layers rather than the total available water.

There appears to be a strong soil-related signal in the NDVI dynamics. However, the complexity of soil rainfall interactions may require a very large sample size to

allow for an automated extraction of site conditions from the time series of NDVI for empirical models. Furthermore, there is substantial variability within a MODIS pixel that is averaged out in the NDVI time series and higher resolution imagery may be useful to assess this spatial variability. Another factor that needs to be considered is the scale issue of having a single soil sample that may or may not be representative (Ostendorf, 2011).
The results presented here allow suggestion for the structure of future PAWC models based on NDVI dynamics. Inverse models of PAWC from NDVI should include the rate of greening and the relative timing of the peak NDVI with a stronger consideration of the later part of the season. Whilst there is potential, validation using larger sets of soil core data needs to carefully evaluate if the soil samples are truly representative of a paddock area at the size of the MODIS pixel. Though, this technique can potentially used to zone paddocks based on the MODIS NDVI time series growth pattern.

ACKNOWLEDGMENTS

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Appendix D

Abstract for presentation on 2014 Australia National Soil Science Conference, in Melbourne, Victoria, 23 -27 November 2014

Time Series analysis of Satellite Imagery to improve agricultural soil management

Sofanit Araya, Bertram Ostendorf, Megan Lewis, Greg Lyle

Spatial Information Group (SIG), school of Earth and Environmental Sciences, The University of Adelaide

sofanitgirma.araya@adelaide.edu.au

Abstract

Soil is natural resource with high spatial variability. Plants growth reflects this variability in complex interactions with other factors. Precision agriculture is based on utilising crop growth variability data and, in its simplest terms, delineates zones with similar productivity so that the most suitable management approach can be implemented. However, pattern of variability may vary considerably from year to year. This adds a level of complexity for management. In Mediterranean-type dryland cropping region of South Australia, water is reported to be the main cause of crop growth variability. Plant Available Water holding Capacity (PAWC) of soil measures the maximum amount of water which could be held in the soil. It has a strong interaction with weather condition, which governs crop growth variability. We hypothesise that by keeping management and climate constant by focusing on a small geographic area, the dynamic response of plants is largely due to soil functions. This study demonstrates the use of high temporal frequency satellite imagery for paddock zoning in the south Australian agricultural region. The research aims to use time series clustering of NDVI data for zoning of two paddocks in the upper EyrePenninsula. Pixel level clustering analysis was carried out on the time series Moderate Resolution Imaging Spectroscopy (MODIS) NDVI data, of 250m spatial resolution biweekly images. The result shows classification of the paddock into zones of similar dynamics, indicative of differences in plant-soil-climate interactions. This suggests that time series of MODIS-NDVI imagery provide a tool to assess spatial heterogeneity of soils-plant-climate interactions.