School of Earth & Environmental Sciences

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Spatial and Temporal Monitoring of Soil Erosion Risk with Satellite Imagery

Land Condition Monitoring Reports | Report 4

K.D. Clarke[1], M. Lewis[1], A. Dutkiewicz[2], G. Forward[2] and B. Ostendorf[1]

[1]School of Earth and Environmental Sciences, The University of Adelaide

[2]Department of Environment and Natural Resources, South Australia

Please direct correspondence to: kenneth.clarke@adelaide.edu.au

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Executive summary

Mediterranean climate agriculture is of key economic and social importance to South Australia, and protection of soil resources from erosion is therefore a high priority for the State Government. To ensure that South Australian soils are conserved, the South Australian Department of Environment and Natural Resources (DENR) conducts erosion protection field surveys (EPFS) to monitor soil cover and disturbance on agricultural lands.

However, while very valuable, field surveys are expensive and have limited spatial extent and temporal frequency. Consequently there is growing interest within State and Australian governments in the potential of remote sensing to assess soil cover at appropriate spatial and temporal resolutions.

This project was initiated in response to this interest, and is an Australian Research Council Linkage Project collaboration (LP 0990019) between the University of Adelaide and DENR. The goals of this project were to:

1. develop a remotely sensed image index of soil exposure capable of accurately measuring the magnitude and duration of soil exposure across South Australia's cereal cropping regions;
2. evaluate the accuracy of the image indices so that they might be used to assess soil erosion risk with confidence, and
3. to provide demonstrations of how the image indices might be used to report against the South Australian State Strategic Plan soil protection target.

Outcomes of this project of relevance for image-based soil exposure monitoring can be broadly divided into two categories; reporting on soil exposure across South Australia's cereal cropping regions and scientific advances. Reporting outcomes illustrate how the satellite image-based Land Condition Index (LCI) or Relative Spectral Mixture Analysis (RSMA) might be used to monitor and report on soil exposure, and how image-based reporting would differ from the current field-based method. Scientific outcomes are the use of rigorous empirical methods to evaluate the sensitivity of the LCI, the RSMA and the Absolute Relative Spectral Mixture Analysis (ARSMA). This advances the science of satellite based soil exposure measurement and monitoring, and provides confidence in the ability of the LCI to support image-based soil exposure reporting. These science outcomes will be submitted to, and published in, peer reviewed scientific journals.

Reporting outcomes include the following.

1. Visualisations of temporal profiles of LCI and RSMA against EPFS assessments of soil cover are provided, and demonstrate the ability of the LCI and RSMA to report more frequently than the EPFS. These profiles also demonstrate that LCI and RSMA detect all general

seasonal patterns, and all major deviations from average seasonal patterns (*e.g.*, unusually wet or dry years).

2. A proposed method for using LCI to visualise fortnightly changes in soil exposure, by reporting region, from 2000 to 2010.
3. A proposed method for using LCI to calculate and visualise magnitude of erosion vulnerability (duration of soil exposure multiplied by severity of soil exposure).
4. A proposed method for using LCI to calculate and visualise change in land protected from erosion relative to 2003. This method will assist in reporting against the South Australian State Strategic Plan soil protection target.

Scientific outcomes include:

1. Evaluation of the LCI, RSMA and ARSMA against specifically-collected high quality field fractional soil exposure data in one region of South Australia. The LCI, RSMA and ARSMA were demonstrated to be good measures of soil exposure in this region.
2. Evaluation of the LCI against the EPFS assessments of soil cover in all cropping regions. The LCI was demonstrated to be a consistent predictor of soil exposure in all South Australian cropping regions.

Thus, we have demonstrated strong agreement between LCI and high quality field fractional cover data in one area and consistent agreement between LCI and the DENR EPFS Cover Rating throughout the cropping regions. Furthermore, we have demonstrated that the LCI is capable of measuring trends in soil exposure over time, and how the LCI can be used to report against the SASSP soil protection target.

Recommendations

The LCI is ready for incorporation into the DENR soil erosion risk monitoring program. This satellite image-based monitoring has advantages of being objective and consistent, spatially and temporally comprehensive, and cost-effective. Adoption of the LCI is a low-risk move for DENR. If a better soil exposure image index is discovered in the future, DENR could easily switch to that index. The reporting methods we have demonstrated in this report could equally easily be produced from another image index. Such a change would require minimal disruption to production, and would be invisible to report users.

If DENR chooses to adopt the LCI, we recommend that a detailed transition and implementation plan should be drawn up, including the following components:

- both the LCI and EPFS be conducted in tandem for a period;

- some additional high quality field fractional cover data be collected in the Eyre Peninsula and Murraylands regions to increase confidence in performance of the LCI across a wider range of South Australian soil types;
- the target audiences and means for delivery of image-based erosion protection information be further clarified;
- the means and capability for on-going production and delivery of image-based erosion protection reports be identified.

In the near future, the Adelaide AusCover node of the Terrestrial Ecosystem Research Network (TERN) will undertake further development of the LCI, RSMA and ARSMA. These will be developed from 2011 to the end of 2013, and may lead to improvements in soil exposure remote sensing that DENR could incorporate into an image-based soil exposure monitoring program.

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Thanks to the land-holders, Clinton Tiller and Greg Barr, who graciously gave permission for collection of cover data from their properties. Finally, thanks to University of Adelaide staff, Victoria Marshall, Kelly Arbon, Valerie Lawley, Yuot Alaak and Lydia Cape-Ducluzeau for the many enthusiastic hours of step-point data collection.

Table of contents

List of tables

List of figures

1. Introduction

1.1 Background and aims

Mediterranean climate agriculture is of key economic and social importance to South Australia, and protection of soil resources from erosion is therefore a high priority for the State Government. When this project was conceived South Australia's Strategic Plan (SASP) 2007 reflected this importance in target T3.3 Soil protection, "By 2014, achieve a 20 % increase in South Australia's agricultural land that is adequately protected from erosion". Since project conception, the importance of soil conservation has been given even greater recognition in the revised SASP 2011 target 70, Sustainable land management, by increasing the target for agricultural land and adding a adding a target for pastoral land "By 2020, achieve a 25 % increase in the protection of agricultural cropping land from soil erosion [as compared to 2003] and a 25 % improvement in the condition of pastoral land."

To ensure that South Australian soils are conserved, the South Australian Department of Environment and Natural Resources (DENR) conducts erosion protection field surveys (EPFS) to monitor soil cover and disturbance on agricultural lands. This EPFS is extensive, covering more than 3,500 km of transects throughout the agricultural districts of South Australia, visually assessing land condition at approximately 5500 sites, and is run at four critical times each year. These visual estimates are combined with site-based records of topography and soil type and then extrapolated to estimate soil erosion risk for the cereal cropping regions.

However, while very valuable, field surveys are expensive and have limited spatial extent and temporal frequency. Consequently there is growing interest within state and national governments in the potential of remote sensing to assess soil cover at appropriate spatial and temporal resolutions.

This project was initiated in response to this interest, and was an Australian Research Council Linkage Project collaboration (LP 0990019) between the University of Adelaide and DENR. The goals of this project were to:

1. develop a remotely sensed image index of soil exposure capable of accurately measuring the magnitude and duration of soil exposure across South Australia's cereal cropping regions;
2. evaluate the accuracy of the image indices so that they might be used to assess soil erosion risk with confidence, and
3. to provide demonstrations of how the image indices might be used to report against the SASP soil protection target.

1.2 Report structure

Section 2 of this document is a paper submitted to the scientific peer reviewed journal, *Remote Sensing of Environment*. This section presents the satellite image-based Land Condition Index (LCI), evaluates the LCI and the Normalised Difference Vegetation Index (NDVI) against high quality field fractional cover data, and demonstrates that the LCI is a good predictor of soil exposure.

Section 3 is also a paper submitted to *Remote Sensing of Environment*. It evaluated the LCI and NDVI against the DENR EPFS Cover Rating (CR), demonstrating that LCI performs consistently across the cereal cropping regions of South Australia.

Section 4 presents two additional image indices, the Relative Spectral Mixture Analysis (RSMA) and the Absolute Relative Spectral Mixture Analysis (ARSMA). These image indices measure the relative and absolute fractional cover of photosynthetic vegetation (PV), non-photosynthetic vegetation (NPV) and soil respectively. This section also includes an evaluation of the performance of these two indices against the high quality field fractional cover data. This evaluation demonstrates that RSMA and ARSMA are very promising indices of soil exposure, as well as PV and NPV fractional cover.

In Section 5 we demonstrate some of the potential uses of the image indices for monitoring and reporting on soil erosion risk. These include temporal profiles (graphs of variation over time) of LCI, NDVI and RSMA, and comparisons of these with temporal profiles of other variables including the DENR EPFS and precipitation. Additionally, measures specifically designed for reporting against the SASP soil protection target are demonstrated.

Section 6 provides a short case study in one reporting region, and demonstrates the advantages of the image-based LCI over the field-based EPFS for monitoring soil exposure.

Finally, Section 7 provides a summary of the report findings, recommends that the LCI is ready for operational use with little additional work, and outlines the work that would be required before the ARSMA could be used operationally. Finally, we conclude with a description of how the TERN AusCover project will advance the remote sensing of soil exposure, and the potential impacts this could have for South Australia.

2. Paper I. Direct evaluation of a new MODIS Land Condition Index (LCI) and NDVI against large-scale field-assessed fractional cover[1]

Authors

Clarke, K.,[1] Lewis, M.,[1], Dutkiewicz, A.[2], Forward, G.[2] and Ostendorf, B.,[1]

[1]School of Earth and Environmental Sciences, The University of Adelaide.

[2]Department of Environment and Natural Resources, South Australia.

Corresponding author email: kenneth.clarke@adelaide.edu.au

2.1 Abstract

The protection of soil resources from erosion is an issue of global importance. The viability of agriculture and the ability to feed the expanding human population is contingent on continued soil fertility. To protect soils from erosion it is essential that adequate cover levels be maintained for as long as possible, to limit both the severity and duration of erosion. However, there are no current methods for measuring soil exposure severity and duration at extents and temporal frequencies appropriate for monitoring of broad cropping regions. This paper is Part I of a two-part study aiming to address the need for a spatially extensive remotely sensed index of soil exposure with moderate resolution and high temporal frequency. We introduce a new MODIS index of soil exposure, the Land Condition Index, and test it in an area of uniform soils and topography in the South Australian Mediterranean cropping region. The LCI was tested against field fractional photosynthetic vegetation (PV) , non-photosynthetic vegetation (NPV) and soil cover measurements collected at a large field scale, appropriate for direct comparison with of MODIS. The performance of the LCI was also compared to the widely used NDVI. Both image indices were produced from the MODIS NBAR product. Since this image product is cloud free and has high temporal frequency it is ideal for measuring the duration of soil exposure. We demonstrated that LCI has a stronger correlation with fractional soil cover than NDVI (R^2 = 0.48 and R^2 = 0.21 respectively). This paper establishes that the LCI is a strong predictor of soil exposure through comparison with quantitative field data collected at a MODIS-appropriate scale. This relationship was based on measurements of cover from a single region. In Part II we evaluate whether LCI is a consistent predictor of soil exposure across much broader extents.

[1]Submitted to *Remote Sensing of Environment*

2.2 Introduction

The protection of soil resources from erosion is an issue of global importance. Indeed, the continued economic viability of almost all agriculture and the ability to feed the expanding human population are contingent on the protection of soil resources. As Lal (2003) notes, this importance is illustrated by the strong focus on sustainable management of soil in Agenda 21 from the 1992 Rio summit (UNCED 1992), the UN Framework Convention on Climate Change (UNFCCC 1992), the 1994 UN Framework Convention to Combat Desertification (UNFCD 1996), and Articles 3.3 and 3.4 of the Kyoto Protocol (UNFCCC 1997).

If soil resources are to be protected from erosion, then both the severity and duration of soil exposure must be minimised. To this end, it is essential that an adequate level of soil cover is maintained for as much of the year as possible. In seasonally cultivated Mediterranean cropping areas, the focus of this study, adequate soil cover is achieved through effective management of crops, pastures and crop residues. In recent decades, adoption of conservation-farming practices has helped to minimise soil disturbance and exposure throughout the cropping cycle (Thomas et al. 2007). However, areas of low cover still persist. Some managers have not adopted conservation-farming practices, and even when adopted, some soil problems such as salinity or sodicity make the retention of protective levels of soil cover difficult.

However, soil conservation does not rely solely on land managers. Within most cropping regions at least one government agency is responsible for the protection of soil resources. To be effective, these agencies must be able to locate regions of inadequate cover and then through incentives, disincentives or education encourage better soil-cover retention. At present, it is difficult for these agencies to monitor soil cover within their jurisdictions. Cropping areas are often extensive, and in-field assessment is expensive and time consuming. Consequently, even the best field assessments only directly assess some of the area several times a year, and this limits the ability to measure both the severity and duration of soil exposure. There is a clear need for a means of accurately measuring soil exposure with a high temporal frequency, at broad spatial scales and with a spatial resolution appropriate to field sizes in extensive cropping areas.

Remote sensing technology has the potential to provide this information. For example, the NOAA AVHRR sensor collects data at appropriate temporal frequency and extent , and at a spectral resolution suitable for regional monitoring, although the spatial resolution is too coarse for regional monitoring of cropping fields. A large body of research over the past two decades has shown that AVHRR-derived vegetation indices, particularly NDVI, can be used to predict fractional photosynthetic-vegetation cover (Wittich and Hansing 1995; Gutman and Ignatov 1998; De Ridder 2000; Omuto et al. 2010). Furthermore, this knowledge has been applied in other fields of remote sensing, such as surface temperature measurement.

The remote sensing of surface temperature has for a long time been used to account for the influence of 'fractional vegetation cover' on land surface temperature (LST) (see review by Petropoulos et al. 2009). However, the measure of 'fractional vegetation cover' used in LST remote sensing is usually based on NDVI, and should therefore be more accurately called a 'fractional photosynthetic vegetation cover' (fr_{PV}). This is of concern, since both dead and green vegetation fraction have been demonstrated to strongly influence surface emissivity, and hence surface temperature (French et al. 2000). Therefore, a measure of fractional total vegetation cover (fr_{TV}) would be more appropriate than fr_{PV} and may improve the accuracy of LST remote sensing in areas with significant amounts of senescent vegetation such as rangelands and cropping regions.

While AVHRR data has been used widely and successfully for regional and continental assessments of fr_{PV}, it lacks the spectral resolution for discrimination of soils from non-photosynthetic vegetation (NPV). Consequently most research on discrimination of PV, NPV and soil using satellite imagery has used high spatial and spectral resolution measurements, with less attention given to broad-scale, high-temporal frequency imagery. This research has demonstrated considerable potential for distinguishing these important cover types. A variety of indices have been used successfully with a range of image and spectral data including field spectrometers, airborne imaging spectrometer and moderate to high resolution multispectral and hyperspectral satellite imagery (Asner and Heidebrecht 2002; Daughtry et al. 2004; Sullivan et al. 2004; Arsenault and Bonn 2005; Daughtry et al. 2005; Daughtry et al. 2006; Marsett et al. 2006; de Asis and Omasa 2007; de Asis et al. 2008; Gowda et al. 2008). In summary, these studies identify the utility of the shortwave infrared region of the spectrum for discrimination of PV, NPV and soil, and one index in particular stands out: the cellulose absorption index (CAI) (Nagler et al. 2000; Nagler et al. 2003).

The monitoring of soil exposure in broad scale cropping or pastoral regions requires high spectral resolution, broad extent and high temporal frequency. However, the high-spectral resolution sensors in the studies cited above have inadequate extent and temporal frequency, while AVHRR has inadequate spectral resolution. However, the MODIS sensor collects data over an extent and with a temporal frequency similar to AVHRR but with greater spectral resolution. Indeed, the high temporal frequency of MODIS has recently been utilised to map land cover types across Australia (Lymburner et al. 2010).

However, there has been little research examining the potential of MODIS for soil exposure monitoring. A recent notable exception is the work of Guerschman et al. (2009) which developed an unmixing approach based on MODIS NDVI versus band 6/band 7. While this method showed promise in producing fractional cover estimates of PV, NPV and soil, the method was not comprehensively validated with field measurements. Validation was mostly qualitative in one climatic region, and quantitative validation restricted to comparison of two datasets of greatly different spatial scales: an image index at 500 m resolution, and a field measure of fractional PV and NPV cover collected from two perpendicular 20 m transects.

We hasten to add that we do not intend this as a criticism of the work by Guerschman et al. (2009). Quantitative validation of moderate resolution satellite image products is a difficult task. Accurate field data is usually derived from point measures (e.g. Gower et al. 1999) and there is therefore a scale mismatch between the field data and the image product we wish to evaluate. A common solution to this problem is the one taken by the MODIS Land Discipline (MODLAND) Team: they bridge the gap between fine scale field data and moderate resolution satellite imagery by first establishing relationships between the field data and high resolution remotely sensed data (Morisette et al. 2002). These relationships can then be used to extrapolate the point measures to an appropriate scale for comparison with moderate resolution satellite imagery, such as MODIS (Milne and Cohen 1999; Reich et al. 1999).

2.2.1 A new land cover index

This paper is Part I of a two-part study detailing the development and validation of a remotely sensed index of soil exposure. In Part I we introduce a new MODIS index of soil exposure, the Land Condition Index (LCI), and demonstrate its efficacy by evaluating it against quantitative field data collected at a MODIS-appropriate scale. In Part II we evaluate the LCI against an existing field-based soil exposure monitoring method and demonstrate that the image-based monitoring can augment field assessments (Clarke et al. 2011).

The broader goal of this study is to develop an image-based method for assessing and monitoring soil exposure across extensive agricultural regions at risk of soil erosion. Specifically, our research aimed to 1) develop a new MODIS index as a predictor of soil exposure that is capable of discriminating total vegetation fractional cover (fr_{PV} and fr_{NPV}) from fractional soil cover (fr_{S}) more accurately than NDVI, and 2) to validate this index against field fractional cover measurements at a scale appropriate to MODIS ground resolution. To this end we propose a new index inspired by, but not identical to, the Cellulose Absorption Index (CAI) developed by Nagler et al. (2003). The CAI measures the average depth of the cellulose absorption feature at 2.1 µm by subtracting the reflectance at 2.1 µm from the average of the reflectance at 2.0 µm or 2.2 µm (Equation 1).

$$CAI = \frac{R_{2.0} + R_{2.2}}{2} - R_{2.1} \qquad (1)$$

where $R_{2.0}$, $R_{2.1}$, and $R_{2.2}$ are the reflectance at 2.00 – 2.05, 2.08 – 2.13, and 2.19 – 2.24 µm, respectively (Nagler et al. 2003).

The index we propose must differ from the CAI because MODIS does not incorporate any wavebands at 2.0 µm or 2.2 µm. Hence, we propose the Land Cover Index (LCI), a normalised measure of the difference in reflectance between MODIS bands at 1.628 – 1.652 µm and 2.105 – 2.155 µm, the latter of which is positioned within the cellulose absorption feature (Equation 2) while the former is positioned in a neutral region not influenced by cellulose. Additionally, we hypothesise that LCI will be a more accurate measure of soil exposure than NDVI.

$$LCI = \frac{R_{1.6} - R_{2.1}}{R_{1.6} + R_{2.1}} \tag{2}$$

where $R_{1.6}$ and $R_{2.2}$ are reflectance factors from MODIS bands 6 and 7 at 1.628 – 1.652 µm, and 2.105 – 2.155 µm respectively.

To illustrate the ability of the NDVI and LCI to differentiate PV and NPV cover from soil, we provide the following representative example, using spectra for PV (green Eucalyptus leaves), NPV (Pea Straw) and a range of soils. Reflectance values at 0.7 µm, 0.9 µm, 1.6 µm and 2.1 µm, taken from these spectra for the different cover and soil types, were used to calculate NDVI and LCI (Table 1). NDVI produces values of 0.8 for PV, 0.2 for NPV and 0.08 – 0.23 for different soils, and hence the index allows for PV to be distinguished from NPV and soil, but does not distinguish NPV from soil. On the other hand, the LCI values potentially allow separation of PV (0.35) and NPV (0.13) from soils (-0.07 – 0.03).

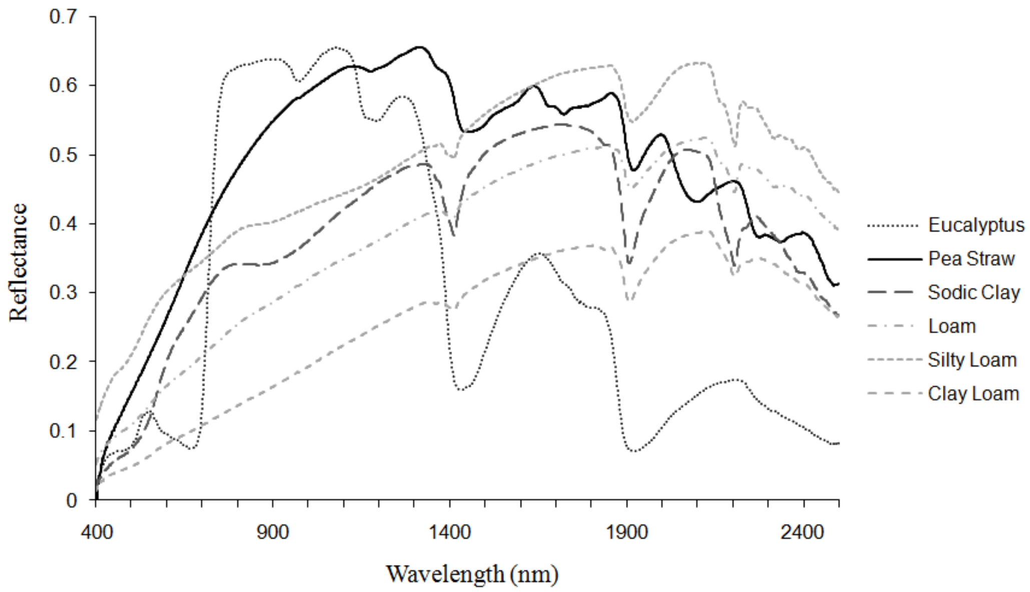

Figure 1. Indicative reflectance spectra for different soils, one photosynthetic vegetation (PV), and one non-photosynthetic vegetation (NPV). Adapted from Summers et al. (2011).

The aim of this paper is to address the clear need for a means of accurately measuring soil exposure with a high temporal frequency, at extensive spatial scales and with moderate spatial resolution. To this end, we present an evaluation of the LCI as a measure of soil exposure for broad agricultural regions.

Firstly we collect field fr_{PV}, fr_{NPV} and fr_S measurements at a large paddock scale appropriate for direct validation of MODIS image products and then calibrate the LCI against these field data. By collecting the field data at a MODIS appropriate scale we eliminate the potentially confounding step of up-scaling from field data to high-resolution imagery and then treating the high-resolution image product as validation data. Finally we compare the performance of the LCI with the widely-used NDVI. This approach aims to provide confidence that the relationships reflect the actual correspondence between field and remotely sensed variables.

Table 1. Example MODIS reflectance and image index values for a photosynthetic vegetation (green eucalyptus), non-photosynthetic vegetation (pea straw) and several soils.

	Reflectance				Index	
Cover type	**$Red_{0.7}$**	**$NIR_{0.9}$**	**$R_{1.6}$**	**$R_{2.1}$**	**NDVI**	**LCI**
Green Eucalyptus	0.07	0.64	0.33	0.16	0.80	0.35
Pea Straw	0.36	0.54	0.57	0.44	0.20	0.13
Sodic Clay	0.27	0.34	0.53	0.50	0.11	0.03
Loam	0.20	0.28	0.48	0.52	0.17	-0.04
Silty Loam	0.34	0.40	0.59	0.64	0.08	-0.04
Clay Loam	0.10	0.16	0.34	0.39	0.23	-0.07

2.3 Methods

2.3.1 Study area

Our study was based in a rain-fed cropping region of South Australia with a Mediterranean climate (Figure 2). The region experiences hot dry summers (December - February) and mild wet winters (July - August), and receives an average annual rainfall of approximately 500 mm. Agriculture in the region is dominated by annual rotations of cereal crops, legumes and rapeseed (*Brassica napus*, also known as canola).

In the study area, annual crop and pasture phenology follows a predictable annual pattern. Through summer, the landscape is largely dry although limited rainfall can lead to significant summer weed and pasture growth. In an average year, this is followed by rain in late March through to May and subsequent weed and pasture growth, until chemical spraying of weeds and seeding, or direct-drill seeding, which reduce cover to a minimum in May-June. Following seeding, annual crops germinate and growth peaks in September. Finally crops ripen, senesce and are harvested in November and December. Stubble remaining after harvest is commonly grazed by stock throughout summer.

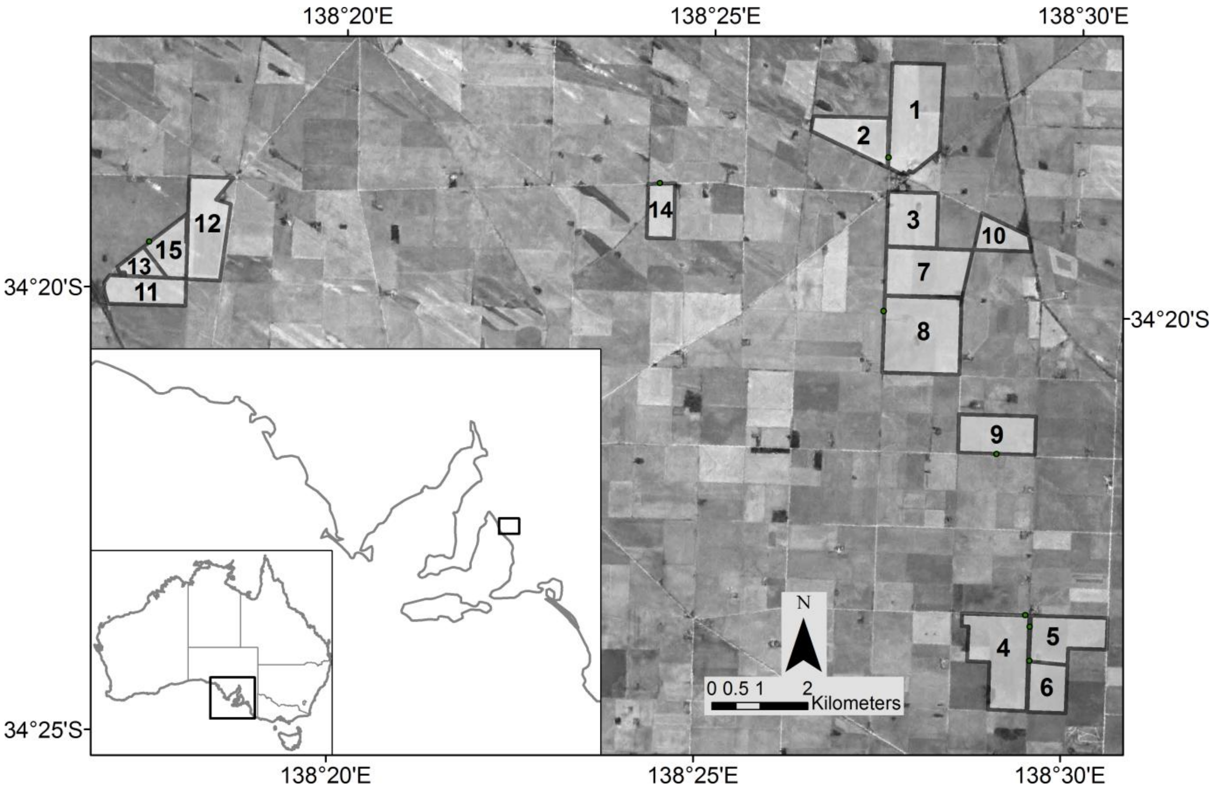

Figure 2. Location of study fields within South Australia.

This study focussed on 15 fields ranging in size from 61 to 257 hectares which are generally cultivated with a range of cover types including cereal, rapeseed and lentil crops (Table 2). These fields were chosen for their extremely large size, relative uniformity of soil and uniformly flat topography. This design allowed us to obtain fractional cover from fields corresponding to several MODIS ground resolution elements, with reasonable expectation of homogenous soil-cover due to minimal soil variability and minimal topographic redistribution of rainfall.

2.3.2 Field data

Field fractional cover data was collected on four dates using two field survey methodologies, one step-point and the other photographic (Table 3). Four dates were sampled to ensure the full range of fr_{PV}, fr_{NPV} and fr_{S} were characterised. The April and June survey dates were chosen to capture maximum fr_{S}. The October survey was timed to coincide with the expected time of peak green canopy cover, but before any crop senescence, to capture maximum fr_{PV}. Finally, the November date was timed as late as possible, but before harvest, to coincide with maximum fr_{NPV}.

The step-point method was used on the first two field survey dates (April and June) when crops were either not present, or were so new that little damage was caused. The photographic method was used on the last two field survey dates when crop canopies were full and green (October) or full and ripe (November). The photographic method was used to minimise crop disturbance, but unlike the step-point method did not cover the whole field. For this reason the photographic method was only applied after a field had been visually assessed to have homogenous cover. Table 3 summarises the two survey methods.

Table 2. Study field sizes (ha), post cultivation crop type, and the number of MODIS image elements with centres within the field extent.

Field number	Area (ha)	Post cultivation crop type	MODIS image elements (n)
1	231.53	Lentils	14
2	105.32	Rapeseed	5
3	120.03	Cereal	5
4	210.65	Lentils	10
5	129.45	Cereal	4
6	84.73	Cereal	2
7	171.52	Cereal	8
8	257.42	Lentils	15
9	129.45	Lentils	4
10	60.90	Cereal	3
11	96.20	NA	8
12	167.69	Cereal	7
13	36.19	Weeds*	1
14	62.66	Cereal	6
15	75.31	Cereal	4

*Field was not cultivated. Cover was a mixture of broadleaf weeds and cereal.

Table 3. Field survey dates and survey method employed, and MODIS satellite image middle dates[1].

Field survey date	Satellite image mid-date[1]	survey method
27th April 2010	1st May 2010	step-point
22nd June 2010	20th June 2010	step-point
8th October 2010	8th October 2010	photographic
26th November 2010	25th November 2010	photographic

[1]MODIS images used in this study are composites of images collected over 16 consecutive days. The date reported here is the middle of that 16 day period.

Step-point method

To record field fractional cover with our step-point method surveyors walked step-point transects (Evans and Love 1957; Mentis 1981) bisecting each field from fence to fence in a “W” shape. On every second step (approx. 1.5 m intervals) surveyors recorded the cover type (PV, NPV or soil) directly under a thin line drawn on the end of their shoe. For each field, fractional cover was determined by combining the step-point tallies of both surveyors, and then calculating the proportion of each cover type out of the combined tallies. The total number of step-point recordings taken within each field ranged from approx. 560 to 2500 (Table 4; n for April and June).

Photographic method

Vertical, nadir-oriented high-resolution colour digital photographs were taken from approximately one metre above the crop canopy. Fractional cover was determined by using software to overlay a regular grid of 100 points (10 x 10) over each photograph, and visually scoring the cover type at each point as either PV, NPV, soil or shadow/unidentified. For each field fractional cover was determined by combining the point tallies from all photographs for that field, excluding shadow/unidentified, and calculating the proportion of each cover type out of the total tally for that field.

On the first photographic sample date (October) between six and thirty photographs were taken in each field to ensure within-field variability was adequately captured. However, there was little variation in cover levels between photographs within each field. Consequently fewer photographs were taken on the second photographic sample date (November), ranging from eight to nine photographs per field. The total number of points assessed from all photographs for each field ranged from 600 to 2500 (Table 4; n for October and November).

2.3.3 Satellite imagery

The United States Geological Survey (USGS) Land Processes Distributed Active Archive Center (LP DAAC) MCD43A4v5 MODIS product was used for this project. This is a 500 m resolution nadir bidirectional reflectance distribution function adjusted reflectance (NBAR) 16 day composite data product. The NBAR correction normalises reflectance values across the image to what would be recorded if viewed from directly above.

Four MODIS composite images were used in this study, with mid-dates chosen closest to each of the four field sample events to ensure optimal correspondence between image and field data (Table 3).

2.3.4 Image index calculation and evaluation

Both LCI (Equation 2) and NDVI were calculated for the four image dates. Average image indices were calculated for the 15 fields on each survey date and were compared with the corresponding field-assessed fr_{PV}, fr_{NPV} and fr_{S}. For a given field, only image elements with centres within the field extent were included in the average. The number of image elements within each field extent is listed in Table 2. Field 13 encompassed only one MODIS image element centre, therefore the image index values recorded for that field are not an average, but are the index values for that individual image element.

2.4 Results

2.4.1 Field fractional cover

Field assessed fr_{PV}, fr_{NPV} and fr_S values (Table 4) followed the expected temporal pattern described in for the study area. In April (mid-Autumn), fields were dominated by crop residues resulting in high fr_{NPV}, while summer weeds provided some fr_{PV}. In some fields, inadequate crop-residue retention or overutilisation of crop residues lead to high fr_S. In June (winter), all but one field (13) had been cultivated and crop germination resulted in a mixture of low to moderate fr_{PV}, fr_{NPV} and fr_S. Field 13 was not cultivated or grazed, and weeds were not controlled, which resulted in very high fr_{PV} relatively early in the season. The October survey was timed to coincide with the expected period of maximum green crop canopy density and succeeded in recording universally high fr_{PV}. Finally, the November survey was conducted as late as possible in the cropping season, but before harvest, to record universally high fr_{NPV}.

2.4.2 Remotely sensed indices

Mean LCI and NDVI for each field and survey date (Table 4) followed the expected patterns outlined in Table 1. NDVI produced high values for high fr_{PV} fields and equally low values for fields dominated by high fr_{NPV} and fr_S. Likewise LCI produced high values for high fr_{PV} fields and low values for high fr_S fields, but differed by producing moderate values for high fr_{NPV} fields.

2.4.3 Relationship between field fractional cover and MODIS indices

Relationships between the three cover components, fr_{PV}, fr_{NPV}, and fr_S, and LCI and NDVI are presented in Figure 3 and examined in detail below. In Figure 3, the month of field data collection is clearly indicated and it is important to remember that different cover types dominated in each month. In April, fields were dominated by high fr_{NPV} and moderate fr_S, in June fields contained a mix of low to moderate levels of fr_{PV}, fr_{NPV}, and fr_S, in October fields were dominated by universally high fr_{PV}, and in November fields were dominated by universally high fr_{NPV}.

Firstly, fr_{PV} correlated strongly with LCI (Figure 3A, $R^2 = 0.76$) and very strongly with NDVI (Figure 3B, $R^2 = 0.93$). The slightly reduced ability of LCI to predict fr_{PV} was expected, and is due to the differential response of NDVI and LCI to NPV dominated spectra. NDVI is designed to respond strongly only to PV, and hence is determined by and correlates strongly with fr_{PV}. On the other hand, LCI was designed to differentiate PV and NPV cover from soil, and hence is not solely determined by PV, resulting in a slightly weaker correlation. This effect can be seen in the difference in NDVI and LCI values for April and November for samples with 0 fr_{PV}. The NDVI values for April and November are almost identical, while the LCI values for November are higher than those for April.

Table 4. Fractional cover and mean image indices for the sample fields. A blank line indicates a field was not surveyed on that date.

Field number	n	Fractional cover (%) PV	NPV	S	Image indices (mean) NDVI	LCI	n	Fractional cover (%) PV	NPV	S	Image indices (mean) NDVI	LCI
	24th April 2010						**22nd June 2010**					
1	805	7.58%	60.37%	32.05%	0.231	0.127	1590	16.35%	55.72%	27.92%	0.373	0.157
2	2209	5.48%	63.24%	31.28%	0.248	0.109	1326	40.27%	41.25%	18.48%	0.614	0.256
3	693	6.64%	64.50%	28.86%	0.245	0.133	2471	27.48%	42.57%	29.95%	0.467	0.201
4	970	14.64%	52.06%	33.30%	0.260	0.166	2334	15.51%	60.54%	23.95%	0.339	0.184
5	2406	20.37%	50.50%	29.14%	0.254	0.134	1549	34.22%	26.34%	39.44%	0.544	0.239
6	561	9.63%	64.88%	25.49%	0.249	0.154	1148	38.50%	29.62%	31.88%	0.505	0.240
7	2462	11.62%	58.12%	30.26%	0.225	0.122	2106	23.22%	43.02%	33.76%	0.407	0.145
8	1666	0.00%	65.85%	34.15%	0.218	0.148	2130	38.54%	42.91%	18.54%	0.467	0.190
9	552	3.99%	70.29%	25.72%	0.219	0.145	1949	23.14%	49.46%	27.40%	0.426	0.196
10							956	41.84%	24.37%	33.79%	0.591	0.259
11	2008	1.69%	14.39%	83.91%	0.262	0.085						
12	1186	2.53%	30.94%	66.53%	0.210	0.068	2306	50.26%	11.45%	38.29%	0.541	0.225
13	738	19.38%	32.25%	48.37%	0.237	0.058	740	91.89%	1.62%	6.49%	0.715	0.294
14	1628	3.93%	29.05%	67.01%	0.240	0.121	1970	32.03%	17.51%	50.46%	0.434	0.191
15							689	14.95%	36.28%	48.77%	0.511	0.209
	8th October 2010						**26th November 2010**					
1	1300	98.13%	1.25%	0.62%	0.815	0.404	900	0.00%	98.26%	1.74%	0.298	0.209
2	1300	88.95%	11.05%	0.00%	0.757	0.404						
3	1700	76.38%	11.93%	11.69%	0.816	0.404	900	0.00%	92.25%	7.75%	0.282	0.211
4	1000	98.37%	0.71%	0.92%	0.824	0.412	900	0.00%	98.86%	1.14%	0.294	0.223
5	3000	90.48%	5.44%	4.08%	0.845	0.445	800	0.00%	99.08%	0.92%	0.262	0.241
6	600	83.11%	7.94%	8.95%	0.845	0.421	900	0.00%	94.93%	5.07%	0.267	0.250
7	2300	93.01%	5.87%	1.12%	0.862	0.455	900	0.00%	99.29%	0.71%	0.286	0.215
8	900	98.75%	0.79%	0.45%	0.862	0.454	800	0.00%	98.60%	1.40%	0.299	0.214
9	900	99.77%	0.00%	0.23%	0.836	0.403	900	0.00%	97.40%	2.60%	0.287	0.197
10	2500	89.81%	8.39%	1.80%	0.759	0.374						

Secondly, fr_{NPV} did not correlate as strongly with LCI (Figure 3C, $R^2 = 0.28$) as with NDVI (Figure 3D, $R^2 = 0.59$). This is due to the fact that LCI produces lower values for high fr_S samples (April, LCI ≈ 0.05) than for high fr_{NPV} samples (e.g. November, LCI ≈ 0.2), whereas NDVI produces similar values for high fr_S and high fr_{NPV} samples (NDVI ≈ 0.23 in both cases). Thus NDVI has a closer to linear correlation with fr_{NPV} than LCI.

Finally, fr_S was much more strongly correlated with LCI (Figure 3E, $R^2 = 0.48$) than with NDVI (Figure 3F, $R^2 = 0.21$). The strong correlation of LCI with fr_S was due to the relatively narrow range of LCI values for very high fr_{PV} (October, LCI ≈ 0.4) and fr_{NPV} samples (November, LCI ≈ 0.2) and the low LCI values for high fr_S samples (April, LCI ≈ 0.05). Conversely, the weak correlation of NDVI with soil fractional cover was due to the large difference in NDVI values for samples with very high fr_{PV} (October, NDVI ≈ 0.8) and fr_{NPV} (November, NDVI ≈ 0.23), in combination with the fact that NDVI produces a very similar response for high fr_{NPV} and high fr_S samples (NDVI ≈ 0.23 in both cases). Finally, it is worth noting that soil fractional cover is the inverse of total vegetation cover, and that LCI is therefore a better predictor of total vegetation cover than NDVI.

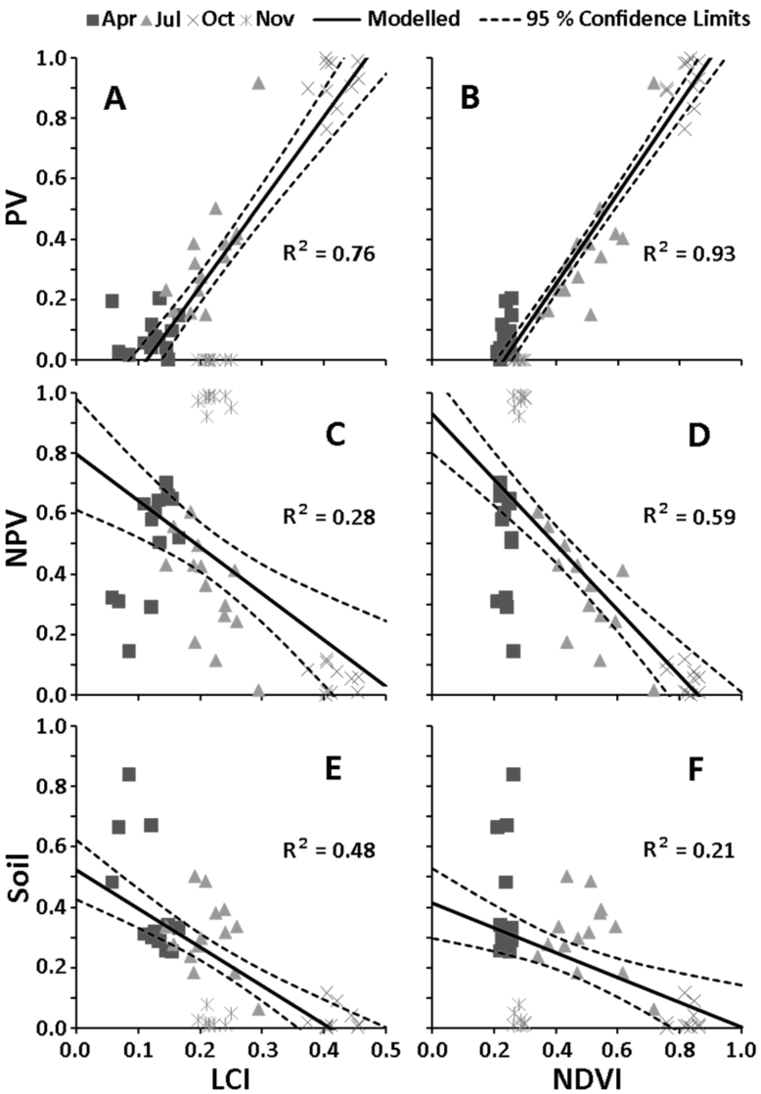

Figure 3. Relationship of per-field samples of LCI and NDVI image indices to PV, NPV and soil fractional cover. Regression relationships (solid line) and 95 % confidence limits (dashed line) are overlain.

2.4.4 The LCI as a tool for mapping soil exposure

In the previous section, we established that LCI is a reasonable predictor of soil exposure. Figure 4 presents the spatial distribution of predicted soil exposure on each survey date, as mapped by LCI. NDVI is presented for comparison.

The LCI shows noteworthy heterogeneity of soil exposure throughout the study region on all survey dates. Conversely, NDVI is quite uniform in May and November and less spatially variable than LCI in June and October. This is significant, and illustrates that at all time periods the LCI is mapping variation in soil exposure that the NDVI is incapable of discriminating.

The fact that LCI is spatially heterogeneous during May, and NDVI is not, is important. May was the period during which we recorded the greatest soil exposure (Table 4), and is therefore the time in which mapping soil exposure is of greatest importance.

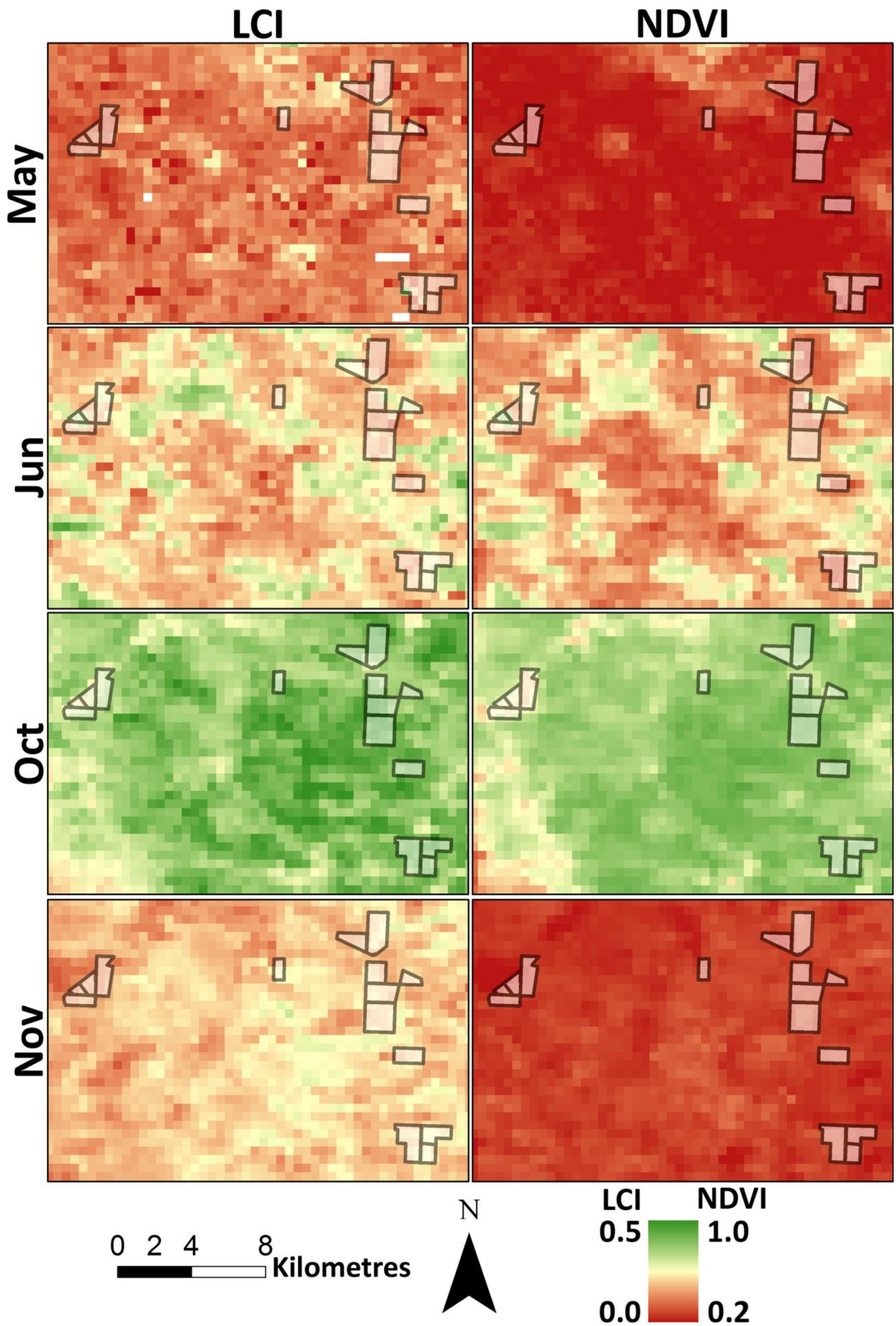

Figure 4. LCI and NDVI image indices in the study area on all four survey dates. LCI is presented as an index of soil exposure, with low index values (red) corresponding to high soil exposure and high index values (green) corresponding to low soil exposure. NDVI is presented for comparison.

2.5 Discussion

These results strongly support our hypothesis that the new MODIS Land Cover Index (LCI) is a more accurate measure of soil exposure than NDVI. We have demonstrated that LCI has a stronger correlation with fr_S than NDVI (R^2 = 0.48 and R^2 = 0.21 respectively). Furthermore, since soil fractional cover is the inverse of total vegetation cover, we have demonstrated that LCI is a better predictor (through an inverse relationship) of total vegetation cover than NDVI.

We have also demonstrated that LCI is strong predictor of fr_{PV} (R^2 = 0.76), but as expected not as strong a predictor of fr_{PV} as NDVI (R^2 = 0.93). This finding is in agreement with the vast body of literature on NDVI and fr_{PV}. We have also demonstrated that LCI is a mediocre predictor, and NDVI is a reasonable predictor of fr_{NPV} (R^2 = 0.28 and R^2 = 0.59 respectively).

In addition, we have explained why LCI is a strong predictor of fr_S. To reiterate, the ability of the LCI to predict fr_S comes from its formulation, which produces low values for soil, and moderate to high values for NPV and PV respectively.

Our specific finding, that an image index based on MODIS bands 6 and 7 allows separation of fr_{PV} and fr_{NPV} from fr_S, is in general agreement with the findings of Guerschman et al. (2009). However, as a normalised difference index, the LCI has advantages over the unmixing approach of Guerschman . Firstly, as a normalised difference index the LCI is more easily computed, and should minimise the influence of any illumination or viewing geometry effects not already accounted for by the NBAR correction. Secondly, the LCI is designed to differentiate soil from vegetation signatures, regardless of whether that vegetation is photosynthetic or non-photosynthetic. Thus, the LCI is a fair method of mapping soil exposure that may be produced quickly and with few resources.

Our findings add to the body of literature that has identified the utility of the shortwave infrared region of the spectrum for discrimination of fr_{NPV} (Nagler et al. 2000; Asner and Heidebrecht 2002; Nagler et al. 2003; Daughtry et al. 2004; Sullivan et al. 2004; Arsenault and Bonn 2005; Daughtry et al. 2005; Daughtry et al. 2006; Marsett et al. 2006; de Asis and Omasa 2007; de Asis et al. 2008; Gowda et al. 2008).

In validating the MODIS LCI, we have taken an uncommon approach. Most MODIS image products take one of two validation approaches. The first validates the MODIS product against a higher resolution image index which is used to extrapolate field data to a MODIS appropriate scale, and is the approach used by the MODLAND Team (Morisette et al. 2002). The second approach, due to limited resources or other constraints, validates the MODIS product against field data collected at an inappropriately fine scale. It is this second approach which Guerschman et al. (2009) used for their quantitative validation when they compare their MODIS product against a field measure of fr_{PV} and fr_{NPV} collected from two perpendicular 20 m transects.

Our validation approach differed from both of the above: we collected rigorous field validation data from homogenous areas larger than the IFOV of several MODIS image elements. While time consuming and necessarily limited to an area with very large fields, this approach should maximise confidence in our results.

The limitations of the study presented here stem from its main strength: the field data was collected over a relatively small area of relatively uniform soils and uniformly flat topography. This method minimised the potentially confounding effects of soil colour and topographic factors. However, this necessarily means that the results may not hold for different soil colours or for steep or complex terrain. Additionally, our field fr_{PV} and fr_{NPV} samples were obtained from a partial set of four cover types: cereal, lentil, rapeseed and mixed broadleaf weeds and cereal. However, we address this limitation in Part II of this paper by testing LCI against field data across the entire South Australian agricultural districts.

A final limitation possibly lies in the current formulation of LCI. The LCI seeks to separate fr_S cover from fr_{PV} and fr_{NPV}, but the current formulation does not produce equal index values for PV and NPV cover. Comparatively, the strength of the NDVI lies in the equality of values it produces for soil and NPV, and the great difference between these values and values for PV. Future work should therefore focus on a modification to the LCI formulation to produce equal values for PV and NPV, and maintain or enhance the production of significantly different values for soil. A possible source of inspiration is the Soil Adjusted Total Vegetation Index (SATVI) for Landsat (Marsett et al. 2006) which may more equally separate fr_{PV} and fr_{NPV} from fr_S. An added benefit of a MODIS index based on the SATVI is that it should be insensitive to soil colour.

In conclusion, we have identified the need for a new remotely sensed index of fr_S capable of measuring the severity and duration of soil exposure over extensive cropping areas. We identified that such a tool must be spatially extensive, of moderate resolution and high temporal frequency. Acknowledging the limitations discussed above, the LCI is a strong candidate for satisfying this need. The LCI could greatly improve global soil conservation by allowing the measurement of severity and duration of soil exposure. The spatial and temporal scale of the MODIS data used by the LCI would enable identification of areas vulnerable to erosion at fields and property scales, while the spatial extent of MODIS data enables cheap and easy production at national and even continental extents.

This paper established that the LCI is a strong predictor of soil exposure by comparison with quantitative field data collected at a MODIS appropriate scale in one region. In Part II we evaluate whether LCI is a consistent predictor of soil exposure across much broader extents (Clarke et al. 2011).

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3. Paper II. Broad scale evaluation of the new MODIS Land Condition Index (LCI) and NDVI against operational rapid field cover assessment[2]

Authors

Clarke, K.,[1] Lewis, M.,[1], Dutkiewicz, A.[2], Forward, G.[2] and Ostendorf, B.,[1]

[1]School of Earth and Environmental Sciences, The University of Adelaide.

[2]Department of Environment and Natural Resources, South Australia.

Corresponding author email: kenneth.clarke@adelaide.edu.au

3.1 Abstract

Global protection of soil resources from erosion requires a remotely sensed measure of soil exposure with a high temporal frequency, extensive scale and moderate spatial resolution. This paper presents Part II of a two part study. In Part I we demonstrated that the new MODIS Land Condition Index (LCI) was a strong predictor of soil exposure in one area of the South Australian Mediterranean cropping regions. Here we evaluate the LCI and NDVI against a spatially and temporally extensive field-based measure of soil cover, an erosion field protection survey (EFPS), with the aim of determining whether the LCI performs consistently throughout the extensive cropping districts of South Australia. Image index values from four MODIS image dates were matched to EFPS locations from four EFPS field surveys for May 2006, June 2006, October 2006 and March 2007. Matched image element / EFPS location pairs were divided into calibration and validation sets, linear relationships were derived from the calibration sets, and predictive ability was tested against the validation sets. In most cases LCI was more strongly correlated with EFPS soil cover than NDVI. Furthermore, both LCI and NDVI were consistently able to predict EFPS soil cover with a moderate degree of accuracy, though overall LCI was a better predictor of EFPS soil cover than NDVI. These results demonstrate that the LCI is, overall, better than NDVI at measuring soil exposure, as represented by FPFS soil exposure. Furthermore, this study establishes that LCI is a consistent predictor of soil exposure throughout the South Australian Mediterranean cropping districts. Differences between the MODIS image indices and EPFS assessment areas, viewing geometries and recording/sensing methods limited the strength of the correlations obtained in this study. However, Paper I compared the image indices to field data collected over appropriate assessment areas with comparable viewing geometry, and demonstrated that LCI was a good predictor of soil exposure.

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[2]Submitted to *Remote Sensing of Environment*

Combined, Parts I and II demonstrate that LCI is a strong and consistent predictor of soil exposure suitable for Mediterranean cropping regions.

3.2 Introduction

The global need to protect soil resources from erosion has been highlighted by Clarke et al. (2011): to accomplish this there is a need for a remotely sensed measure of soil exposure with a high temporal frequency, extensive scale and moderate spatial resolution.

Within Australia there is an increasing recognition at both state and federal levels of government that there is a need for an objective, spatially extensive and nationally consistent method for monitoring soil cover across arable and rangeland areas of Australia. This recognition is reflected in the Australian Government investment in the Groundcover Monitoring for Australia project, which focuses on arid rangelands, and the soil erosion risk monitoring programs (in particular wind erosion) operating in four Australian States (New South Wales, South Australia, Victoria and Western Australia). While the national Groundcover Monitoring for Australia project is developing remotely sensed products, it is not yet operational.

Within this context, this study focuses on soil cover management across the extensive agricultural belt of the state of South Australia in central-southern Australia, an area of approximately 8 million hectares. All current operational programs for monitoring soil cover throughout Australia are field-based, taking the form of either assessment at specific sites or more extensive roadside surveys, dubbed ‘roadside field surveys' (see Leys et al. 2009 for a summary of current monitoring methods). In South Australia, the context for this study, the State Government initiated a program of land condition monitoring of South Australian cropping regions in 1998, which included the aim of measuring changes in soil erosion risk, including soil cover, over time.

The South Australian Department of Environment and Natural Resources (DENR), now has responsibility for this monitoring, and conducts a roadside erosion protection field survey (EPFS) four times a year to monitor trends in soil erosion protection, using observational assessments of soil cover and disturbance (Forward 2011). The EPFS involves teams of surveyors driving more than 3,500 km of transects throughout the 113,000 km^2 of the South Australian cropping districts and visually assessing approximately 5,500 sites for land condition. These visual estimates, in conjunction with site-based records of topography and soil type, are used to calculate soil erosion risk for reporting regions.

The information collected by this survey allows DENR to report against the current State Strategic Plan 2011 (SASP) target to increase South Australia's agricultural cropping land that is adequately protected from erosion by 25 % by 2020, as compared to 2003. Additionally, the survey results inform the targeting of funding to assist in the improvement of land-management practices to reduce soil erosion risk.

However, field survey assessments for broad scale monitoring are expensive and have limited spatial extent and temporal frequency. Only areas along transects are assessed, and the results are extrapolated to reporting regions; likewise the EPFS is run four times a year and takes a number of employees several days to conduct. Furthermore, oblique visual estimates of soil cover, the basis of the EPFS, have been demonstrated to be prone to operator bias (Corak et al. 1993; Morrison et al. 1993). Despite the known limitations, records from this field survey are valuable because they span more than 10 years, assess a large number of sites and are applicable to significant areas of cropping land across the southern part of the continent.

With the increasing availability of higher resolution imagery with broad scale coverage, the opportunity exists for remote sensing technology to satisfy the need for objective, spatially extensive method for monitoring soil exposure (and hence soil erosion risk) at continental scales and to inform state monitoring requirements.

This paper is Part II of a two-part study developing and validating a new MODIS index of soil exposure. In Part I (Clarke et al. 2011) we calibrated the new Land Condition Index (LCI) against field measurements of fractional cover and demonstrated that the index was a good measure of soil exposure in a study area with relatively uniform soils. In Part II we evaluate the LCI against a spatially and temporally extensive field-based measure of soil cover made as part of the DENR erosion protection field surveys (EPFS), with the aim of determining whether the index performs consistently throughout the extensive cropping districts of South Australia. The LCI is also compared with the widely-used NDVI, with the ultimate aim of developing an image-based method of monitoring soil erosion risk.

The EPFS is currently used to inform policy and management in relation to soil protection. Before the MODIS LCI can be adopted as a policy mechanism to measure soil exposure, it is important to understand its correspondence with the valuable EPFS data. Furthermore, similar field data are currently used in other Australian states for the same purpose. Therefore this study also aimed to establish the relationship between LCI and the operational field survey data, in order to provide confidence that the LCI and field assessment both measure soil cover.

3.3 Methods

3.3.1 Study Region

Whereas Part I of this study (reference) was based in a small cropping area, Part II focuses on the entire South Australian Mediterranean cropping region. This region is an extensive belt of approximately 11.3 million ha across the southern portion of the State (Figure 5), of which 8 million hectares are cropped or grazed annually. The climate is Mediterranean, with hot dry summers (December – February) and mild wet winters (July – August); winter rainfall predominates, ranging from 600 mm in the south to 250 mm pa in the north (Figure 6). Agriculture in the region is dominated by annual rotations of cereal crops, legumes, pasture and fallow.

The temporal pattern of crop and pasture growth and senescence in the study has been described by Clarke et al (ref). Throughout summer the landscape is largely dry, although summer weeds and perennial plant-based pastures can thrive and produce significant green vegetation growth in some areas. Rainfall in late March through to May produces germination of winter weeds and annual pasture plants, until chemical spraying or tillage of weeds, management of stubbles and seeding, which typically reduce cover to a minimum in May-June. Following seeding, annual crops germinate and growth peaks in September. Finally crops ripen, senesce and are harvested in November and December. Stubble remaining after harvest is commonly grazed by stock through summer and autumn. Retention of stubble and pasture cover is encouraged to minimise soil exposure, but it is observed that the risk of erosion is usually greatest in late autumn when plant residues and pastures have been grazed down and early cultivation takes place.

Because of the broad geographic extent of this agricultural belt, there is considerable variability in rainfall (Figure 6), soil types and land management practices. The Eyre Peninsula region has extensive sandy soils that are cropped, and which are water repellent or susceptible to wind erosion, particularly in lower rainfall areas. Significant areas of shallow soils on sheet limestone are used mainly for grazing. The southern Eyre Peninsula has more reliable and higher annual rainfall, and is more intensively cropped. The Northern and Yorke region is extensively cropped, with some perennial horticulture in the ranges with higher rainfall. Much of the cropping occurs on sloping, hilly land along the northern Mt Lofty Ranges and southern Flinders Ranges that is susceptible to water erosion. Conversely, on the coastal plains and Yorke Peninsula sandy soils dominate and are prone to wind erosion. The Murraylands region is dominated by sandy soils, including dune/swale systems that are susceptible to wind erosion. The annual rainfall in cropping areas ranges from 275 – 460 mm. In the South East region, cropping is less common, and permanent pasture is the main land use in areas receiving more than 600 mm pa. Most soils are sandy and many are also water repellent, although not particularly prone to wind erosion due to relatively reliable rainfall. Permanent pastures predominate in the higher rainfall zone of the Mt Lofty Ranges and Kangaroo Island, which are excluded from the DENR EPFS due to minimal soil erosion concerns.

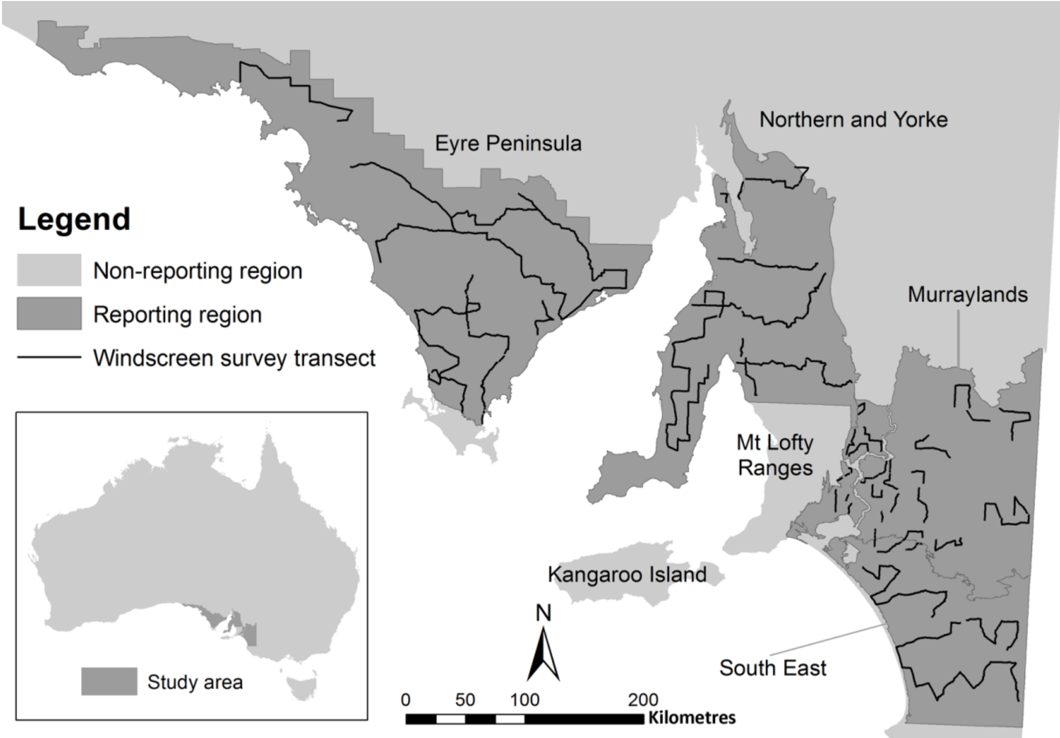


Figure 5. Department of Environment and Natural Resources Erosion Protection Field Survey reporting regions and transect locations, and study area within southern Australia.

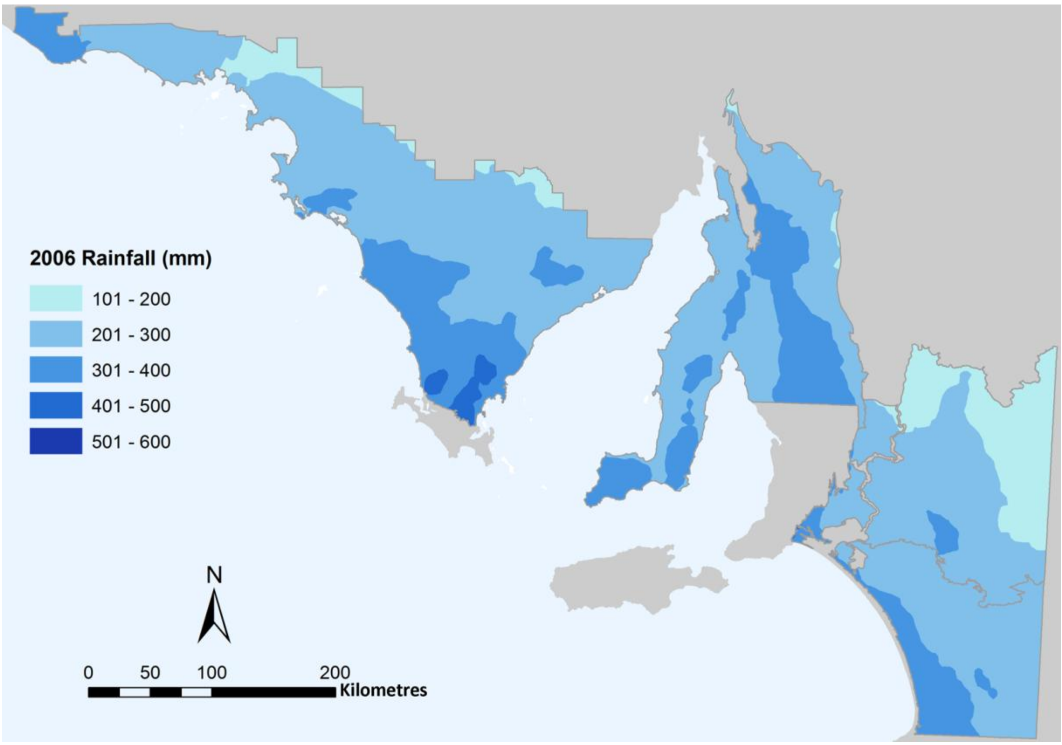


Figure 6. Total rainfall, 2006 (mm), data obtained from the Australian Bureau of Meteorology.

3.3.2 Field Data

South Australia's EPFS methodology has been described in detail by Forward (2011). In summary, the cropping regions were divided into 45 zones of similar climatic, soil and land-use characteristics. These zones were grouped into regions for reporting purposes. Road transects were designed to cover as much variability within zones as possible, except where precluded by a lack of roads or by roadside native vegetation obscuring views of agricultural land. Both the reporting regions and EPFS transects are presented in Figure 5.

The EPFS is conducted four times a year (March, May, June and October), with each survey date timed to coincide with critical phases in the annual cropping cycle. The survey team assesses sites within fields that are intended to be representative of the region, hence anomalies are avoided. Prior to surveying, teams are trained, and a quality assurance program has been instituted to minimise observer bias.

Erosion protection field survey sites are visually assessed obliquely from the vehicle and cover an estimated 200 x 200 m square, beginning at least 10 metres from the roadside fence and 50 metres from any fences perpendicular to the road to exclude unrepresentative areas. At each site five variables are recorded: cropping phase, erosion severity (if any), severity of soil surface disturbance, whether the site has been burnt recently, and vegetation Cover Rating. It is this Cover Rating that is used for comparison with MODIS image indices in this study.

Cover Rating is an estimate of the relative amount of wind or water erosion protection provided by vegetation cover. For wind erosion protection, the cover height architecture is the primary determinant, whereas for water erosion protection (raindrop impact), percentage of soil coverage is the primary determinant. Secondary factors include the degree of cover attachment or detachment from the soil, and the relative volume of vegetation material. Cover Rating assesses the level of erosion protection provided by cover, and is not influenced by whether that cover is live (fr_{PV}) or dead (fr_{NPV}). Assessments of Cover Rating are made with the aid of visual and descriptive standards, which range from a score of 1 (complete cover above knee height or greater, maximum erosion protection) to 8 (no cover, minimum erosion protection). The visual standards, and more information on the EPFS field methods can be found in Forward (2011).

In March 2006 survey site coordinates were recorded with global position system receivers (GPSR), and after this time exactly the same locations were assessed each survey date. This has enabled the direct comparison of field and satellite measures of soil cover at a given location, and hence this study. Prior to March 2006 no GPSR site location information was recorded, so precise sites observed in each field were not fixed, nor were they necessarily revisited in successive surveys.

To cover an annual cycle of crop growth and a full year of field data this study compared 2006/07 EPFS records with coincident MODIS image indices.

3.3.3 Satellite imagery

The United States Geological Survey (USGS) Land Processes Distributed Active Archive Center (LP DAAC) MCD43A4v5 MODIS product was used for this project. This is a 500 m resolution nadir bidirectional reflectance distribution function adjusted reflectance (NBAR) 16 day composite data product. The NBAR correction normalises reflectance values across the image to what would be seen if viewed from directly above.

Image composite dates were chosen to coincide with the periods during which EPFS observations were made in 2006 and 2007 (Table 5). LCI (Clarke et al. 2011) and NDVI indices were calculated for each image composite date.

Table 5. MODIS NBAR image composite start and end dates.

Start date	End date
23-Apr-06	8-May-06
10-Jun-06	25-Jun-06
30-Sep-06	15-Oct-06
06-Mar-07	21-Mar-07

3.3.4 Relationships between field data and MODIS indices

The principal aim of this paper is to examine relationships between MODIS indices and the extensive field survey of land cover undertaken with the DENR EPFS. The relationship is examined with an understanding that the field data and satellite imagery differ in relation to viewing geometry, type of measure, spatial resolution and period of observation. The field data is an oblique visual assessment of the amount of erosion protection provided by vegetation cover, while the satellite imagery is a nadir, or close to nadir, measure of passive reflectance. The field assessment is of a 200 m x 200 m area, while the satellite image elements are 500 m x 500 m, which after compositing nominally represent an area of approximately 463 m x 463 m. Finally, the field surveys are observations made on single days within a one to two week period, while the MODIS indices are derived from 16-day composites of cloud-free imagery.

Despite the differences in these data, there is a strong desire to understand correspondence between the MODIS indices and the valuable EPFS data. Furthermore, similar field data are currently used in other Australian states for the same purpose. We have already demonstrated that one of the satellite image indices, the LCI, is strongly correlated with fractional soil exposure (fr_S) (Clarke et al. 2011). To consider the LCI as a measure of soil exposure to inform policy and management, we must establish its relationship to the field surveys, and provide confidence that LCI and field assessment measure the same thing.

3.3.5 Pre-processing and analysis

To enable comparison of the EPFS and MODIS image indices, the centre-points of all EPFS observation sites were calculated. The EPFS Cover Rating assessment for each centre-point was then linked with the MODIS image element covering that point.

Due to the spatial frequency of field sampling and resolution of the MODIS imagery some image pixels covered multiple EPFS Cover Rating assessments. In these cases the variation in EPFS Cover Rating allowed assessment of the homogeneity of the pixel: large differences in Cover Rating between sites within one pixel suggest heterogeneous surface cover, most likely because several fields were included. Consequently, pixels covering multiple field assessments with an average difference in Cover Rating of greater than 1 were excluded from further analysis.

The field data was divided randomly into two sets: two-thirds for development of regression relationships and one-third for validation of those relationships (n, Table 6).

Table 6. Number of calibration samples (n) for each sample region and period.

Region	May 2006	Jun 2006	Oct 2006	Mar 2007	May-06 to Mar-07
Eyre Peninsula	477	498	522	529	2026
Murraylands	540	532	575	564	2211
Northern and Yorke	760	799	765	821	3145
South East	424	412	435	428	1699
All regions combined	2201	2241	2297	2342	9081

3.4 Results

Histograms presenting counts of EPFS Cover Rating by sampling period for all cropping regions in South Australia for May, June and October 2006 and March 2007, are presented in Figure 7: soil cover ranges from complete cover at Cover Rating of 1, to no cover (i.e. completely exposed soil) at Cover Rating of 8.

These histograms reveal that maximum soil exposure occurs in June, closely followed by May. May is also noteworthy for having the widest range of exposure levels. The wide range of cover levels in May and June is expected due to cropping preparation or sowing activities which may either retain most vegetative cover (i.e., low disturbance sowing with intact stubbles), or substantially remove vegetative cover or loosen the soil (i.e. cultivation, burning or heavy grazing, or full disturbance sowing). The period of minimum exposure occurs in October, as expected, shortly before harvest. It is worth noting that 2006 was an unusually dry year, hence cover would often be even higher in

October. A wide range of Cover Ratings is evident in March, likely due to contrast between fields with almost complete depletion of cover through grazing and natural decay or early cultivation and fields with comparatively high cover due to minimally grazed pastures, summer weeds and intact cereal crop stubbles.

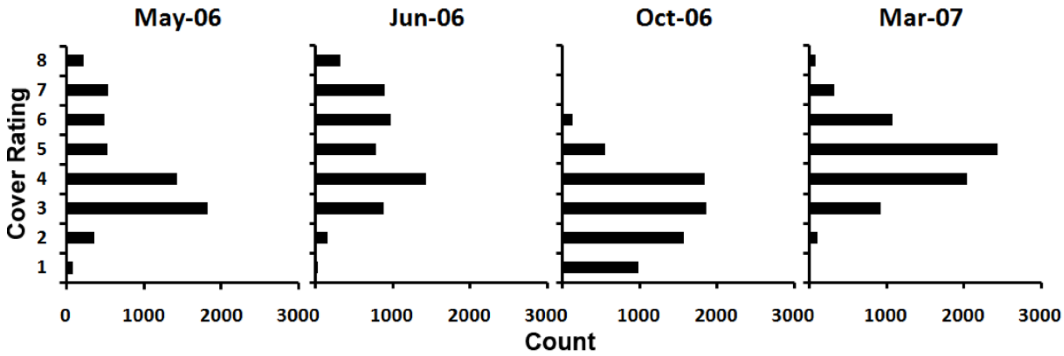


Figure 7. Erosion protection field survey Cover Rating count by sampling period for South Australia, May 2006 to March 2007. Soil cover ranges from complete cover (Cover Rating 1) to no-cover (Cover Rating 8). October is the month in which PV cover is expected to be highest. Total cover is expected to decline over summer and early autumn (March) due to grazing and natural decay of crop residues. Cultivation causes a sudden reduction in remaining cover around May, followed by a steady increase in PV due to germination and crop growth through June to a peak again in October.

3.4.1 Calibration

Pearson's correlation coefficients for the calibration relationships (linear regression of Cover Rating with NDVI and LCI), are presented in Table 7. These coefficients are negative due to the inverse nature of the scales of Cover Rating and the MODIS image indices: Cover Rating increases as soil cover decreases; both image indices decrease in value as soil cover decreases.

Examining the data in each region by month, seven out of ten of the strongest correlations occur in May or June, the period of maximum soil exposure. Additionally, is most cases LCI performs better than NDVI, although only marginally. Considering the entire May 2006 to March 2007 data, the strongest relationships are obtained in the Northern and Yorke and Eyre Peninsula regions, (both relatively dry regions), while generally poor relationships are obtained for the South East (a relatively wet region with low soil exposure).

Table 7. Pearson's correlation coefficient (r), Cover Rating versus image index. Significance levels are denoted in superscript.

Region/ index	May 2006	Jun 2006	Oct 2006	Mar 2006	May-06 to Mar-07
NDVI					
Eyre Peninsula	-0.32**	-0.52**	-0.47**	-0.09**	-0.31**
Murraylands	-0.34**	-0.25**	-0.19**	-0.29**	-0.09**
Northern and Yorke	-0.28**	-0.38**	-0.42**	0.12**	-0.36**
South East	-0.04**	-0.16**	-0.03**	-0.22**	-0.20**
All regions combined	-0.35**	-0.42**	-0.29**	-0.23**	-0.27**
LCI					
Eyre Peninsula	-0.34**	-0.51**	-0.43**	-0.29**	-0.40**
Murraylands	-0.37**	-0.28**	-0.12**	-0.28**	-0.18**
Northern and Yorke	-0.40**	-0.37**	-0.42**	0.00	-0.45**
South East	-0.08**	-0.24**	0.01	-0.18**	-0.20**
All regions combined	-0.40**	-0.44**	-0.30**	-0.16**	-0.34**

* p = 0.01

** p = 0.005

3.4.2 Validation

Applying the calibration relationships to the validation data demonstrated that it was consistently possible to predict Cover Rating from the image indices with a moderate degree of accuracy (Table 8). Overall LCI was a better predictor of Cover Rating than the NDVI.

Table 8. Normalised root mean squared error (NRMSE) for the validation relationship, specifically prediction of remotely sensed index from measured Cover Rating.

Region/ index	May 2006	Jun 2006	Oct 2006	Mar 2007	May-06 to Mar-07
NDVI					
Eyre Peninsula	23.94 %	19.93 %	17.88 %	18.59 %	23.64 %
Murraylands	22.97 %	24.82 %	21.80 %	21.53 %	22.29 %
Northern and Yorke	23.49 %	21.52 %	20.95 %	16.68 %	25.65 %
South East	13.94 %	17.15 %	21.14 %	20.46 %	15.60 %
All regions combined	21.70 %	20.89 %	20.46 %	18.83 %	24.55 %
LCI					
Eyre Peninsula	23.87 %	21.27 %	17.98 %	18.02 %	23.19 %
Murraylands	22.97 %	24.35 %	22.04 %	20.91 %	22.08 %
Northern and Yorke	22.89 %	21.26 %	21.05 %	16.76 %	24.36 %
South East	13.89 %	17.19 %	21.26 %	20.78 %	15.72 %
All regions combined	21.56 %	20.81 %	20.43 %	19.10 %	23.47 %
Difference (NDVI-LCI)					
Eyre Peninsula	0.07 %	-1.34 %	-0.10 %	0.57 %	0.45 %
Murraylands	0.00 %	0.48 %	-0.24 %	0.62 %	0.20 %
Northern and Yorke	0.59 %	0.25 %	-0.10 %	-0.08 %	1.30 %
South East	0.06 %	-0.04 %	-0.11 %	-0.32 %	-0.12 %
All regions combined	0.14 %	0.08 %	0.03 %	-0.27 %	1.08 %

3.4.3 Annual average index

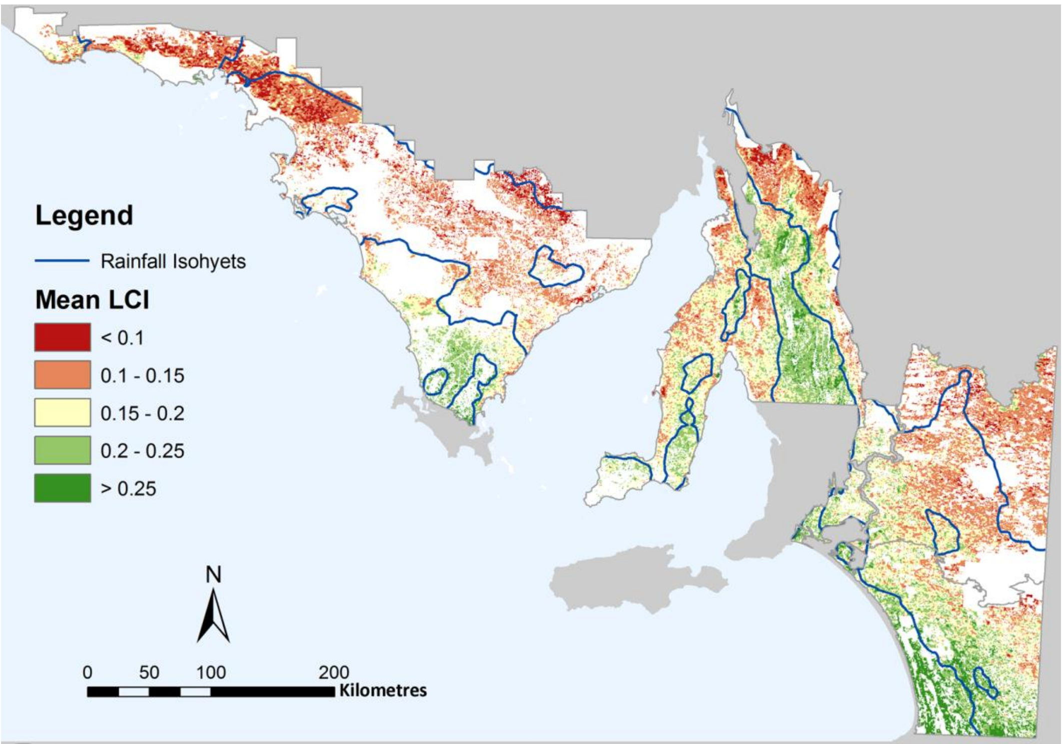
Maps of the mean indices for 2006 show the same overall regional pattern across southern Australia for both LCI (Figure 8 a) and NDVI (Figure 8 b), despite the slightly different range of the two indices (approximately 0.08 to 0.5 for LCI, and 0.2 to 0.9 for NDVI). Visual differences between maps of the indices may be indicative of true differences or simply differences in the values of the indices relative to the display scales.

The predominant spatial pattern in both indices relates strongly to the distribution of total rainfall for 2006, which is illustrated by the overlain 2006 total rainfall isohyets and Figure 6. Low index values in the north of Eyre Peninsula and north east of the Northern and Yorke and Murraylands regions correspond to the regions of lowest rainfall. High index values in the mid-east of the Northern and Yorke, south west of the South East and south of the Eyre Peninsula regions coincide with the areas of highest average annual rainfall. However, closer inspection reveals moderate and fine scale variation in index values, below the scale of broad climatic influences, although possibly resulting from fine-scale rainfall patterning. An example of this scale of variation can be seen in the centre of the Northern and Yorke region, where index values are very low despite being on the border of a zone of higher rainfall. The fine scale variation across all regions is likely a result of a combination of edaphic and land-management influences. For instance, Figure 9 shows an enlargement of the LCI distribution over a section of Yorke Peninsula, in the South Australian Mediterranean cropping districts. There is little variation in rainfall throughout this region, and yet there is significant variation in LCI.

3.5 Discussion

The results presented in this paper demonstrate that our new Land Condition Index is, overall, better than NDVI at measuring soil exposure, as represented by EPFS Cover Rating. When survey data from all seasons is combined LCI is as strongly, or more strongly correlated than NDVI with Cover Rating in each region. Additionally, when survey data from all regions is combined LCI is more strongly correlated with Cover Rating than is NDVI on all dates except one.

The differences between the two image indices can be understood as a result of their relative responses to PV and NPV: NDVI differentiates PV from NPV and soil, whereas LCI differentiates both PV and NPV from soil. Indeed, this was demonstrated in Part I (Clarke et al. 2011). Therefore we would expect exposed soil, as recorded by the EPFS Cover Rating, to be more strongly correlated with LCI than NDVI.



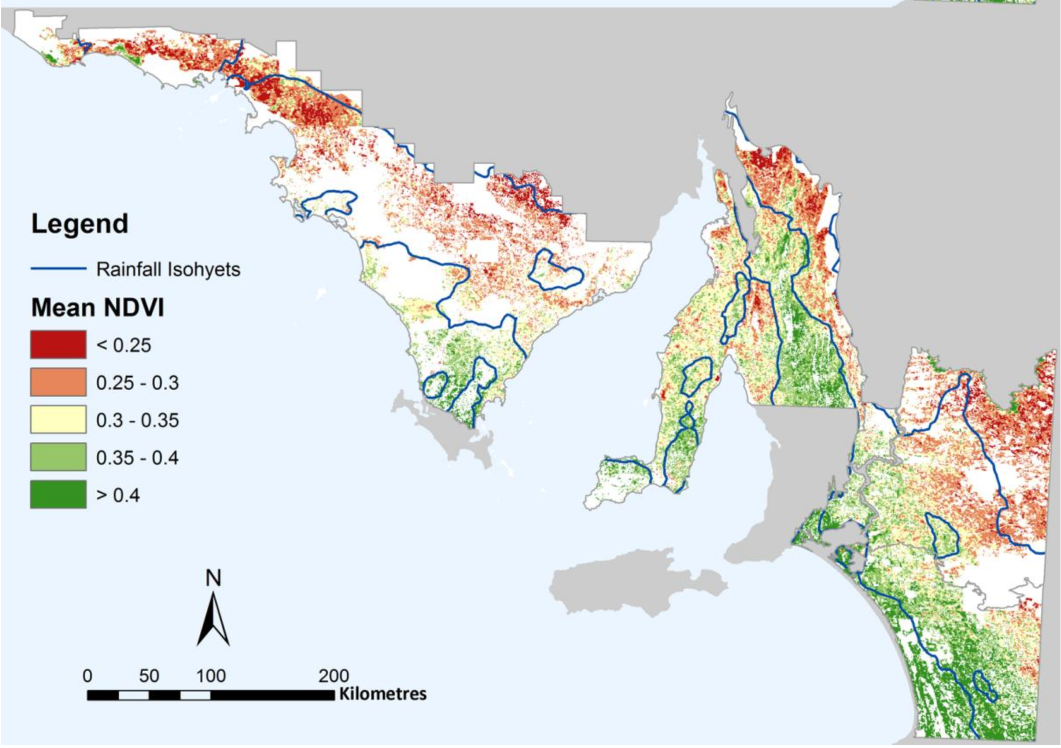


Figure 8 a) Mean LCI, and b) mean NDVI, all erosion protection reporting regions in South Australia, 2006. Total 2006 rainfall isohyets overlain for reference.

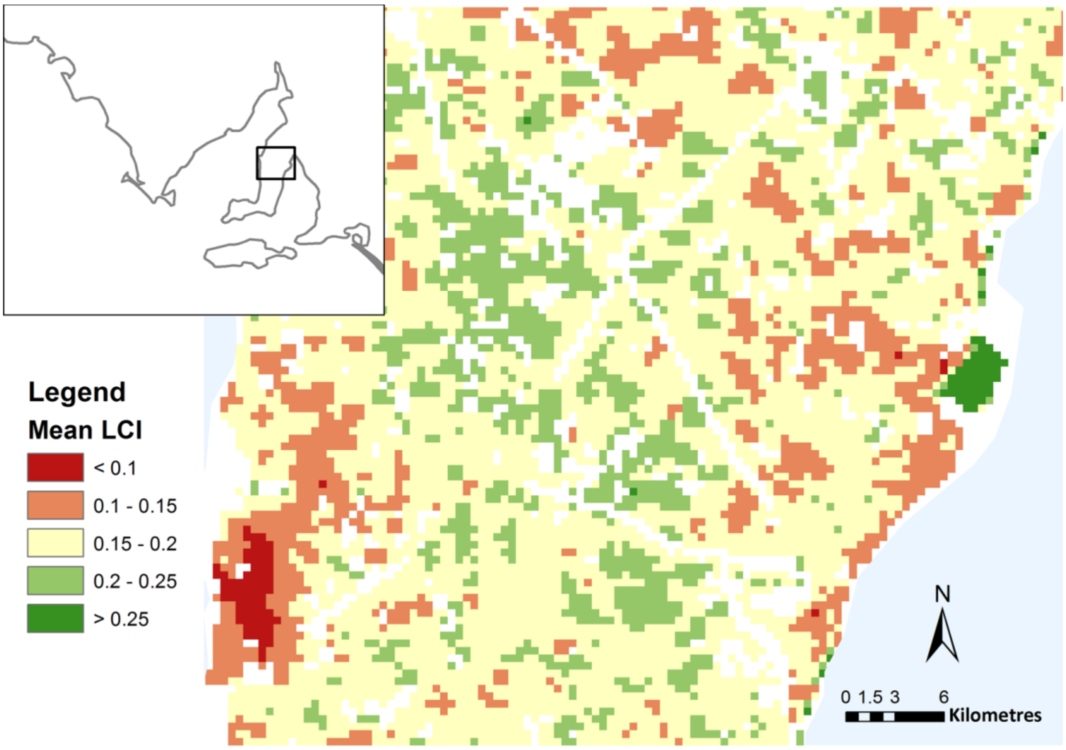


Figure 9. Map of mean LCI showing localised variation most likely attributable to edaphic factors and land management.

The overall poor performance of both indices in the South East region is most likely due to the differences in land use between this and the other regions. Despite the South East being considered a cereal cropping region for state government erosion risk reporting purposes, the region is dominated by perennial pasture, a much lower proportion of land is cropped, and fields contain many scattered large eucalyptus trees. Consequently there is consistently higher soil cover, and less variation in soil cover in the South East at any one time, and throughout the year as a whole. The lack of variation in cover in the South East may go some way towards explaining the generally poor relationships between image indices and cover rating in this region. Conversely, the LCI and NDVI performed better in the Northern and Yorke and Eyre Peninsula regions, which are dominated by cereal cropping. These regions experience a large temporal variation in the relative fractions of PV, NPV and soil is expected. Furthermore, in these regions LCI performed as well as, or better than NDVI, which is expected if soil exposure is greater in these regions and if LCI is more sensitive to soil exposure than NDVI.

The poorer performance of both indices in March, as compared to other months, might indicate that both are less capable of separating dead vegetation from soil than green, as the landscape is dominated by dead crop residue and exposed soil in this period. However, while the NDVI has weak and non-significant correlations with Cover Rating in all regions in March, the LCI has moderate to strong significant correlations with Cover Rating in two regions. This suggests that the LCI is more sensitive to dead vegetation cover than the NDVI.

Importantly, the overall relationship between image indices and Cover Rating for the state-wide data is strongest in June and May, when soil exposure is greatest. This is the period when the land is at greatest risk of erosion, and when monitoring of broad-scale land condition is most critical. Consequently, this suggests that LCI assessment of soil exposure could be used with greatest confidence during the periods when it is most needed.

However, while the link between image indices and cover rating is statistically sound on the majority of dates and for the majority of regions, the relationship is never strong, ranging from non-existent (r = 0.00) to moderate (r_s = -0.52). Thus, while overall LCI explains more of the variation in Cover Rating than NDVI, neither index explains the majority of variation. We believe that this inability of the remotely sensed indices to explain the majority of variation in Cover Rating stems from one of the key limitations of this study.

This limitation is that the MODIS image indices and the EPFS assess soil cover over appreciably different areas, with different viewing geometries, and with different recording/sensing methods. The area of the MODIS image elements are approximately 25 ha, while the EPFS assessments cover visually estimated 4 ha plots. The viewing geometry of the MODIS imagery is modelled to represent reflectance recorded from a nadir view, while the EPFS views the sites from an oblique angle which also varies at sloping or undulating sites. Finally, the image indices are derived from MODIS imagery that records the combined spectral response of projected cover averaged over a 16-day period. By contrast the EPFS assessment is conducted by several observers, and is an oblique visual assessment of erosion protection provided by cover, which is determined by plant and residue height or percentage cover, volume and anchorage to the soils.

Despite these differences, the broad geographic extent of the EPFS and its numerous survey locations across a variety of agricultural landscapes has allowed broad-scale testing of the MODIS derived LCI. This paper has established that the LCI is a consistent indicator of soil exposure across the broad extents of the South Australian Mediterranean cropping districts.

3.6 Conclusion

This paper is Part II of a two-part study developing and validating a new MODIS index of soil exposure. The research responded to a clear need for a remotely sensed means of accurately measuring soil exposure with high temporal frequency, at extensive spatial scales and with moderate spatial resolution (Clarke et al. 2011). Furthermore, in this paper we have identified a national, state and regional Australian policy need for such a remotely-sensed measure of soil exposure.

In Part I (Clarke et al. 2011) we directly calibrated the new Land Condition Index (LCI) against field measurements of fractional cover in a small study area and demonstrated that the index was a good measure of soil exposure in a region with relatively uniform soils.

Here in Part II we evaluated the LCI against the most comprehensive, widespread set of field records of soil cover, made as part of the South Australian Department of Environment and Natural Resources erosion protection field surveys (EPFS). We established that the relationship between LCI and the field survey data is consistent throughout the extensive cropping districts of South Australia, which provides confidence that the LCI and field assessment both measure the same thing. The MODIS image-based monitoring of soil exposure, however, offers the benefits of being spatially comprehensive, temporally frequent, objective and cost-effective.

Together, Parts I and II present a compelling argument that the MODIS LCI is a reliable and consistent predictor of soil exposure, capable of addressing the Australian policy need for such.

Furthermore, the LCI may fill the global need for a high temporal frequency, moderate resolution remotely sensed measure of soil exposure. Further quantitative validation is necessary before such widespread application could be considered. However, such testing should be easy, and we believe is likely to bear fruit. The simple normalised difference formulation makes the LCI easy to implement and understand. The sound design of the LCI, in light of the well understood reflectance of soils and photosynthetic and non-photosynthetic vegetation in the relevant spectral regions, should ensure that the LCI consistently indicates the degree of soil exposure.

3.7 Acknowledgements

This research conducted under an Australian Research Council Linkage Project grant (LP 0990019) with erosion protection field survey Cover Rating data and co-funding provided by the South Australian Department for Environment and Natural Resources (DENR).

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4. Relative and Absolute Relative Spectral Mixture Analysis

4.1 Introduction

This section presents the relative spectral mixture analysis (RSMA) method, and a comparison of RSMA values to field fractional cover data. Further comparisons of RSMA results to LCI, NDVI, EPFS Cover Rating and precipitation are presented in Section 5.

Simply put, the RSMA measures changes in the relative contributions of PV, NPV and soil reflectance compared to a baseline date. These spectral changes correspond to changes in fractional cover relative to the baseline date. Full details on the RSMA method are presented in Okin (2007). One of the key advantages of the RSMA, it's insensitivity to changes in soil spectra, is a result of the fact that it does not require us to know the soil reflectance profile for a region. This strength is also the cause of a major weakness in RSMA. Since the measure is relative to a baseline date, and the absolute cover levels for every pixel are unknown at the baseline, the RSMA does not convey the absolute cover levels at any other point in time. However, if the absolute cover levels are known at any point in time, it is theoretically possible to convert the RSMA to absolute relative spectral mixture analysis (ARSMA).

This section concludes with some preliminary research into the conversion of RSMA to ARSMA, an absolute measure of variation in fractional cover components. This conversion is based on the field fractional cover data presented in Section 2 and corresponding MODIS images.

4.2 Methods

4.2.1 Satellite imagery

MODIS Nadir Bidirectional Reflectance Distribution Function (NBAR) imagery was acquired for the four image dates corresponding to the field fractional cover survey dates reported in Section 2. The MODIS NBAR image product corrects for viewing geometry and surface roughness effects, and each NBAR image is a composite of MODIS images from a 16 day period. All images and survey dates were within 2010, and the first days of each 16 day MODIS image composite were 23 April, 12 July, 30 September and 17 November.

Prior to generation of the RSMA index, the MODIS Reprojection Tool (MRT) was used to transform the base MODIS NBAR images from the supplied sinusoidal global projection to South Australian Lamberts Conformal Conic projection.

4.2.2 Reference spectra

Reflectance signatures for the pure samples of PV and NPV were provided by G. Okin (Table 9 and Figure 10).

Table 9. Reflectance values of the PV and NPV reference spectra for input to the RSMA algorithm.

			End-member (reflectance)	
Bandwidth (nm)	**MODIS band**	**Band description**	**PV**	**NPV**
459 - 479	3	Blue	4.23	22.37
545 - 565	4	Green	10.94	31.00
620 - 670	1	Red	5.57	39.83
841 - 876	2	NIR	49.92	57.06
1230 - 1250	5	SWIR	48.46	66.79
1628 - 1652	6	MIR	31.58	59.93
2105 - 2155	7	MIR	15.17	45.40

* Near infrared (NIR); **Short-wave infrared (SWIR); ***Mid infrared (MIR).

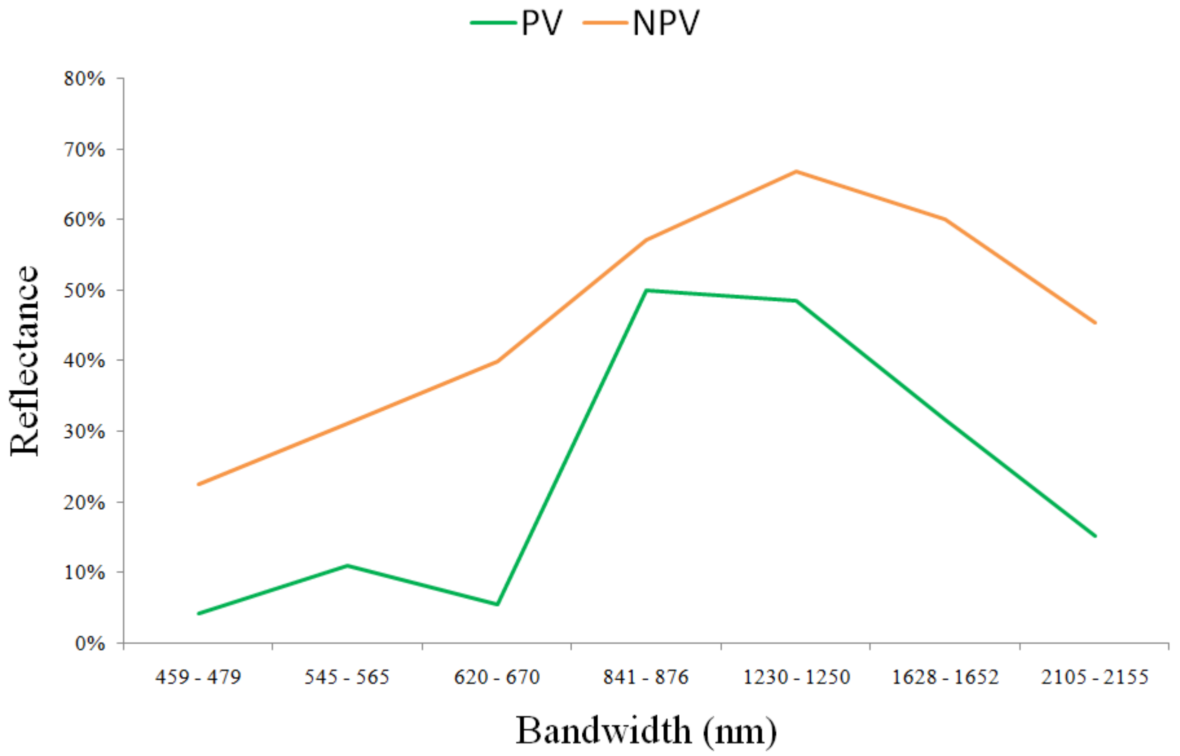

Figure 10. Reflectance signatures for pure PV and NPV for input to the RSMA algorithm.

4.2.3 RSMA production

The RSMA index presented in this report was produced with a modified version of the RSMA software developed and demonstrated by Okin (2007) in North America. The original RSMA algorithm attempted to map the landscape in terms of four cover types, photosynthetic vegetation (PV), non-photosynthetic vegetation (NPV), soil and snow. Initial trials in South Australia revealed that the inclusion of a snow component in the algorithm caused mapping errors in all cover classes at certain times of the year: for instance, at cultivation (approximately May) the original RSMA mapped an increase in snow cover, an increase NPV, a decrease in PV and a decrease in soil cover. Only very rarely is there any snow cover in South Australia and when it does occur it is restricted to very small areas, and it is unlikely to occur in May.

The modified version of the RSMA software used in this research (3EM RSMA) attempts to map the landscape in terms of only three cover types, PV, NPV and soil (i.e., excluding snow). Unless otherwise noted, all subsequent uses of the term "RSMA" refer to the modified, three component RSMA.

The 3EM RSMA software supplied by Okin was used to produce the RSMA index. The RSMA index was produced for the four image dates and directed to use the PV and NPV reference spectra in Table 9. The baseline image date was set to 23 April 2010, which was a period of high soil exposure according to the field fractional cover survey.

The RSMA algorithm produced three relative fraction image-stacks, for PV, NPV and soil. Each image stack contained 4 layers, with each layer corresponding to one MODIS composite image date. The RSMA indices were evaluated against field fractional cover (presented in this section). Another evaluation of RSMA, against temporal profiles of EPFS Cover Rating, and precipitation was also conducted and is presented in Section 5.

4.2.4 ARSMA production

The ARSMA was produced from the RSMA with the aid of the field data reported in Section 2. Full details of the method will be published in a peer reviewed scientific journal article.

4.2.5 Evaluation of RSMA and ARSMA with field data

The field fractional cover data reported in Section 2 was used to evaluate the RSMA and ARSMA. The first field survey date, 24 April 2010, was used as the baseline date for RSMA since this was the date with the greatest soil exposure. Comparison of the field cover and RSMA was performed by Pearson's correlation, and RMSE.

Evaluation of RSMA relative fractions with field fractional cover is perfectly valid if all fields share the same baseline spectra (i.e., same soil colour and fractional exposures of PV, NPV and soil).

However, this evaluation becomes less valid the more the baseline spectra differ. For the baseline survey date used herein this comparison is quite valid, as there is little variation in fractional cover levels across all fields on the baseline survey date (Table 10). Because the ARSMA presents actual fractions for each date, evaluation of the ARSMA index with the field fractional cover is valid regardless of any potential differences in the baseline spectra between fields.

Table 10. Mean and standard deviation of fractional cover for the survey fields on the baseline field survey date, 24 April 2010.

	fr_{PV}	fr_{NPV}	fr_{Soil}
Mean	0.08	0.61	0.30
St Dev	0.06	0.06	0.03

4.3 Results

4.3.1 RSMA

The field fractional cover and RSMA relative spectral contributions are presented in Table 11. The results of interest, Pearson's correlation and RMSE, are presented in Table 12.

Examining the Pearson's correlation coefficient for the data excluding the November 26 survey, the majority of variation in fr_{PV}, fr_{NPV} and fr_S is explained by the RSMA. Additionally, the RMSE is low for PV, but high for NPV and soil.

In comparison, the Pearson's correlation coefficient for the data including the November the 26th survey explain approximately as much of the variation in fr_{PV}, much less of the variation in fr_{NPV} and somewhat less of the variation in fr_S. While the RMSE is acceptable for PV it is very high for NPV and soil.

The contrast between analyses including and excluding the 26 November data may result from either of, or a combination of two factors. The first is simply that the assumption that the baseline spectra from each field were similar enough to allow correlation with the field fractional cover data, is only partially valid. The second is that the contrast could be a result of the difference in the collection period of the field data, which was collected on 1 day, and the RSMA image, which was composited over 16 days. This would not normally cause a problem if the field fractional covers measured on the field survey date were representative of the field fractional cover for the period over which the MODIS image was composited. However, the MODIS image used for comparison to the 26 November field data was collected from 17 November to 3 December. In the week immediately following the 26 November field survey crops in the study area were harvested, causing an increase in soil exposure, and a decrease in NPV cover. This change in field cover components would have influenced the reflectance recorded in the MODIS image, but was not recorded in the field data.

The 26 November field data could be compared to the preceding MODIS image, although this would introduce different problems. The preceding MODIS image was composited from 9 to 25 November, and would therefore not be influenced by post-harvest reflectance. However, there was still significant green cover in most fields at this time. In both the cereal and lentil crops, chlorophyll was present in the plants themselves as they finished senescing, and within the lentil field in the form of broadleaf weeds.

Table 11. Field assessed fractional cover for photosynthetic vegetation (fr_{PV}), non-photosynthetic vegetation (fr_{NPV}), and soil (fr_S); and RSMA spectral contributions relative to the baseline date, 24/04/2010, for PV, NPV and the baseline (B) spectra.

		Field			RSMA		
Field	**Date**	fr_{PV}	fr_{NPV}	fr_S	X_{PV}	X_{NPV}	X_B
1	22/07/2010	0.16	0.56	0.28	0.10	-0.02	0.91
2	22/07/2010	0.40	0.41	0.18	0.23	0.01	0.76
3	22/07/2010	0.28	0.43	0.30	0.31	0.04	0.65
4	22/07/2010	0.16	0.61	0.24	0.14	0.03	0.83
5	22/07/2010	0.34	0.26	0.39	0.37	0.01	0.62
6	22/07/2010	0.39	0.30	0.32	0.37	0.02	0.61
7	22/07/2010	0.23	0.43	0.34	0.16	-0.01	0.84
8	22/07/2010	0.39	0.43	0.19	0.25	0.00	0.75
9	22/07/2010	0.23	0.50	0.27	0.14	0.02	0.85
10	22/07/2010	0.42	0.24	0.34	0.24	0.04	0.73
1	8/10/2010	0.98	0.01	0.01	0.81	0.20	0.04
2	8/10/2010	0.89	0.11	0.00	0.77	0.18	0.06
3	8/10/2010	0.76	0.12	0.12	0.71	0.16	0.13
4	8/10/2010	0.98	0.01	0.01	0.83	0.15	0.02
5	8/10/2010	0.91	0.05	0.04	0.74	0.16	0.10
6	8/10/2010	0.83	0.08	0.09	0.72	0.18	0.10
7	8/10/2010	0.93	0.06	0.01	0.82	0.17	0.03
8	8/10/2010	0.99	0.01	0.01	0.83	0.20	0.02
9	8/10/2010	1.00	0.00	0.00	0.81	0.19	0.00
10	8/10/2010	0.90	0.08	0.02	0.80	0.12	0.08
1	26/11/2010	0.00	0.98	0.02	0.16	0.10	0.74
2	26/11/2010				0.09	0.16	0.75
3	26/11/2010	0.00	0.92	0.08	0.08	0.09	0.84
4	26/11/2010	0.00	0.99	0.01	0.16	0.12	0.72
5	26/11/2010	0.00	0.99	0.01	0.21	0.10	0.69
6	26/11/2010	0.00	0.95	0.05	0.16	0.12	0.72
7	26/11/2010	0.00	0.99	0.01	0.15	0.11	0.74
8	26/11/2010	0.00	0.99	0.01	0.19	0.10	0.71
9	26/11/2010	0.00	0.97	0.03	0.13	0.14	0.74
10	26/11/2010						

In summary, the relatively poor correlations which result from inclusion of the 26 November data are probably a result of either a poor assumption, or rapidly changing cover components which influenced the MODIS imagery, but which were not adequately captured in the field data, or both of these effects. Of these, the latter is the most likely to be the case, since we demonstrated that there was little variation in field fractional cover across fields on the baseline date. Importantly, the relatively poor correlations are probably not a result of failure of the RSMA method.

Table 12. Pearson's correlation coefficient and RMSE for field fractional cover versus RSMA for all field survey dates, and for field survey dates excluding November 26th.

		PV	NPV	Soil
Excluding November 26th	Pearson	0.98	-0.90	0.89
	RMSE	0.12	0.31	0.34
Including November 26th	Pearson	0.96	-0.29	0.51
	RMSE	0.13	0.53	0.48

4.3.2 ARSMA

The Pearson's correlation coefficients and RMSE between ARSMA and the field data are presented in Table 13. In absolute terms correlations are very strong for PV, NPV and soil when excluding the November 26 data, and when including the November 26 data are very strong for PV and NPV, and moderate for soil. Furthermore, the RMSE are low for PV, NPV and soil when excluding the November 26 data, and when including the November 26 data are low for PV and soil, and moderate for NPV.

As with RSMA, correlations are lowered and errors are increased by including the November 26 data. However, the ARSMA performed substantially better than the RSMA when including the November 26 data. We feel this indicates that the relatively poorer performance of the RSMA when including the November 26 data indicates that the assumption on which the RSMA validation is based is somewhat invalid. The baseline spectra from each field may not have been similar enough to allow correlation with the field fractional cover data from all survey dates.

However, we still feel that the rapidly changing cover components around November 26 did influence the MODIS indices and that this influence was not captured in the field data. We believe this effect is responsible for the majority of the poorer performance of the RSMA and ARSMA when including the November 26 data.

Table 13. Pearson's correlation coefficient and RMSE for field fractional cover versus ARSMA for all field survey dates, and for field survey dates excluding November 26th.

		PV	NPV	Soil
Excluding November 26th	Pearson	0.97	0.95	0.84
	RMSE	0.12	0.13	0.08
Including November 26th	Pearson	0.95	0.88	0.46
	RMSE	0.16	0.26	0.13

4.4 Discussion

This component of the study had two goals; to test the RSMA by comparing RSMA relative PV, NPV and soil fractions against field fractional cover data gathered from an area of relatively uniform soils, and; to test the ARSMA by comparing ARSMA absolute PV, NPV and soil fractions against the same field fractional cover data.

4.4.1 RSMA

When considering all survey dates, agreement between the RSMA relative PV, NPV and soil fractions ranged from very strong (PV, $r = 0.96$) through moderate (soil, $r = 0.51$) to low (NPV, $r = -0.29$). However, the November 26 composite MODIS image was acquired over a period of rapidly changing cover components, which were not adequately represented by the single date of field data. It is therefore reasonable to expect poor agreement between the RSMA and field data on this date. By excluding the November 26 data from our analysis, and retaining only the data we have the highest confidence in, results were drastically improved. Agreement between RSMA relative PV, NPV and soil fractions is very strong ($r = 0.98$, $r = -0.90$, and $r = 0.89$ respectively).

Caution must be taken in interpreting these results. These results are for an area of relatively uniform soils, and we cannot yet say that the RSMA will perform equally well in an area with more variation in soil reflectance. However, the RSMA is designed to be insensitive to, and work without *a priori* knowledge of the soil spectrum. A next step in the development of the RSMA would be to perform a test similar to the one presented here, but for a range of regions with diverse soil spectra.

In summary, caution must be taken in comparisons of MODIS composite imagery and field data. The values recorded by the field data must be representative of the field fractional cover over for the majority of the MODIS image composite period.

We have demonstrated that the RSMA is a very good measure of change in PV, NPV and soil fraction relative to a baseline date. Furthermore, the RSMA accomplishes this without *a priori* knowledge of the soil spectrum. However, without knowledge of the fractional covers on that baseline date, RSMA is only a measure of change relative to an unknown initial value. This does not limit the use of RSMA for phenology measures, but it does prevent the use of RSMA for monitoring purposes, where change in absolute cover levels is required. It is this limitation that the ARSMA seeks to overcome.

4.4.2 ARSMA

When considering all survey dates, agreement between the ARSMA absolute PV, NPV and soil fractions ranged from moderate (soil, r = 0.46) through strong (NPV, r = 0.88) to very strong (PV, r = 0.95). Compared to the RSMA results, there is essentially no difference in predictive ability of ARSMA for soil (RSMA, r = 0.51; ARSMA, r = 0.46) and PV (RSMA, r = 0.96; ARSMA, r = 0.95), but a significant improvement for NPV (RSMA, r = -0.29; ARSMA, r = 0.88).

As was the case with the RSMA, the ARSMA performs better when excluding the November 26 data from analysis (PV, r = 0.97; NPV, r = 0.95; soil, r = 0.84). Comparing these results to the RSMA, there is virtually no difference in predictive ability of ARSMA for any of the cover components.

4.5 Conclusion

Both the RSMA and ARSMA are strong predictors of fractional cover components which can be produced from MODIS time-series imagery using representative spectral signatures for PV and NPV, but with no *a priori* knowledge of the soil spectrum. The RSMA may be produced without any field data, and provides information on change in the relative fractional PV, NPV and soil cover across time. The RSMA is therefore suitable for landscape phenology studies, but not for landscape monitoring and assessment, which require measures of absolute fractional cover.

The ARSMA is an accurate measure the absolute PV, NPV and soil fractional cover, which can therefore inform both landscape phenology studies, and landscape monitoring. However, production of the ARSMA requires knowledge of the field fractional PV, NPV and soil cover for each pixel at least once. Theoretically, this requirement might be easily met for most pixels in a Mediterranean cropping district, where crops can be expected to have reached full canopy cover in at least one image in the full MODIS time series.

Finally, this work focused on an area of relatively uniform soils, and therefore does not test the RSMA or ARSMA in areas of different soil backgrounds, or in areas of heterogeneous soils.

5. Regional trends in cover over time

5.1 Introduction

The goal of this section is to illustrate how image indices of soil exposure could be used to provide the information the DENR Policy Directorate needs to monitor and report on soil exposure dynamics, and to provide this information in a form that is easy to communicate and interpret. This takes the form of regional temporal profiles of image indices of soil exposure, and graphs of annual variation in area vulnerable to erosion.

The temporal profiles are graphs of variation in image indices over time, and are presented alongside temporal profiles of the DENR EPFS Cover Rating and precipitation, from the Australian Bureau of Meteorology, to aid in interpretation. The graphs of area vulnerable to erosion present the information in several ways, designed to aid interpretation and to enable clear reporting against the SASP soil protection target.

Finally, the work presented in this section should provide further confidence in the ability of the LCI to measure soil exposure.

5.2 Methods

5.2.1 Phenology of the study area

Although already described in Sections 2 and 3, understanding the phenology of crop and pasture growth and senescence in the study area will be essential to interpretation of the graphs presented in the results of this section. Throughout the summer the landscape is largely dry, although summer weeds and perennial-pastures can thrive and produce significant green vegetation growth in some areas. Rainfall from late March to May results in germination of winter weeds and annual pasture plants, until chemical spraying or tillage of weeds, management of stubbles and seeding, or direct-drill seeding, which typically reduce cover to a minimum in May or June. Following seeding, annual crops germinate and growth peaks in September. Finally crops ripen, senesce and are harvested in November and December. Stubble remaining after harvest is commonly grazed by stock through summer and autumn. Retention of stubble and pasture cover is encouraged to minimise soil exposure, but it is observed that the risk of erosion is usually greatest in late autumn when plant residues and pastures have been grazed down and early cultivation takes place.

5.2.2 Data

Satellite imagery

The same MODIS NBAR satellite imagery and imagery dates were used for production of the RSMA, LCI and NDVI.

Complete temporal coverage of MODIS Nadir Bidirectional Reflectance Distribution Function (NBAR) imagery was acquired from the start of the MODIS archive (18 February 2000) to 3 December 2010. The MODIS NBAR image product corrects for viewing geometry and surface roughness effects, and each NBAR image is a composite of MODIS images from a 16 day period. In total 248 NBAR images were acquired and analysed in this project. The first date of each image composite, the 'image start day' is presented in Table 14.

Table 14. Image start day for all MODIS NBAR image composites acquired and analysed in this project.

Image start day	Approx day (Gregorian)	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
1	1 Jan		x	x	x	x	x	x	x	x	x	x
17	17 Jan		x	x	x	x	x	x	x	x	x	x
33	2 Feb		x	x	x	x	x	x	x	x	x	x
49	18 Feb	x	x	x	x	x	x	x	x	x	x	x
65	6 Mar	x	x	x	x	x	x	x	x	x	x	x
81	22 Mar	x	x	x	x	x	x	x	x	x	x	x
97	7 Apr	x	x	x	x	x	x	x	x	x	x	x
113	23 Apr	x	x	x	x	x	x	x	x	x	x	x
129	9 May	x	x	x	x	x	x	x	x	x	x	x
145	25 May	x	x	x	x	x	x	x	x	x	x	x
161	10 Jun	x	x	x	x	x	x	x	x	x	x	x
177	26 Jun	x	x	x	x	x	x	x	x	x	x	x
193	12 Jul	x	x	x	x	x	x	x	x	x	x	x
209	28 Jul	x	x	x	x	x	x	x	x	x	x	x
225	13 Aug	x	x	x	x	x	x	x	x	x	x	x
241	29 Aug	x	x	x	x	x	x	x	x	x	x	x
257	14 Sep	x	x	x	x	x	x	x	x	x	x	x
273	30 Sep	x	x	x	x	x	x	x	x	x	x	x
289	16 Oct	x	x	x	x	x	x	x	x	x	x	x
305	1 Nov	x	x	x	x	x	x	x	x	x	x	x
321	17 Nov	x	x	x	x	x	x	x	x	x	x	x
337	3 Dec	x	x	x	x	x	x	x	x	x	x	
353	19 Dec	x	x	x	x	x	x	x	x	x	x	

Note that there is always some overlap between the final image in a year and the first image in the following year. In a non leap year the final image covers 19 December to 3 January in the following year, resulting in three days overlap with the first image of the following year.

LCI and NDVI

The MODIS Reprojection Tool (MRT) was used to transform the base MODIS NBAR images from the supplied sinusoidal global projection to South Australian Lamberts Conformal Conic projection. Next, any pixel containing a null or erroneous value in any band was removed (set to null) in all bands. Finally, the LCI image index was calculated according to the equation presented in Section 1, and the NDVI image index was calculated according to the standard formulation.

RSMA

The RSMA index presented in this report was produced with a modified version of the RSMA software developed by Okin (Okin 2007). The modified version of the RSMA software used in this report attempts to map the landscape in terms of only three cover types, PV, NPV and soil (i.e., excluding snow). Unless otherwise noted, all subsequent uses of the term "RSMA" refer to the modified, three-end-member RSMA.

The 3EM RSMA software supplied by Okin was used to produce the RSMA index. The RSMA index was produced for a series of MODIS images covering the period 18 February 2000 to 3 December 2010. The algorithm was directed to use the PV and NPV end-members in Table 9. The baseline image date was set to 7 April 2003, which was a period of high soil exposure according to the DENR EPFS Cover Rating data.

The RSMA algorithm produces three relative fraction image-stacks, for PV, NPV and soil. Each image stack contains 248 bands, with each band corresponding to one MODIS composite image date. The RSMA indices were evaluated against field fractional cover (presented in this section), and temporal profiles of EPFS Cover Rating, and precipitation (presented in Section 5).

DENR EPFS Cover Rating

The DENR erosion protection field survey (EPFS) method, and the Cover Rating measure, were described previously in Section 3 of this report.

Precipitation

Weekly gridded (image format) precipitation data was obtained from the Australian Bureau of Meteorology (BoM) for the Australian continent. From this a pseudo-monthly precipitation product was produced by summing consecutive groups of four weeks' precipitation to produce 13 pseudo-month precipitation images for each study year. The weekly precipitation data was used to produce the 'cumulative annual precipitation' product described below, while the pseudo-monthly data was used to produce the 'monthly precipitation' and 'trend in precipitation' products, also described below.

5.2.3 Temporal profiles

Two methods were used in the production of the temporal profiles, one for the field-sample based Cover Rating, and another for the image-based LCI, NDVI, RSMA and precipitation.

To produce the Cover Rating profile from the field point-based EPFS, average Cover Rating for each region and survey period was extracted from DENR EPFS database for the period 2000 to 2010.

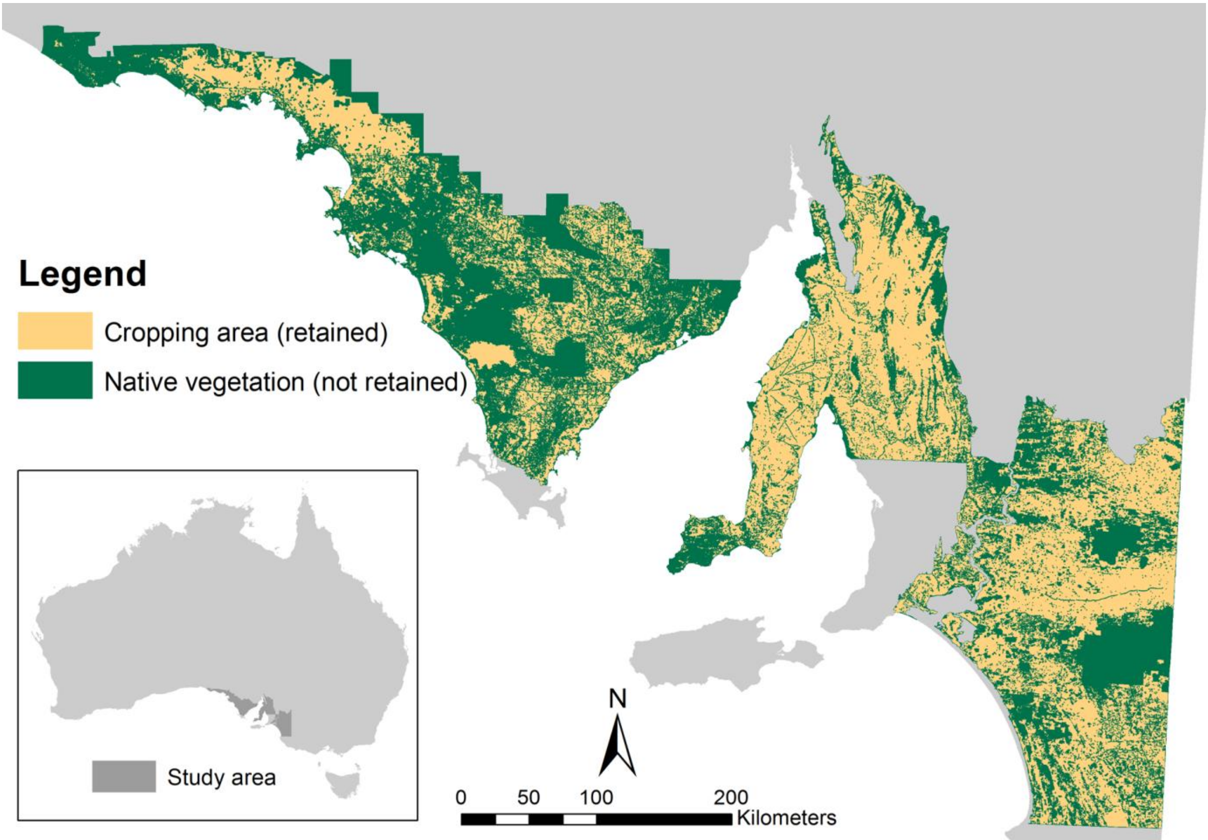

Figure 11. Map displaying the areas that were retained and excluded (set to null) prior to extraction of image index statistics for all temporal profiles.

Creation of the LCI, NDVI, RSMA and precipitation temporal profiles required more care to ensure that non-cropping areas did not influence the results. Prior to extraction of image index statistics all areas of native vegetation were removed (set to null) from all images (Figure 11). After removal of native-vegetation areas, the mean LCI, NDVI, RSMA and precipitation values were extracted for each DENR EPFS reporting region (Figure 5) and image date (Table 14).

All temporal profile data were then plotted, along with period minimum, maximum and average (mean), producing profiles of change in each variable by region for the 2000 to 2010 period.

Cumulative annual precipitation

A special case of temporal profile was the cumulative annual precipitation profile. This profile is a cumulative measure of the precipitation within each year, produced by adding each weeks precipitation to that of all preceding weeks within that year. The results were then graphed for each region. This index of precipitation allows for better inter-annual comparison of total precipitation than the simple monthly precipitation temporal profile.

5.2.4 Temporal trends

Trend in LCI, NDVI and precipitation was calculated for each reporting region. Firstly, an average season was produced for each dataset by calculating the mean of all January 1 samples, then the mean of all January 17 samples, etc. Then the difference of each sample from this average season was calculated, and finally these differences were accumulated to produce a measure of the trend in the variable for the study period.

5.2.5 Area vulnerable to erosion

Given a known relationship between LCI and fr_S it is possible to convert the LCI at each image date into an estimate of fr_S. To this end we defined a mathematical model relating fr_S to LCI (Equation 3) based on the data collected and reported in Section 2: Paper I. When defining this model care was taken to balance over and under-estimation of soil exposure, and thus the modelled relationship appears in the middle of the point-cloud in Figure 12.

$$fr_S = -2.52 \times LCI + 0.83 \qquad (3)$$

This modelled relationship was applied to the LCI images to produce a state-wide estimate of soil exposure for the 2000 – 2010 study period, and from this three products were produced, 1) a temporal profile of area vulnerable to erosion, 2) Magnitude of erosion vulnerability, by reporting year, and 3) land protected from erosion relative to 2002/03.

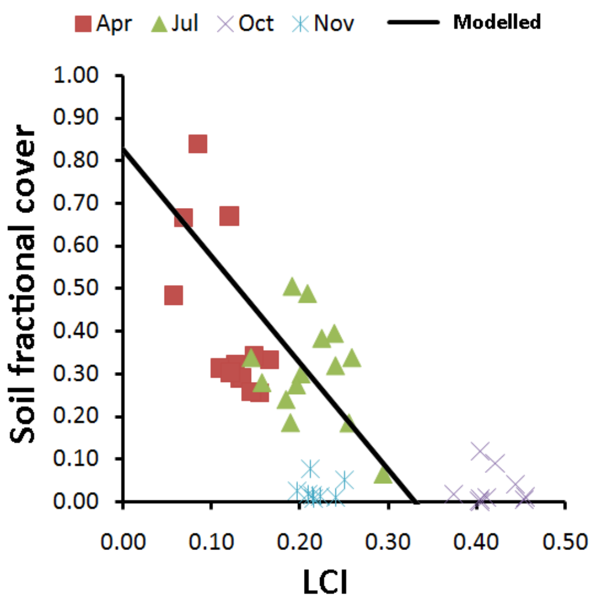

Figure 12. Modelled relationship between soil fractional cover (fr_S) and LCI. Relationship was designed to balance over and under-estimation of soil exposure.

For each of these products soils were considered at risk of erosion if they had greater than or equal to 50 % soil exposure. This is not intended as a definitive statement that soils become vulnerable to erosion at this or any other value, but is chosen for the sake of illustrating the kinds of products which can be created with this process. Later work could chose a single, different value for the entire State, or different values for different soil types (e.g., lower threshold values for sandy soils more prone to erosion).

Temporal profile of area vulnerable to erosion

As with all other temporal profiles (presented here) areas of native vegetation were removed (set to null) prior to statistic calculation. On each image date and for each reporting region a count of image pixels with greater than or equal to 50 % soil exposure was performed. From this, area vulnerable to erosion (in m^2) was calculated by multiplying the pixel count by the MODIS pixel area, which is nominally 250,000 m^2 (500 m x 500 m), but in this report is actually 214,656.16 m^2 (463.31m x 463.31m). This was then converted to hectares and the temporal profile plotted by region for the 2000 to 2010 period. This calculation is summarised in Equation 4:

$$A_v = \mathrm{n_p} \times \mathrm{A_p} \qquad (4)$$

Where A_v is the area vulnerable to erosion (in ha), n_p is the number of pixels vulnerable to erosion and A_p is the area of a single MODIS pixel.

Magnitude of erosion vulnerability

The magnitude of erosion vulnerability is a measure of both area (extent of soil exposure) and time (duration of soil exposure). Therefore this measure is expressed as the area-time (hectare-days) of vulnerability to erosion for each region and reporting year. For the sake of this measure a reporting year was considered to be the period from peak soil cover in one year to peak soil cover in the following year, and it was assumed that peak soil cover was achieved in September.

The first step of calculating hectare-days of vulnerability to erosion was to convert the assessment of area vulnerable to erosion for each date to an assessment of hectare-days. This was a simple process of multiplying the area in hectares by the number of days covered by the MODIS image used to produce each area assessment, which in all cases was 16 days. Next, all assessments of hectare-days vulnerability to erosion (based on 23 image dates covering 16 days each) within each region and reporting year were summed to produce a measure of total hectare-days of vulnerability to erosion for that region and year.

For each region and reporting year the area-time of vulnerability to erosion was plotted as a bar graph.

Land protected from erosion relative to 2003

The South Australian Strategic Plan 2011 soil protection target is " By 2020, achieve a 25 % increase in the protection of agricultural cropping land from soil erosion [as compared to 2003]". Hence a 'Land protected from erosion relative to 2003' image product is highly desirable.

Determination of land protected from erosion is essentially the inverse of the previous measure, the magnitude of erosion vulnerability. Therefore, to determine the area protected from erosion it was first necessary to calculate the total annual hectare-days of cropping land within each reporting region. This was accomplished by calculating the non-native vegetation area within each reporting region in hectares. This was then converted to total annual hectare-days for each reporting region by multiplying by the number of days in an image-based reporting year (23 x 16 = 368). This is longer than a calendar year, and therefore there is some overlap between images. However, this overlap is always between the final image in a year and the first image in the following year, and therefore there is no overlap between the reporting years used in this measure.

Hectare-days protection from erosion for each region and year was calculated by subtracting the hectare-days of vulnerability to erosion from the total annual hectare-days within that region. Finally, all areas were converted to percent values relative to 2003 and plotted.

5.3 Results

5.3.1 LCI and NDVI temporal profiles and trends

This section presents the LCI and NDVI temporal profiles and trends alongside other data to provide context and to aid user interpretation (Eyre Peninsula, Figure 13; Murraylands, Figure 14; Northern and Yorke, Figure 15; and South East, Figure 16). The EPFS Cover Rating is presented to allow comparison of the image index of soil cover against the currently accepted measure of soil cover. Several indices of precipitation are presented to provide context, since precipitation is one of the primary determinants of vegetation growth, and hence soil cover.

Typical seasonal pattern

In all regions the LCI and NDVI follow the pattern we would expect from our understanding of the typical crop phenology (5.2.1) and the index formulation (Table 1). Both LCI and NDVI are strongly influenced by green vegetation, and both start to increase around May, during seeding, and then peak between August and October when crop growth peaks. As crops begin to ripen (senesce) in October, both LCI and NDVI decrease, though NDVI decreases very quickly and then reaches a minimum around late November as crops are harvested, then remains flat through until May, despite the gradual reduction of crop residues. During the same period LCI decreases swiftly at first as crops senesce, then slowly from November until May as crops are harvested and crop residue is slowly depleted by grazing, natural decay, and some management actions aimed at reducing stubble.

Deviations from typical seasonal patterns

There are two notable deviations from the typical seasonal pattern that are common to all regions. Unusually low precipitation in 2002 and 2006 resulted in very low maximum LCI and NDVI in the winters of those years, and very low minimum LCI through the following summer and autumn. This can be interpreted as poor crop growth due to lack of rainfall, resulting in low maximum vegetation cover in winter, followed by crop residue decay and reduction over the following summer and autumn starting from a low maximum cover and resulting in a very low minimum soil cover. Note that NDVI reaches the same minimum in most years, because it is insensitive to NPV cover, and therefore does not decrease as crop residues decay and are removed over summer and autumn. This interpretation of the LCI and NDVI is supported by the Cover Rating profiles, which show very high October minimum Cover Rating (low cover at the period of expected maximum canopy cover), and very high maximum Cover Rating in the following year prior to germination (high soil exposure).

Congruence between image indices and Cover Rating

Comparing LCI and NDVI to Cover Rating, and remembering that in this comparison Cover Rating should be inverted when compared to LCI and NDVI (high Cover Rating score corresponds to low cover, while high LCI and NDVI correspond to high cover), there are some agreements and a number of differences in the two measures.

In all regions the annual minimum of Cover Rating (i.e., maximum soil cover) is recorded approximately a month after the LCI and NDVI peak. This is not a great concern, and is probably a reflection of the slightly different approaches of the field and image based measures. The goal of the October EPFS measure is to record the maximum cover attained within that year, regardless of whether the season will be an early or late finish, and to accomplish this the October EPFS is timed after crop ripening has usually begun. Thus, when the maximum Cover Rating is recorded by the EPFS, crop greenness and hence LCI and NDVI have already begun to decrease.

Of some concern is the timing of the annual maximum of Cover Rating (i.e., minimum soil cover, or maximum soil exposure). First, remember that the LCI and NDVI begin to increase when summer or autumn rain cause germination of weeds or annual pastures, or increased growth of perennial pastures. Therefore, the point just before LCI and NDIV begin to increase represents the period where crop-residue reduction processes (natural and anthropogenic) have had their maximum impact on soil cover, but before new growth can begin to increase soil cover.

In some seasons the EPFS has successfully recorded the magnitude of soil exposure at the period of maximum soil exposure within that year. The maximum Cover Rating coincides with the lowest LCI and NDVI and just before the LCI and NDVI measures begin to increase. However, in most seasons, the EPFS misses assessing the magnitude of soil exposure at the period of maximum soil exposure in that year. In these years the maximum Cover Rating is recorded after the LCI and NDVI have already begun to increase.

Trend in LCI, NDVI and precipitation

The LCI, NDVI and precipitation trend graphs must be interpreted with caution. The absolute values of these indices are not significant. Rather, whether the graph is increasing or decreasing indicates whether the values of that index (LCI, NDVI or precipitation) at that point in time were higher or lower than expected from the corresponding point in the 2000 – 2010 seasonal average. For example, the steadily increasing LCI and NDVI, and the generally increasing precipitation trends in all regions from the beginning of 2000 to early 2002 indicate that LCI, NDVI and precipitation were consistently higher than expected when compared to an average season.

Examining these trend graphs, when there was higher precipitation than usual both LCI and NDVI are higher than usual, and when there is less precipitation than usual, both LCI and NDVI are lower than usual. To interpret this, increased precipitation results in increased vegetation growth and cover, and therefore increased LCI and NDVI. This is expected.

It is also worth noting that while LCI and NDVI follow the same general pattern, the LCI trend varies less than the NDVI trend. We attribute this to the fact that LCI is measuring total vegetation cover (PV plus NPV), while NDVI is measuring only PV, and we expect total vegetation cover to vary more slowly than just PV.

To illustrate with the first of two examples, imagine unseasonal rainfall in early summer (December). Prior to this time there would be little PV cover, but significant NPV crop residue. Therefore we would expect moderate and slowly decreasing LCI values, and very low and static NDVI values. The summer rainfall would result in some summer weed growth, which would slightly increase LCI but significantly increase NDVI. This would result in a small increase in LCI trend, and a large increase in NDVI trend.

To take the second example, and a counter scenario, imagine an early dry finish to a winter (July). Crops would already have germinated and produced significant canopies, resulting in high LCI and NDVI values. The early drying would result in early crop senescence causing a significant drop in NDVI down to approximately annual minimum values, while the transformation of PV to NPV would still leave the soil significantly covered, and hence only cause a moderate drop in LCI. This would result in a small decrease in LCI trend, and a large decrease in NDVI trend.

Eyre Peninsula

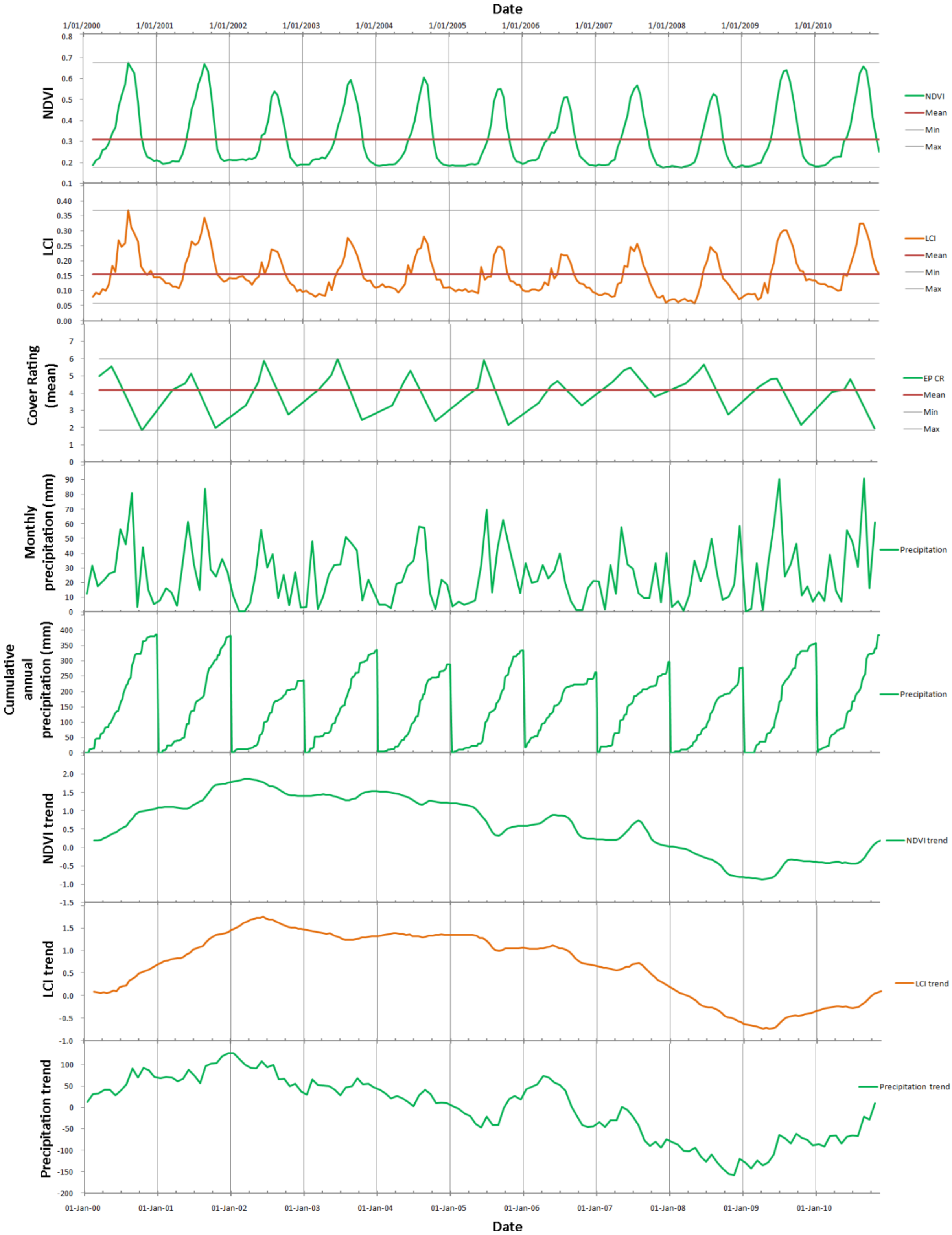

Figure 13. For the Eyre Peninsula reporting region, temporal profiles for LCI, NDVI, Cover Rating and precipitation, and temporal trends for LCI, NDVI and precipitation.

Murraylands

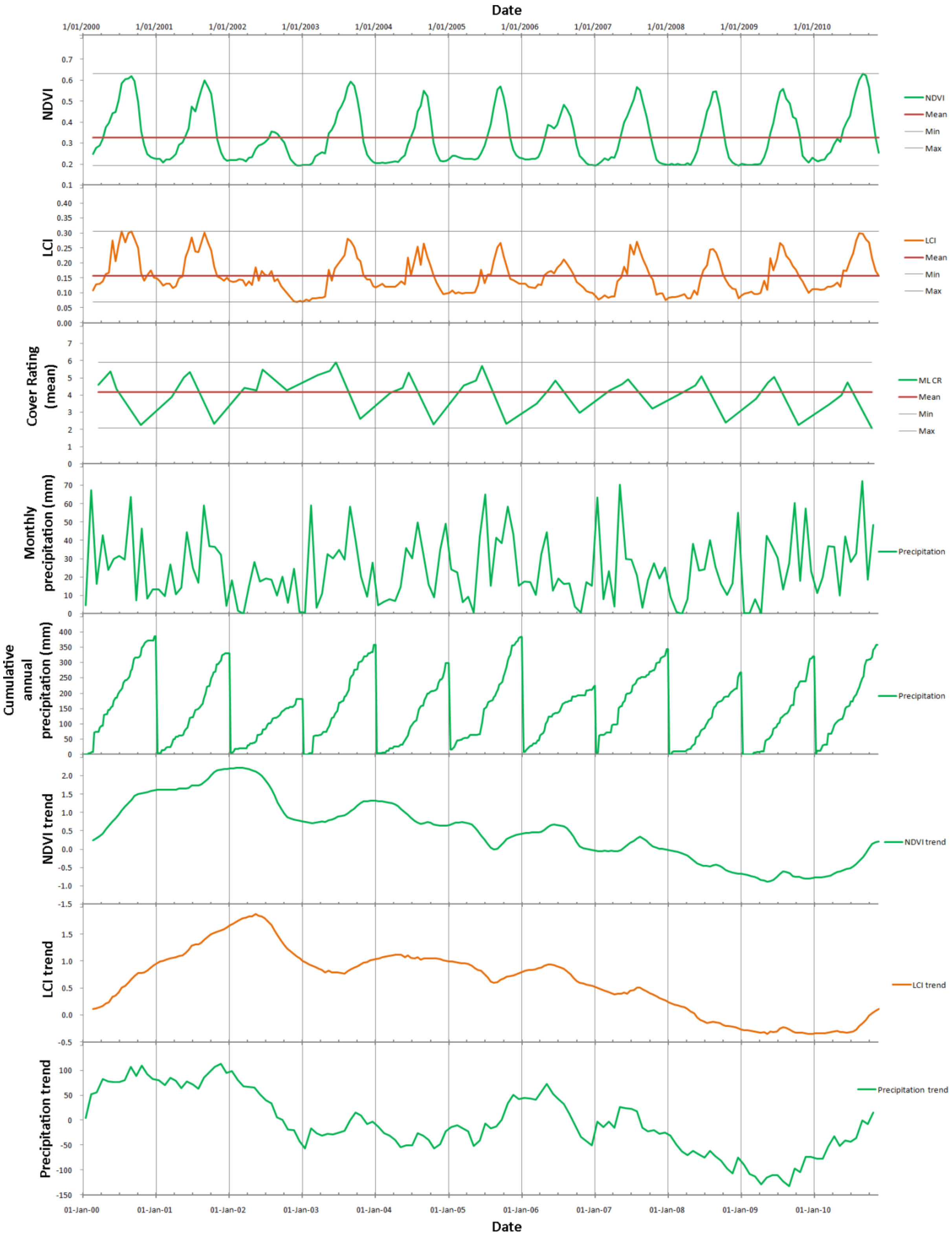

Figure 14. For the Murraylands reporting region, temporal profiles for LCI, NDVI, Cover Rating and precipitation, and temporal trends for LCI, NDVI and precipitation.

Northern and Yorke

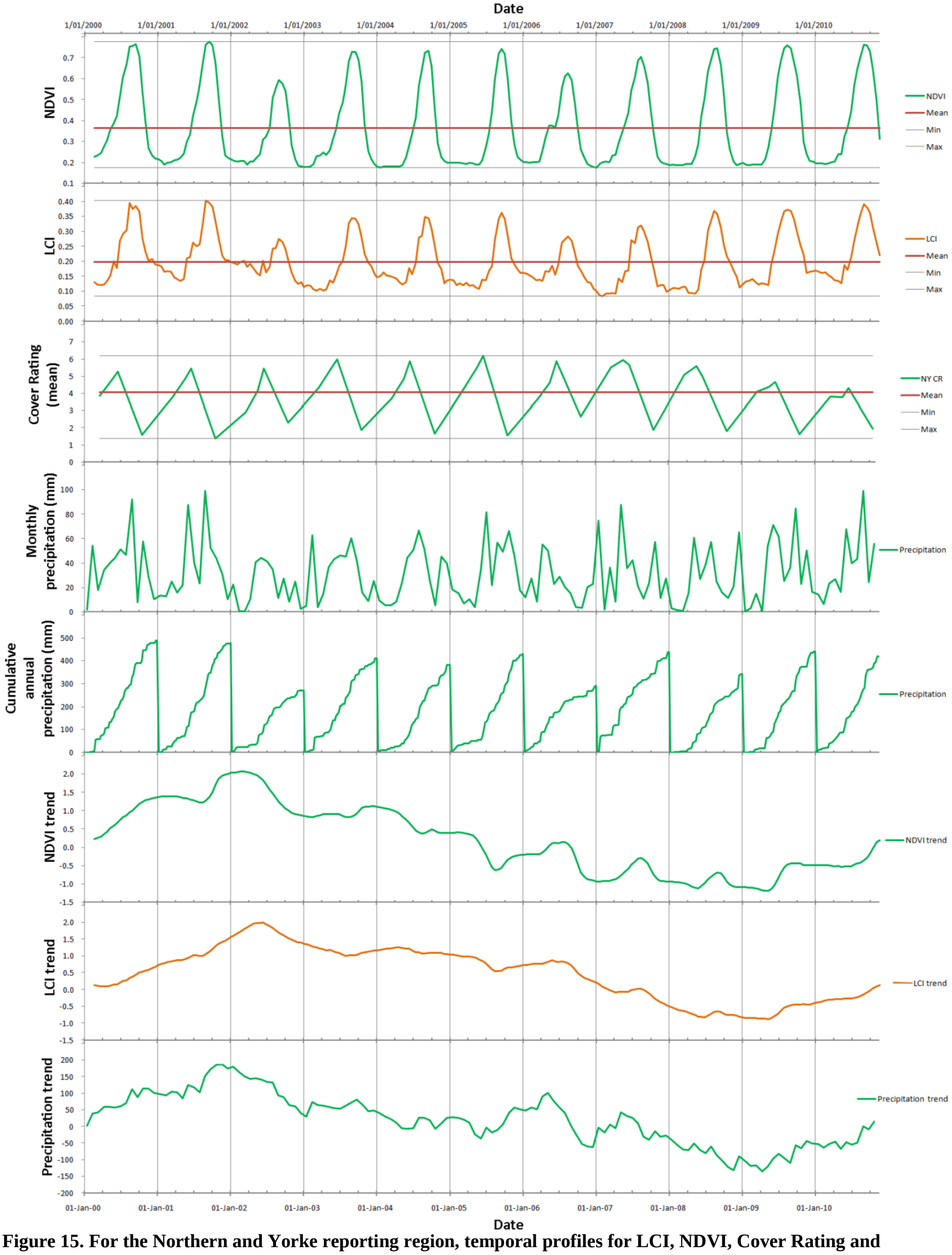

Figure 15. For the Northern and Yorke reporting region, temporal profiles for LCI, NDVI, Cover Rating and precipitation, and temporal trends for LCI, NDVI and precipitation.

Southeast

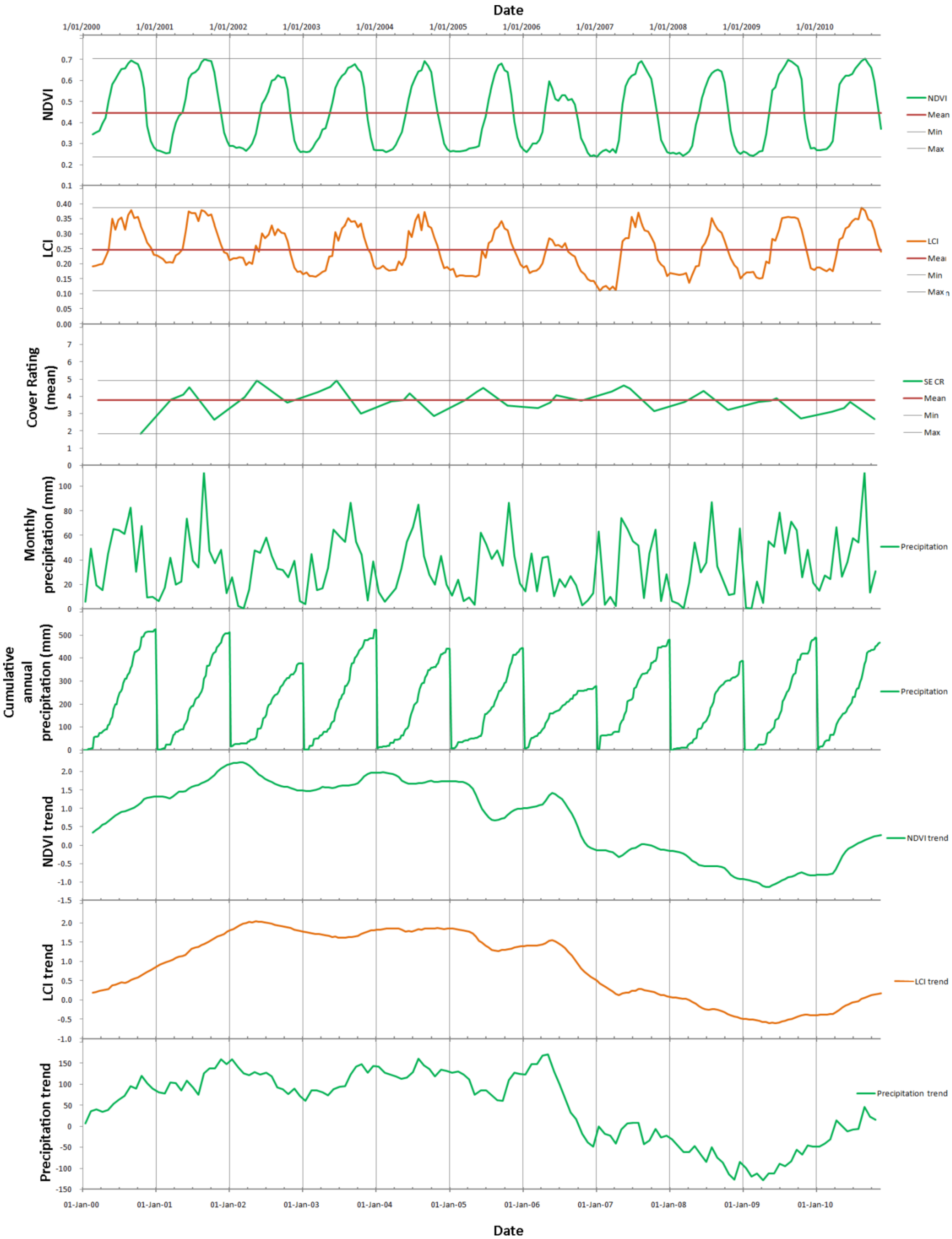

Figure 16. For the South East reporting region, temporal profiles for LCI, NDVI, Cover Rating and precipitation, and temporal trends for LCI, NDVI and precipitation.

5.3.2 RSMA temporal profiles

This section presents the 3EM RSMA relative PV fraction, relative NPV fraction and relative Soil fraction (r_{PV}, r_{NPV}, and r_S respectively) temporal profiles and trends alongside other data to provide context and to aid user interpretation (Eyre Peninsula, Figure 17; Murraylands, Figure 18; Northern and Yorke, Figure 19; and South East, Figure 20). The EPFS Cover Rating is presented to allow comparison of the 3EM RSMA soil fraction against the currently accepted measure of soil cover. Several indices of precipitation are presented to provide context, since precipitation is one of the primary determinants of vegetation growth, and hence soil cover.

Analyses of typical RSMA seasonal patterns, deviations from typical RSMA seasonal patterns, congruence and deviation between RSMA and Cover Rating follow.

Typical seasonal pattern

In all regions the r_{PV} , r_{NPV} and r_S vary largely as expected based on our understanding of the crop phenology in the study area (5.2.1). From January to May r_{PV} often slowly increases as summer weeds and perennial-pastures produce some green vegetation, r_{NPV} slowly decreases as crop residue from the previous growing season is depleted through natural decay, grazing, or active stubble reduction management, and r_S slowly increases as crop residues are depleted at a greater rate than they are replaced by summer weeds. From June to September r_{PV} increases steeply as crops are planted, germinate and grow to a full green canopy, and both r_{NPV} and r_S decrease slowly as crop residues continue to decay naturally and as both are occluded by increasing green cover. From October to December r_{PV} decreases steeply to a minimum as crops ripen, senesce and are harvested, in opposition r_{NPV} increases steeply as crops ripen and senesce, but there appears to be little decrease at harvest. Unexpectedly, r_S increases steadily over this period, possibly reflecting a mis-measurement of the increasing fr_{NPV} as an increase in r_S.

Deviations from typical seasonal patterns

Low precipitation in 2002 and 2006 resulted in two notable deviations from the typical RSMA seasonal pattern that are common to all regions, as was the case with LCI and NDVI. In these years r_{PV} reached a very low maximum followed by an unusually low minimum. Unexpectedly, r_{NPV} did not reach a lower than usual maximum in the summers following this low r_{PV}, and in many cases was higher than usual. As expected, r_S reached a very low minimum in these years, but perhaps unexpectedly did not reach a higher-than-usual maximum in the following autumn.

Interpretation of the r_{PV} is straightforward, and is the result of poor winter crop growth due to a lack of rainfall, followed by the senescence of perennial pastures and the absence of summer weeds which usually result in some photosynthetic vegetation persisting through summer.

There are at least two possible interpretations of the r_{NPV}. The first is simply that NPV production and retention processes outweighed the combined effect of NPV reduction processes and the reduced production of crop NPV. We suggest that NPV production processes may make major contributions to NPV in low precipitation years, but only minor contributions to NPV in normal years. This is the senescence of perennial pastures, and will result in an increase in NPV in unusually low precipitation years. A retention process likely to occur in low precipitation years is crop failure and the following change in management. Crop failure will result in low production of NPV, but then higher-than-usual retention because failed crops are not harvested but are instead simply left, or slowly grazed over the summer.

An alternative interpretation of the observed higher than usual maximum r_{NPV} is that the RSMA may be to some extent confusing soil and NPV, and in this case may be erroneously mapping increasing soil exposure as increasing NPV cover. There is however no direct evidence to test this interpretation.

The high minimum r_S over winter may be interpreted as a result of low winter vegetation growth producing less soil cover than usual. The average maximum r_S in the following autumn is interpreted as the result of land managers effectively adapting to the poor season and managing crop-residues to minimise soil exposure.

Congruence between RSMA and Cover Rating

Here we compare r_S to EPFS Cover Rating since both r_S and Cover Rating are measures of soil exposure. There are some general and specific agreements between r_S and Cover Rating, and some important differences in the specific timing of recorded minimum and maximum values.

The general pattern of both r_S and Cover Rating is in agreement. Soil exposure is at a minimum in approximately September, then over a period of eight to nine months increases to a maximum in approximately May, before quickly decreasing to a minimum in September again.

Specific agreement between the two measures can be seen in the timing of series-minima, and in the magnitude of drought year minima. Both r_S and Cover Rating are at or very close to their series-minimum values (their lowest value for the entire 2000 – 2010 period) in all regions in October 2000, 2001 and 2010. Likewise, both r_S and Cover Rating record very high minima in all regions in the very-low-precipitation years, 2002 and 2006.

Of some concern is difference in the specific timing of annual minimum and annual maximum soil cover as recorded by r_S and Cover Rating. Examining annual minima first, in the Eyre Peninsula (Figure 17, 2001 – 2003, and 2006 – 2010), Murraylands (Figure 18, 2003, 2004 and 2006 – 2010) and Northern and Yorke (Figure 19, 2006 – 2010) the annual minimum Cover Rating (i.e., minimum soil exposure) was recorded between several weeks and two months after the annual minimum r_S. In other words, in these years and in these regions the assessment of minimum soil exposure was made after soil exposure had already begun to increase. In the South East the assessment of minimum Cover Rating was performed at the time of minimum soil exposure, as measured by r_S, in every year examined here (Figure 20).

Examining annual maximum soil exposure, in the Eyre Peninsula (Figure 17, 2001 and 2007 - 2010), Murraylands (Figure 18, 2000, 2006, 2009 and 2010) and South East (Figure 20, 2003, 2006 and 2008 – 2010) the annual maximum Cover Rating (i.e., maximum soil exposure) was recorded after the r_S annual maximum, when soil exposure (as measured by RSMA) has already begun to decline. In those years the EPFS assessment of maximum soil exposure presumably would be lower than it was in reality. It is worth noting that in the Northern and Yorke region the EPFS assessment maximum soil exposure appears to coincide almost exactly with the actual time of maximum soil exposure, as measured by r_S, in every year on record (Figure 19).

Eyre Peninsula

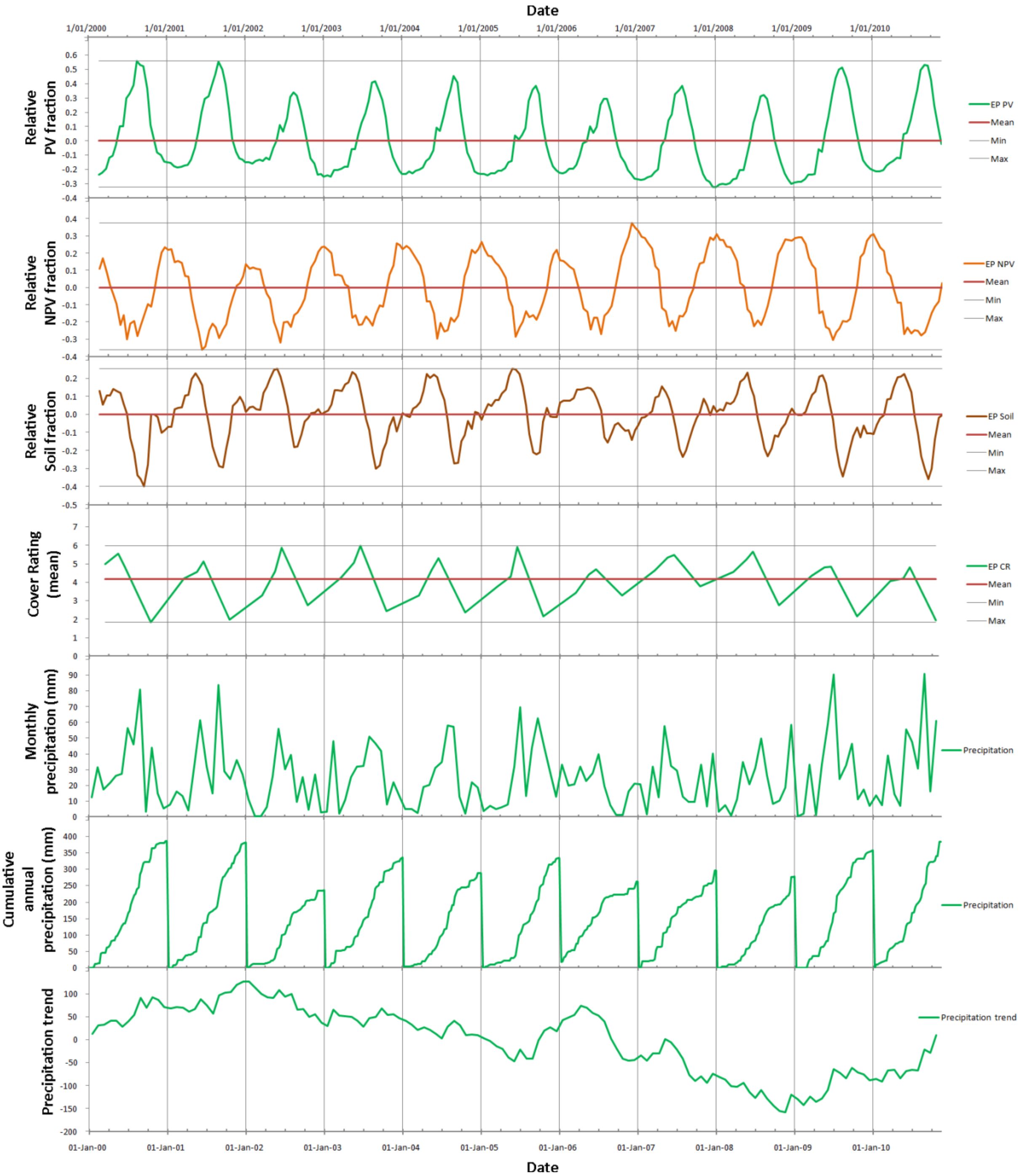

Figure 17. For the Eyre Peninsula reporting region, temporal profiles for Cover Rating, precipitation, and RSMA relative PV, NPV and Soil fractions, and temporal trend in precipitation.

Murraylands

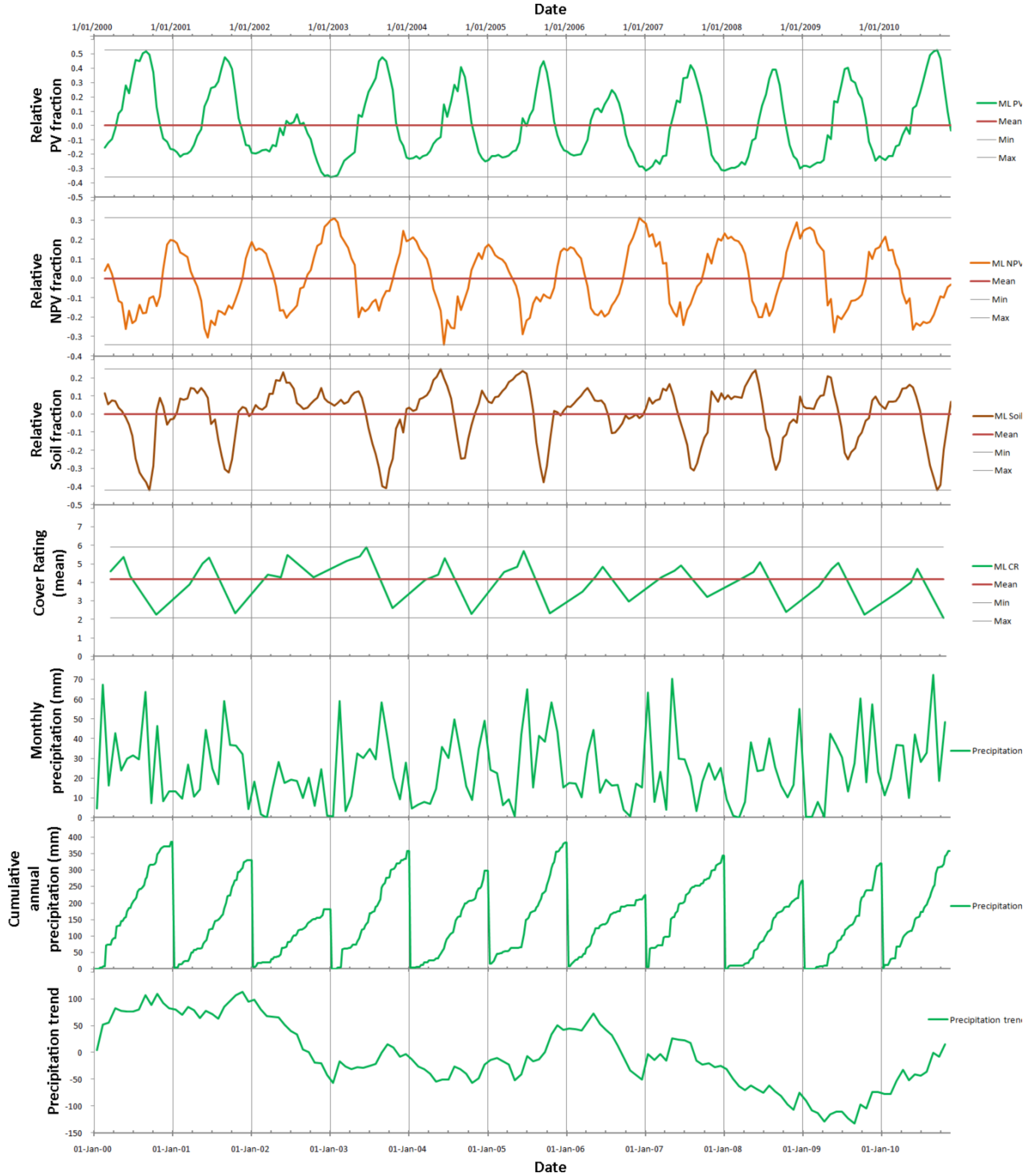

Figure 18. For the Murraylands reporting region, temporal profiles for Cover Rating, precipitation, and RSMA relative PV, NPV and Soil fractions, and temporal trend in precipitation.

Northern and Yorke

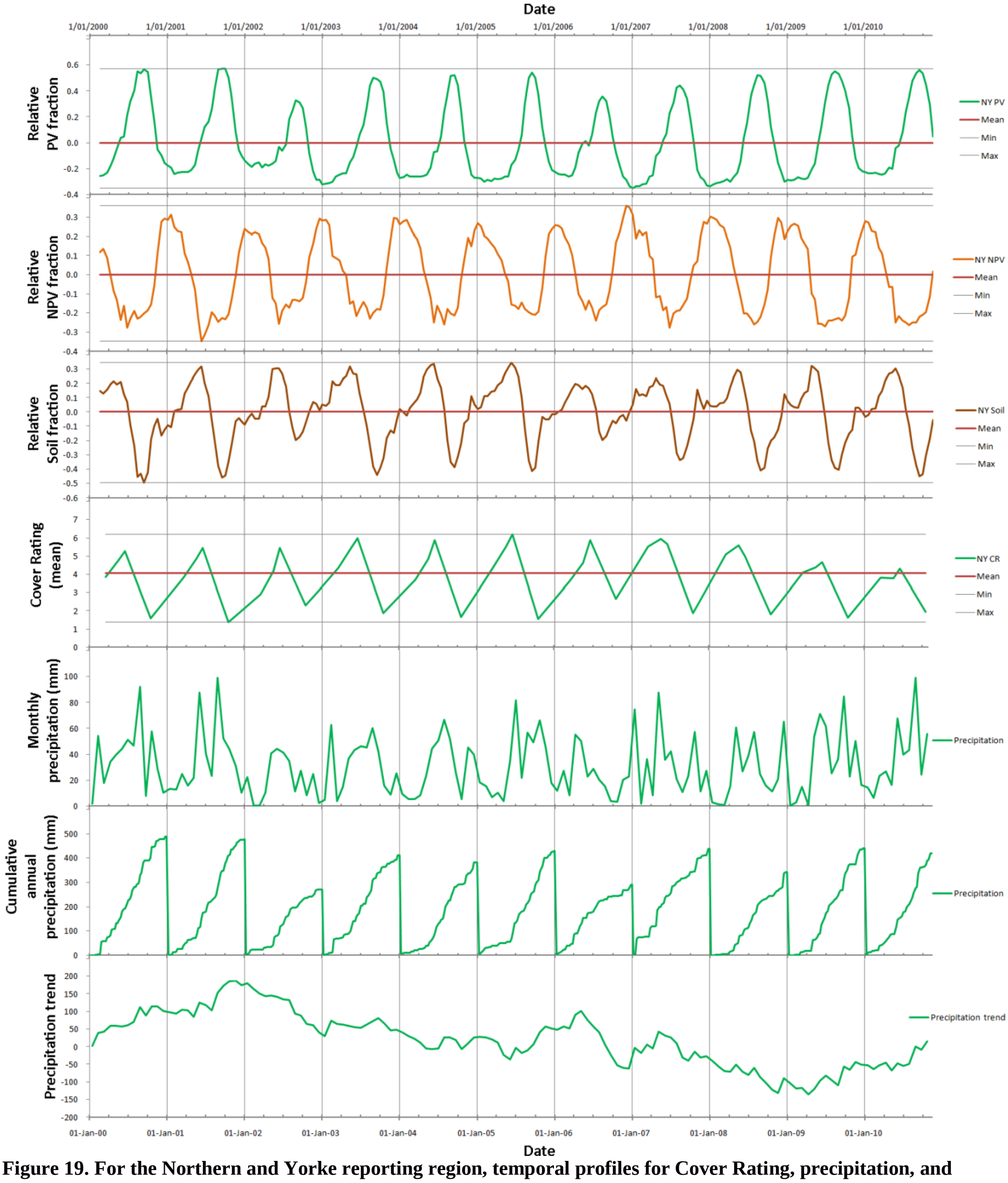

Figure 19. For the Northern and Yorke reporting region, temporal profiles for Cover Rating, precipitation, and RSMA relative PV, NPV and Soil fractions, and temporal trend in precipitation.

Southeast

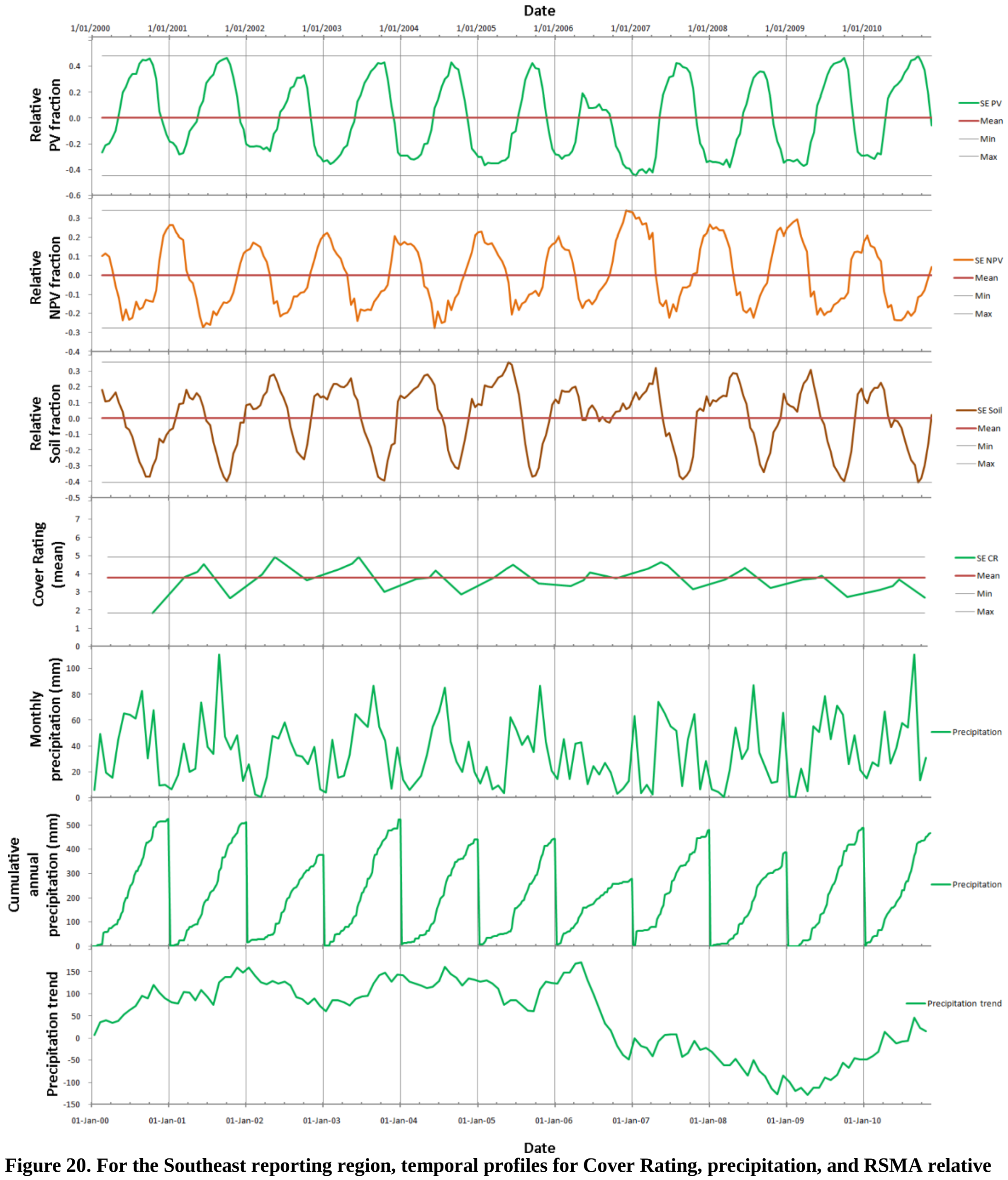

Figure 20. For the Southeast reporting region, temporal profiles for Cover Rating, precipitation, and RSMA relative PV, NPV and Soil fractions, and temporal trend in precipitation.

5.3.3 Area vulnerable to erosion

Temporal profile of area vulnerable to erosion

As an illustration of a possible reporting tool, the temporal profile of area vulnerable to erosion (≥ 50 % soil exposure) is displayed in Figure 21. The two driest years in the study period, 2002/03 and 2006/07, exhibited some of the highest soil exposures across all regions. Another noteworthy point is that while the Northern and Yorke and Eyre Peninsula regions regularly have a similar maximum area of exposure, the duration of exposure in the Northern and Yorke region is less than that in the Eyre Peninsula. Finally, we note that the extremely small proportion of cereal cropping in the South East (< 30 % of the land use), and the relatively high rainfall result in very low erosion risk in that region, except in the previously mentioned exceptionally dry years.

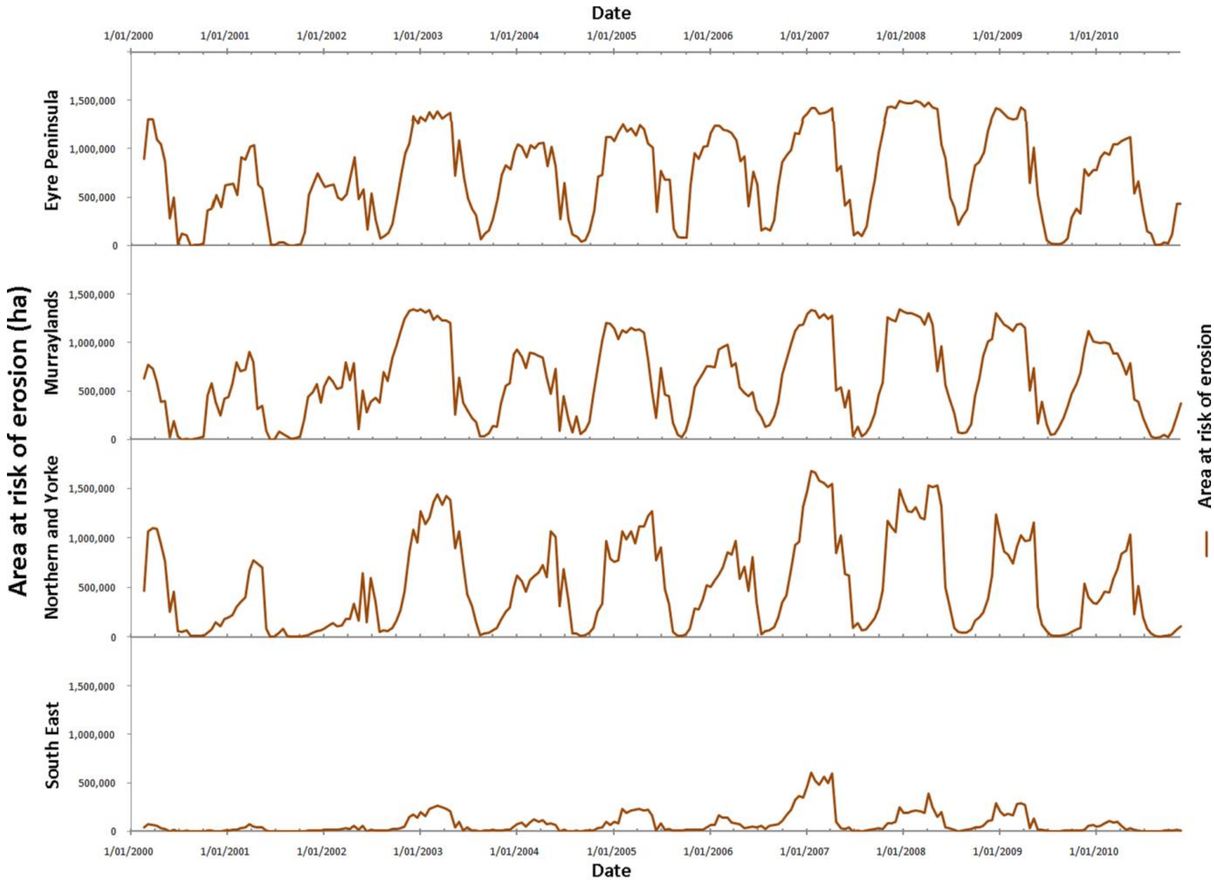

Figure 21. Temporal profile of area at risk of erosion, expressed as hectares ≥ 50 % soil exposure, for the 2000 – 2010 period.

Magnitude of erosion vulnerability

The magnitude of erosion vulnerability, expressed in millions of hectare-days vulnerable to erosion (≥ 50 % soil exposure) is displayed in Figure 22. This measure is essentially the area under the curve in Figure 21, the integral of the preceding temporal profile of area vulnerable to erosion for each reporting year. However, while this and the preceding measure are similar, both convey area and time vulnerable to erosion risk, we believe that the magnitude of erosion vulnerability more clearly conveys the total erosion risk in a region by combining area and time into a single measure for each reporting year. A strong illustration of this can be seen by comparing the two measures for the 2007/2008 reporting year for the Eyre Peninsula and Northern and Yorke regions. Examining the temporal profile first, both regions reached about the same maximum area vulnerable to erosion, but this area was exposed for less time in the Northern and Yorke region, and so the Northern and Yorke had a lower total erosion vulnerability. Examining the magnitude of erosion vulnerability graph now, the Eyre Peninsula vulnerability is over 400 million hectare days, while the Northern and Yorke is just over 300 million hectare days. Simply put this measure allows for intuitive and fair inter-annual and inter-regional comparison of total annual erosion vulnerability.

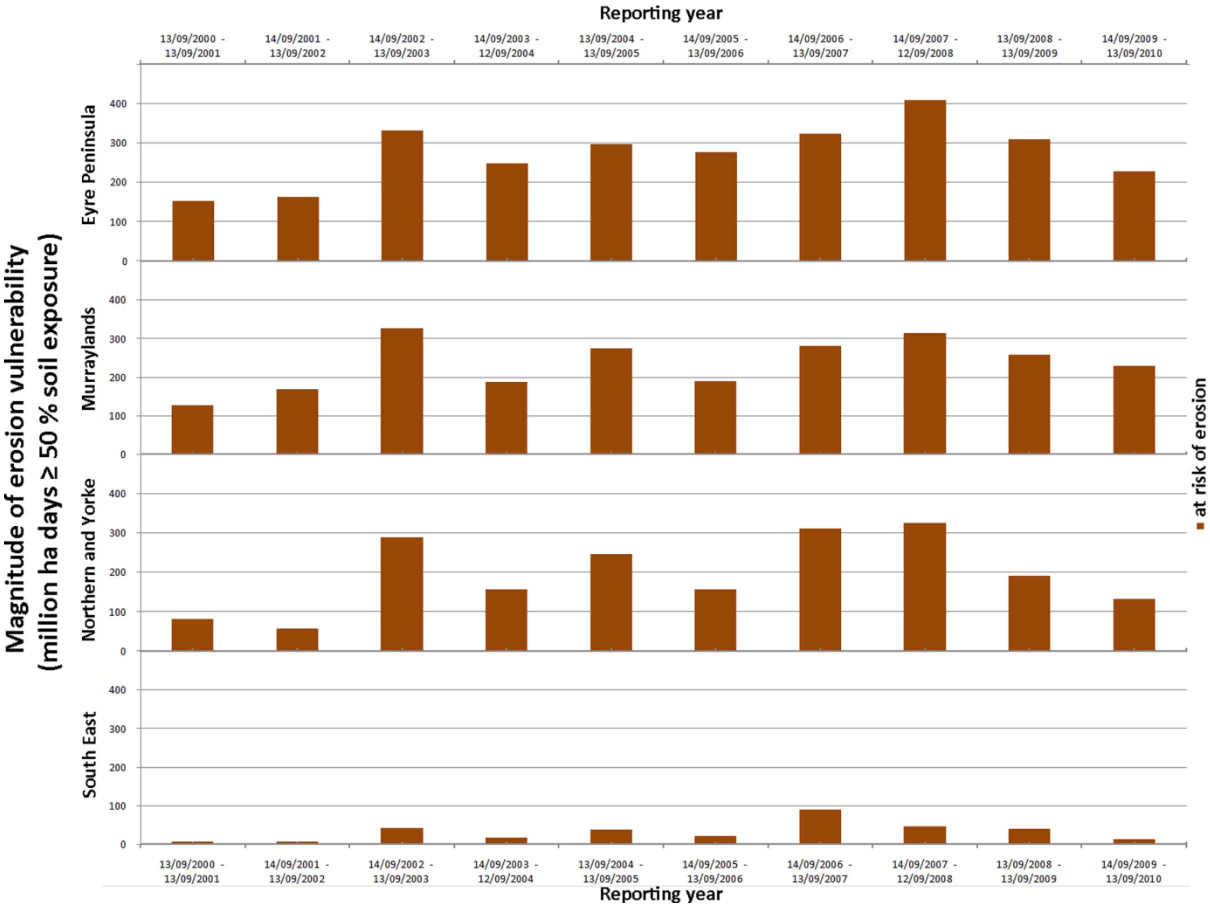

Figure 22. Erosion vulnerability, expressed in millions of hectare days ≥ 50 % soil exposure, for the 2000 – 2010 period.

Land protected from erosion relative to 2002/03

This measure reports the total hectare-days within each region that were *not* vulnerable to erosion, a feature we call the land protected from erosion. This measure is created by subtracting the total hectare-days of erosion vulnerability for a given year from the total hectare-days for that region for a reporting year. Finally, the land protected from erosion is presented relative to the land protected from erosion in the 2002/03 reporting year, to assist in reporting towards South Australia's Strategic Plan 2011 soil protection target.

The strategic plan baseline was set in one of the driest years in the study period. Land protected from erosion in almost all reporting years in all four regions is higher than the baseline. The notable exceptions were the very dry years 2006/07 and 2008/09, in which there was close to or less than the baseline amount of land protected from erosion in all regions and reporting years, except for the Murraylands in 2006/07. This does not mean the Murraylands fared better in this year than the other reporting regions. Examination of the 2002/03 magnitude of erosion vulnerability graph demonstrates that the Murraylands had relatively high erosion vulnerability, comparable to that of the Eyre Peninsula or the Northern and Yorke regions. Rather, this is a result and an artefact of comparing land protected from erosion to a baseline, and that baseline being the worst year on record (in this study). It follows that all years MUST have higher soil protection than the lowest year.

An important caveat to these observations is that DENR are aware of the potential impact unusually dry or wet years can have on soil erosion risk measures and have taken steps to try to minimise this impact. DENR reporting for the baseline and current land protected from erosion are based on three year averages. The current reporting value for 'percent land protected from erosion' is the average of land protected from erosion in the last three years, while the baseline (nominally 2003) is an average of the land protected from erosion in 2001, 2002 and 2003. This is a sensible approach that reduces but does not eliminate the effect of unusually dry or wet years on reporting.

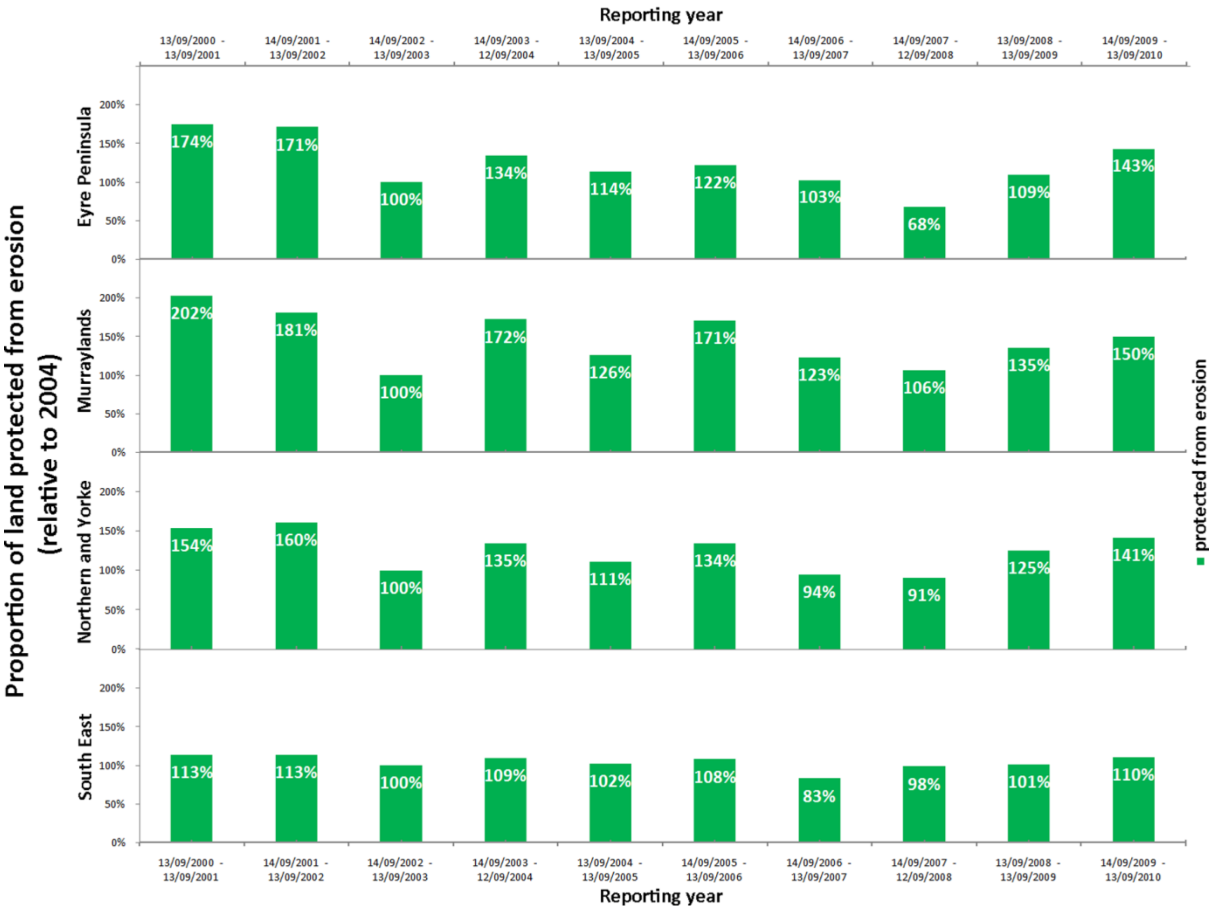

Figure 23. Percent land protected from erosion relative to 2002/03 baseline year.

5.4 Discussion

The goal of this section was to demonstrate methods of extracting and presenting information from image indices of soil exposure that would meet the needs of DENR Policy Directorate to monitor and report on soil exposure dynamics. We accomplished this by developing temporal profiles of LCI, NDVI and RSMA. Furthermore, by employing the relationship between LCI and fractional soil exposure that we established in Section 2, we were able to measure annual variation in area vulnerable to erosion, magnitude of erosion vulnerability, and land protected from erosion relative to 2002 / 2003.

In addition to illustrating potential reporting methods the work presented in this section should provide further confidence in the use of the LCI as an index of soil exposure. These findings are not surprising, in light of sections 2 and 3, but provide a more visual demonstration of the efficacy of LCI. The seasonal pattern of LCI is in strong agreement with the expected seasonal pattern of soil cover (or total vegetation cover), whereas the seasonal pattern of NDVI is in strong agreement with the seasonal pattern of green vegetation cover rather than total soil cover. The period after crop senescence and harvest most strongly illustrates this. At this time NDVI plummets to a minimum value and plateaus because of the absence of green vegetation cover, while LCI continues to decrease as crop residues are depleted by natural decay and grazing. Additionally, LCI performed as expected in very low rainfall years (2002 and 2006), producing its lowest minima on record, indicating high soil exposure. In these years soil exposure is higher than in average rainfall years, and this is demonstrated by the EPFS Cover Rating, which produced some of its highest values on record, also indicating high soil exposure.

The temporal RSMA soil profiles likewise add additional weight to their validity as a measure of soil exposure. As with LCI, the RSMA r_S profiles both agree with expected seasonal patterns of soil exposure, and are observed to respond to unusual deviations from average seasonal patterns, such as exceptionally dry years causing increased soil exposure. However, of some concern is the fact that RSAM r_{NPV} does not decrease as expected at crop harvest, and r_S increases steadily over the period of crop ripening/senescence and harvest, indicating that RSMA may be confusing NPV and soil to some extent.

Visualisation of both LCI and RSMA r_S alongside EPFS Cover Rating raise some questions about the current timing of some of the erosion protection field surveys. Examination of the timing of maximum soil exposure as recorded by both the LCI and RSMA r_S indicates that the May EPFS is often conducted after soil exposure has already begun to decrease. In those years the EPFS will provide the DENR Policy Directorate with an assessment of maximum soil exposure lower than it was in reality.

Furthermore, the side-by-side visualisation of LCI and EPFS Cover Rating highlights the difference in temporal resolution of the two measures. Whereas the EPFS is only conducted four times a year, the

LCI is calculated 23 times a year. The LCI is therefore able to more accurately measure the temporal variation in soil exposure. Additionally, the LCI is more spatially comprehensive than the EPFS. While the EPFS measures Cover Rating at sites along transects the LCI is able to measure soil exposure across the entire cropping districts on each of the 23 composite image dates. Thus, these two factors combine to make the EPFS a relatively coarse, and the LCI a relatively fine spatiotemporal measure of soil exposure.

While users can have confidence in the ability of the LCI to measure soil exposure, care must be exercised in the specific data extraction and visualisation methods employed. The regression relationship used to produce the estimates of area vulnerable to erosion was somewhat arbitrarily defined, the field data it was based on were collected in the Northern and Yorke region over a relatively small area, and the threshold level of vulnerability to erosion of 50 % soil exposure was arbitrarily set. Prior to operational use the possibility of defining a different regression relationship should be considered, and should balance the errors of commission and omission (areas that are falsely mapped as vulnerable to erosion, and areas that are falsely mapped as protected from erosion) depending on whether a more conservative or more aggressive classification is desired. Additionally, it would be advisable to collect high quality field fractional cover data in each of the reporting regions. This would enable verification of whether it is appropriate to use one LCI to fractional soil cover regression relationship for all regions, or whether separate relationships should be defined for each region.

An additional issue is how to report to the SASP soil conservation target. The baseline year was set in one of the driest years in the study period, and consequently land protected from erosion in almost all reporting years and in all regions is higher than the baseline. This does not necessarily indicate that management is improving as simple regression to the mean would produce the same result. In future, it would be advisable to set SASP soil conservation targets in terms of long-term averages, or in terms of the influence of management on soil cover rather than total soil cover. The latter approach especially would enable attention to be focussed on what is controllable, land management practices, and ensure that the ability to report against a valuable strategic goal was not determined largely by the vagaries of the climate.

In summary, the work presented in this section illustrates several possible methods for extracting information from LCI relevant for soil exposure monitoring and reporting and provides further confidence in the LCI as an index of soil exposure. These reporting methods could be used to extract the same information from any image index of soil exposure, such as the ARSMA once further developed and validated, or the Guerschman et al. (2009) unmixing index once validated. Therefore, the methods developed and presented in this section will continue to be valuable to DENR even if the LCI is replaced by another index of soil exposure in the future. However, we hasten to add that the LCI is currently the best validated index of soil exposure available.

6. Northern and Yorke Region case study

The Land Condition Index (LCI) is a remotely sensed index of soil exposure that offers greater temporal and spatial resolution, and greater spatial extent than the current DENR erosion protection field survey (EPFS). This section demonstrates these advantages in the Northern and Yorke region (Figure 24).

6.1 Temporal resolution

The LCI is produced from MODIS composite images every two weeks, which enables LCI mapping of soil exposure 23 times a year. By comparison, the EPFS is conducted four times a year. To illustrate the advantage of this increased temporal resolution the graph in Figure 24 presents LCI and EPFS Cover Rating for the period 2000 to 2010.

Clearly both LCI and Cover Rating are recording the same overall pattern in soil exposure, with relative magnitude of minimum and maximum annual values closely corresponding. However, the increased temporal resolution of the LCI allows for more detailed measurement of soil exposure between the Cover Rating survey dates.

6.2 Spatial resolution and extent

The graph draws attention to four dates representing minimum and maximum cover in a dry and a wet year, and maps of LCI are presented for these four dates. These maps demonstrate the increased spatial resolution and extent of the LCI as compared to EPFS transects (overlain).

The LCI measures soil exposure in each of more than 84,000 MODIS pixels in the Northern and Yorke region (this does not include the areas of native vegetation, which are displayed in white). This contrasts with the EPFS which assess soil exposure at more than 2000 sites along transect routes.

Furthermore, the LCI allows objective measurement of the proportion of the entire region below a target cover level. On the other hand, while transects are expertly placed to make them as representative as possible, they do not sample the whole region. Consequently, the EPFS only allows for subjective (though controlled) measurement of the proportion of transect sites below a target cover level.

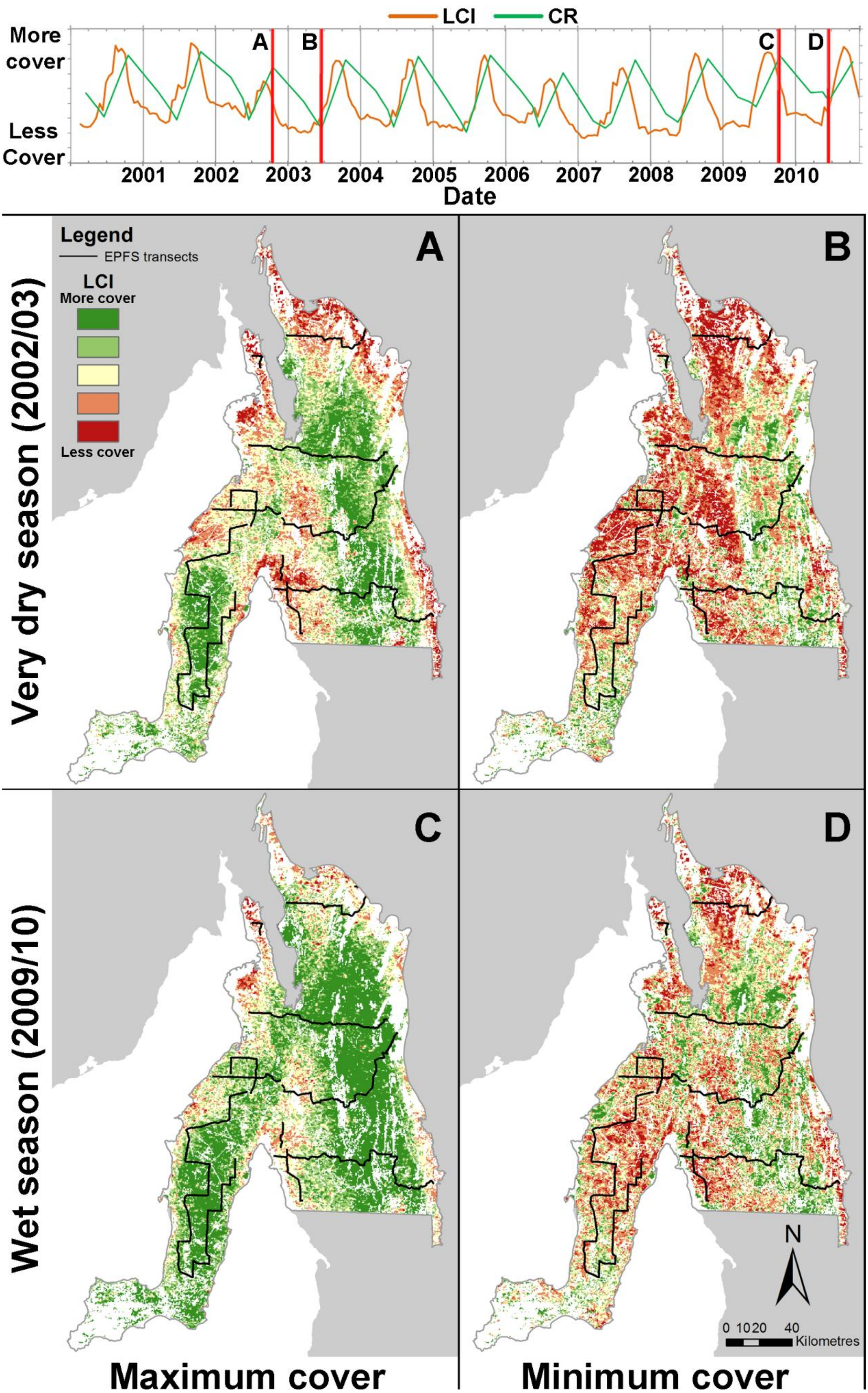

Figure 24. LCI image cover index and DENR Cover Rating for 2000 – 2010 for the Northern and Yorke region. Red lines highlight the maximum and minimum cover in a dry (A and B respectively) and wet (C and D respectively) year. Maps of LCI show spatial variation in cover at times A, B, C and D.

7. Summary and conclusions

7.1 Summary

The goals of this project were to:

1. develop a remotely sensed image index of soil exposure capable of accurately measuring the magnitude and duration of soil exposure across South Australia's cereal cropping regions,
2. evaluate the accuracy of the image indices so that they might be used to evaluate soil erosion risk with confidence, and
3. provide demonstrations of how the image indices might be used to report against the SASP soil protection target.

In Sections 2 and 3 we developed and tested the Land Condition Index (LCI), a new satellite image index of soil exposure derived from MODIS time series data. Section 2 presented the LCI method, and tested it against the Normalised Difference Vegetation Index (NDVI) and high quality field fractional cover data, and demonstrated that the LCI was a good predictor of soil exposure. Section 3 evaluated the LCI and NDVI against the DENR EPFS Cover Rating (CR), and demonstrated that LCI performs consistently across the cereal cropping regions of South Australia. Sections 2 and 3 are papers submitted to the scientific peer review journal, *Remote Sensing of Environment*.

In Section 4 we presented two additional MODIS image indices, the Relative Spectral Mixture Analysis (RSMA) and the Absolute Relative Spectral Mixture Analysis (ARSMA). The RSMA and ARSMA were evaluated against the same high quality field fractional cover data used in Section 2. We demonstrated that the RSMA was a very good measure of change in relative fractional PV, NPV and soil cover, and that the ARSMA was a very good measure of change in absolute fractional PV, NPV and soil cover. Given that the RSMA is not a measure of absolute fraction, it should not be used for monitoring change in absolute soil exposure through time. However, the RSMA may be used for landscape phenology studies. Alternatively, the ARSMA is a measure of absolute fraction, and may therefore be used for landscape phenology studies, and for monitoring change in absolute soil exposure through time. However, the ARSMA is not ready for operational use yet, as it is still in development, and was produced as a proof of concept.

Thus Sections 2, 3 and 4 addressed goals 1 and 2. In Sections 5 and 6 we address goal 3, by providing demonstrations of how the MODIS image indices can be used to report against South Australia's Strategic Plan 2011 target 70, Sustainable land management. These methods allow the user to visualise fortnightly change in soil exposure, by region, from 2000 to 2010, understand at a glance how the soil exposure at any time compares to the long-term average for that time of year, and to see how the area vulnerable to erosion changes from year to year.

7.2 Adoption recommendation

Based on the current level of validation the Land Condition Index (LCI) is the only new image index examined here that is ready for incorporation into the DENR soil erosion risk monitoring program.

We have demonstrated strong agreement between LCI and high quality field fractional cover data in one area and consistent agreement between LCI and the DENR EPFS Cover Rating throughout the cropping regions. Furthermore, we have demonstrated that the LCI is capable of measuring trends in soil exposure over time, and how the LCI can be used to report against the SASP soil protection target.

The nature of the Relative Spectral Mixture Analysis (RSMA) renders it unsuitable for DENR soil erosion risk monitoring. The RSMA is a measure of fractional cover relative to a baseline date, whereas the DENR soil erosion risk monitoring requires a measure of absolute soil exposure.

By contrast, the new Absolute Relative Spectral Mixture Analysis (ARSMA), which converts the RSMA to absolute fractional cover, would be suitable for DENR soil erosion risk monitoring needs. Furthermore, early results suggest that the ARSMA is an even better index of soil exposure than the LCI. However, the ARSMA is in early development, and is not yet adequately validated for adoption into an operational monitoring program.

We note that the Guerschman index (Guerschman et al. 2009) may also potentially satisfy the DENR soil erosion risk monitoring needs. While early evidence makes this index look promising (Guerschman et al. 2009), and the index is currently undergoing broad scale validation, it is not yet adequately validated for adoption into an operational monitoring program.

Thus, while there are other image indices which may in the future be demonstrated to satisfy the DENR needs for a measure of soil erosion risk, we believe that the LCI is the only index that is adequately validated for operational use. The reasons for this assessment are threefold:

1. the LCI meets the needs of soil protection monitoring in South Australia now;
2. development and refinement of these and other indices, and the appearance of new remote sensing satellites may lead to incremental improvements in accuracy for years or decades to come; and
3. adoption of one image index now will not lock DENR in to the use of that index forever. The reporting methods we have demonstrated in this report (the temporal profiles and trends, and the change in area protected) were produced from the LCI, but they could equally easily be produced from another image index. In short, any future change to a different image index would require minimal disruption to production, and would be invisible to report users.

7.2.1 Adoption method

If the LCI is adopted by DENR, a detailed transition plan should be drawn up. We recommend that such a plan include the following key elements: that both the LCI and EPFS be conducted in tandem for a period; and that some additional high quality field fractional cover data be collected in the Eyre Peninsula and Murraylands regions in areas of differing soil colour or brightness.

Running the LCI and the EPFS concurrently will build user familiarity and will give advocates of the LCI time to demonstrate the advantages of the new method. We hope that this would prevent users from experiencing transitional shock, and the resentment some users experience when forced to make sudden changes in work practices.

High quality field fractional cover data was collected in the Northern and Yorke region as part of this study. This provided confidence that LCI was a good measure of soil exposure for lentil and cereal crops in the Northern and Yorke region in an area of relatively uniform soils.

Therefore, the sensitivity of the LCI to differing soil colours and brightness has not been established. Performing similar validations that capture the major variations in soil colour and brightness in the Eyre Peninsula and Murraylands regions would provide confidence in the performance of the LCI throughout all of the cropping districts.

Collecting the field validation data would be relatively inexpensive. For each survey, two personnel would travel to the region and spend two days surveying fields. Two surveys would be conducted in each of the two regions, for a total of four surveys. The first surveys would be conducted early in the year during a period of high soil exposure, while the second surveys would be conducted after harvest, during a period of high NPV cover.

Finally, the target audiences for the information derived from LCI regional and State-wide monitoring should be clarified, and within each target audience user preferences and needs should be determined. It should also be recognised that different user groups may have different needs and levels of competency.

The means and capability for on-going production of the erosion image index, and derived image-based erosion reports should also be identified. Additionally, a means of delivering image-based erosion reporting data should be developed, and should take into account the preferences and needs of key target audiences. A web delivery interface is a suggested delivery tool, capable of supporting a variety of different user needs.

Three possible solutions are:

1. DENR appoint or train scientific staff with the required skills and knowledge, and acquire the required software and hardware to allow in-house production of the erosion image index and extraction of required reporting information; or

2. DENR contract developers at University of Adelaide to produce the erosion image index and extracted reporting information on an agreed frequency.
3. AusCover will produce this or a similar erosion image index at a continental scale. DENR could rely on this product, but would still need relevant expertise to extract and analyse the required reporting information. In this scenario DENR would have some influence over, but no direct control of the erosion image index production schedule.

7.3 Future research

Some of the research we would recommend as necessary following this report is already planned and funded, while some is not. In the following two subsections we provide overview details of this research.

7.3.1 Planned and funded

The Adelaide AusCover node will undertake further development of the LCI, RSMA and ARSMA as part of its core focus from mid 2011 through to the end of 2013.

Both the LCI and RSMA will be produced for the Australian rangelands. Calibration and validation of both of these indices will utilise field data collected by TERN AusPlots, field and airborne data collected for AusCover super sites, and field data collected for the National Groundcover Project with the SLATS method.

Both LCI and RSMA could potentially make major contributions to landscape monitoring and science in arid and semi-arid rangelands of Australia. The LCI could allow DENR to set a baseline and report against the new South Australian Strategic Plan 2011 sustainable land management target for the pastoral lands *"a 25 % improvement in the condition of pastoral land"* leading to better rangeland management, and could provide the information required for dust storm forecasting. The RSMA can be used for research into national, landscape scale PV, NPV and soil dynamics which may provide insights into the impacts of climate change.

The ARSMA will be produced for the South Australian Mediterranean cropping regions and evaluated with DENR EPFS data and the high quality field data presented in this report. The ARSMA will provide highly accurate data on absolute PV, NPV and soil fractional cover dynamics. The ARSMA soil cover data has the potential support DENR Policy Directorate reporting towards the SASP sustainable land management target, while the PV and NPV data could provide insight into total land cover dynamics previously not elucidated solely by soil exposure data.

7.3.2 Recommended: high strategic value to DENR

The following research is identified as being of very high potential value to DENR.

1. None of the current image indices allow determination of the relative influences of management and climate on cover levels. Being able to separate these two influences would allow reporting targets to be based on cover management, which can be influenced by DENR and growers. This would remove the possibility that the vagaries of weather and climate might cause reporting targets to be missed (drought years causing reduced cover) or met (wet years causing surplus cover). Specifically, targets could be based on 1) adequacy of cover management, or 2) improvement in cover management. Additionally, this method could also be used to measure the impact of climate change on cover.

   Research Goal: Develop a method for measuring the relative contributions of climatic and management influences on soil cover levels.

7.3.3 Recommended

The following research is identified as important, but currently un-funded:

1. The LCI should be highly useful in other Mediterranean cropping regions, and should function therein equally well, however this is currently an un-tested assumption.

   Research Goal: The LCI should be trialled in other Mediterranean cropping regions.

2. The effect of differing soil colours and soil chemistries on the LCI is unknown.

   Research Goal: The effect of differing soil colour on LCI should be examined in a lab-based hyperspectral study.

3. Understanding the effect of soil colour on LCI is of theoretical value. However, this knowledge could be applied to reduce or remove the influence of soil colour on LCI, and potentially other image indices, if the spatial variation in soil colour throughout South Australia was mapped.

   Research Goal: The soil colour and chemistry throughout South Australia's Mediterranean cropping regions should be mapped.

4. The LCI does not separate soil equally well from PV and NPV cover, and this limits its potential as a soil exposure index.

   Research Goal: Future work should produce a refinement of the LCI, or an entirely new index that separates soil equally well from PV and NPV cover.

5. A key uncertainty in this report is the result of not understanding the relationship between oblique and nadir assessments of cover.

Research Goal: Research should be conducted to elucidate the exact relationship that differing cereal crop heights, shoot densities and canopy densities have on oblique and nadir cover assessments.

Research Goal: Furthermore, it would be useful to know whether sun-elevation has an influence on the accuracy of oblique or nadir cover assessments.

Research Goal: Finally, It is also conceivable that soil colour has an influence on the accuracy of oblique or nadir cover assessments, but this is also unknown.

7.4 References

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