Detecting trends in cereal crop sowing dates using Landsat

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Abstract

Agronomic research suggests Australian farmers may increase wheat yields by 13 to 47% and reduce risk of crop failures by sowing crops earlier than is currently practiced. This study investigated the potential to use remote sensing to assist in evaluating changes in farmer sowing date practices in response to research recommendations, using study paddocks in the southern Australian cropping region. Vegetation Indices (VIs) derived from Landsat imagery were utilised by fitting a 5 parameter logistic curve (5PL) to the VIs from days 50 to 250 of each year, encompassing the crop green-up period. This method was applied to 10 co-located paddocks with sowing time records spanning years 1988 to 2014, and 17 dispersed paddocks with two years of sowing history. The method shows promise in detecting crop green-up, but only in years and locations where cloud cover does not prevent successful image capture at key crop growing times.

1 Introduction

Wheat is a major crop in Australia, and is grown on 55% of the total cropland, which averaged 12.6 million ha between 1998-9 and 2011-12 (ABARES 2012). Maximising water use efficiency (WUE) is seen as a key to optimizing wheat production nationally (Hochman, Holzworth, and Hunt 2009). Wheat crop simulations using the Agricultural Production Systems Simulator (APSIM; Keating et al. 2003) have identified that earlier sowing of wheat can increase average farm wheat yields by 13 to 47% and reduce risk of crop failures (Kirkegaard and Hunt 2010) through improved soil moisture usage efficiency and increased radiation interception.

Information on these expected benefits of early sowing have been available to grain growers for several years but it is difficult to assess whether practices are changing in response to the these research recommendations. So this study investigates the potential to use remote sensing to monitor trends in sowing dates, and to assist in evaluation of changes in farmer practice. The study seeks to develop a methodology that could be suitable for application across the entire Australian cereal cropping region, although proof-of-concept work will initially be carried out on selected small regions. The approach taken first involved selecting suitable sources of remote sensing data. Then a method using these data to estimate the date on which crops were sown was developed and evaluated by comparing estimated dates for paddocks with known crop sowing dates.

2 Methodology

2.1 Study paddocks

Paddock management records were obtained for 10 paddocks in central Victoria (‘Merriwa’; 143.738 °E, 35.829 °S) (Figure 1), with sowing dates and crop type records covering the period from 1988 to 2013. Boundaries of these paddocks were digitised to exclude patches of perennial vegetation, dams etc. These paddocks lie within an area of 4.4 x 1.4 km, with paddock areas ranging from 9.9 ha to 87.6 ha (mean 52.4 ha). To apply the analysis over a broad geographic extent, sowing dates and crop types in 2013 and 2014 were obtained for 17 paddocks from 13 farms distributed across Western Australia, South Australia and Victoria (‘NPS’ paddocks; Figure 1).

2.2 Remote sensing options

Except perhaps by using Synthetic Aperture Radar (SAR), or extremely high-resolution satellite imagery, detecting actual sowing operations or the disturbance of paddock soil surfaces that occur during sowing, seems unlikely. Furthermore these options are currently infeasible for assessment of trends due to lack of historical imagery with extensive coverage over the grain cropping regions of Australia. To monitor ‘sowing dates’ from space requires detecting land cover or surface change, from which an estimate of crop sowing date might be obtained. The most apparent change that might be detected is the early green-up of paddocks that occurs as crops emerge after sowing, using this as a surrogate for sowing date. To assess year-to-year trends in sowing dates and/or timing of paddock green-up requires selecting remote sensing data sources which:

- capture the entire Australian broad acre cropping region

- have spatial resolution (pixel size) smaller than the typical land management unit (i.e. paddocks ranging from tens to a few hundred of hectares in area)
- capture spectral bands suitable for vegetation monitoring, including visible and NIR.
- provide regular revisits at intervals suitable for capturing the timing of green-up
- provide archival data to enable trends to be analysed over several years

The imagery sources that appear most suitable are MODIS (250 m pixels, daily revisit) and Landsat (25 m pixels, revisits every 8 to 16 days). The spatial resolution of Landsat being finer than the typical land management unit therefore appears to be the most suitable candidate. Three different Landsat satellites provide varied coverage frequency over the period of interest from 1988 to 2014 (Table 1).

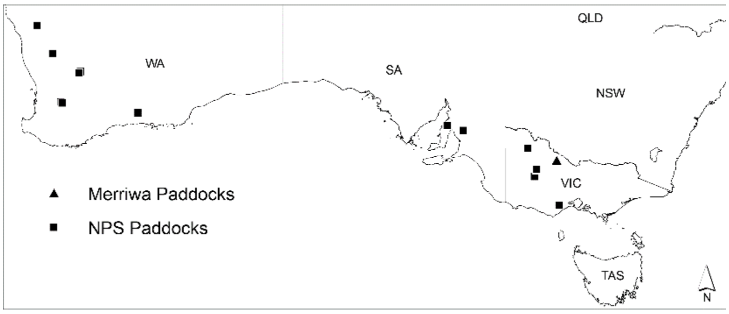

Figure 1. Location of the study paddocks showing wide geographic range across the broad acre cropping regions.

Table 1. Revisit frequency of the Landsat series of satellites as captured by the Geoscience Australia ground station network (Geoscience Australia 2015).

Years	Revisit frequency
1986-2003	16 days
2003-2011[1]	8 days
2011-2013[2]	16 days
2013-present[3]	8 days

2.3 Remotely sensed data and the Australian Geoscience Data Cube (AGDC)

The Australian Geoscience Data Cube (AGDC) is a collaboration between Geoscience Australia, CSIRO and the National Computational Infrastructure (NCI) developed to improve the accessibility and usability of national datasets. AGDC is an approach to storing, organising and analysing gridded geospatial information to enable time-series analysis to be undertaken efficiently. The AGDC hosts a geo-referenced, calibrated and standardised time-series of Landsat imagery from 1987 to the present, which can be analysed as spatio-temporal ‘stacks’ covering the whole Australian continent. These images are corrected to ARG25 (Geoscience Australia 2014) which results in data that are sensor agnostic, meaning that images can be compared over the period of several decades, during which time several versions of the Landsat sensors have captured the data. The ARG25 product includes data from Landsat missions 5, 7 and 8, and applies pixel quality array (PQA) and Water Observations from Space (WOFS) to remove pixels affected by cloud and water, before calculating an aggregated value for the supplied area of interest. A Fractional Cover (FC25) product (Geoscience Australia 2015) is also available. We used an AGDC Python tool ***retrieve_aoi_time_series.py*** which summarises remote sensing data within an area of interest (AOI) defined by a supplied boundary. This enabled each paddock to be treated as a single analysis unit.

2.4 Spectral indices for sparse vegetation cover

Many spectral indices have been applied to vegetation sensing using Landsat bands (e.g. see Broge and Leblanc 2001, Viña et al. 2011). The following vegetation indices (VIs) were calculated using ARG25 data for this analysis:

- Normalized Difference Vegetation Index (NDVI) (Rouse et al. 1974)
- Simple Ratio (SR), also known as Ratio Vegetation Index (RVI) (Pearson and Miller 1972)
- Soil Adjusted Vegetation Index (SAVI) (Huete 1988)
- Green Normalized Difference Vegetation Index (gNDVI) (Gitelson, Kaufman, and Merzlyak 1996)
- Difference Vegetation Index (DVI) (Jordan 1969)
- Optimized Soil Adjusted Vegetation Index (OSAVI) (Rondeaux, Steven, and Baret 1996)

The NDVI and SR distinguish between soil and vegetation, and minimise the effects of different illumination. However they are sensitive to the effect of soil brightness (Broge and Leblanc 2001). The SAVI attempts to correct for soil reflected signal. In this analysis, the constant L in the SAVI calculation was fixed at a value of 1, which is

[1] Both Landsat 5 and 7 were being acquired by Geoscience Australia until Landsat 5 ceased operating in 2011.

[2] The Landsat 7 ETM+ sensor suffered a scan-line-corrector failure in 2003, as a consequence, images acquired after that time have fewer observations and this appears as strips of missing data.

[3] Both Landsat 7 and Landsat 8 were being acquired by Geoscience Australia during this period.

recommended for use with low vegetation densities as is this case when sensing emerging crops. gNDVI has been shown to be more sensitive to chlorophyll than the conventional red NDVI (Gitelson, Kaufman, and Merzlyak 1996). The DVI purportedly performs well at low leaf area index (LAI) values (Barati et al. 2011). Additional to these VIs, the FC25 product, includes a Photosynthetic Vegetation (PV) index which is generated from ARG25 data using the method of Scarth et al. (2010).

2.5 Fitting logistic growth function

Mathematical growth functions such as the generalised logistic function (Richards 1959) is suitable to model biological growth, such as that of plants, where growth rate decreases with size (Paine et al. 2012). Three and four parameter logistic (3PL or 4PL) functions are commonly used, but a 5 parameter logistic (5PL; Equation 1) is more flexible and does not assume symmetry in the same manner as the 4PL (Gottschalk and Dunn 2005)

$$y = f(x; a; b; c; d; g) = d + \frac{(a-d)}{(1+(\frac{x}{c})^b)^g} \quad (1)$$

To convert the discrete VI data to a crop growth curve calculated from the time-series data extracted for each paddock, a 5PL function was fitted to the VIs. Fitting was performed using a Python scipy.optimize.curve_fit routine which applies a non-linear least squares method (Levenberg-Marquardt algorithm) to fit a function to a data series. Successful curve fitting by the scipy.curve_fit routine benefits from 'initial guess' starting parameters, which can reduce time taken to find an optimal fit, and also improve the likelihood of finding a solution or fit for each paddock-year. Initial guess parameters were refined through iterative testing carried out on a subset of data using Python code which automatically refined the input parameters over the test areas for each different VI.

Cereal crops in south eastern Australia are not generally growing before day 100 of each year, and maximum greenness reached before day 250. During initial testing it was apparent that better fitting was achieved if a longer summer period (with a low crop cover baseline) was included, so the 5PL function was fitted to days 50 to 250 of each year. Curves cannot be fitted where there are fewer samples than parameters, so paddock-years with less than 5 Landsat data samples during this period were automatically excluded.

2.6 Assessing suitability of VIs to capture crop sowing and emergence

For crops to grow requires both sowing and adequate rainfall for growth. Adequate rainfall may occur before or after sowing occurs. A general rule was used to determine the day of the year (DOY) of 'opening-rains' (e.g. see Hochman et al. 2016), which was designated as the date after 26th April, when a total of at least 15 mm of rainfall was recorded over 3 days. Since crop emergence requires sowing and the opening rains to have occurred, an 'expected green-up' DOY was designated as the maximum of the recorded sowing date, and the date which met the opening rains rule. Where the opening rains rule was not satisfied between DOY 50 to 250, the sowing date was used as the expected green-up DOY.

To assess the effectiveness of the different VIs, we compared the recorded sowing dates and the expected green-up dates with the VI estimated green-up dates. The estimated green-up DOY was determined using a fixed threshold of 10% above the baseline level for the ARG25 indices, and 300% for the PV index. Dates estimated from the fitted 5PL functions were excluded if they fell outside the range DOY 50 to DOY 250.

3 Results

3.1 Computation and number of available samples per year

The ***retrieve_aoi_time_series.py*** tool took approximately 2 hours to extract each paddock time-series datasets on the Raijin supercomputer at NCI. The extracted time-series data covered 26 years from 1988 to 2014. The number of suitable quality Landsat images available between DOY 50 and 250 for the Merriwa paddocks varies due to cloud cover and the number of operational satellites (Table 1). This is reflected in Figure 2 showing that prior to 2000 between 3 and 10 images were available per year, except for 1998 with zero samples. From 2000 to 2014 between 9 and 28 samples were available per year in the AGDC for these paddocks. The number and distribution of Landsat samples over the key green-up period has important implications for the successful fitting of the 5PL function. Cloud cover reduces the number of observations, and gaps in the data at during the key green-up period means the curve-fitting cannot effectively capture the time at which green-up occurs (Figure 3).

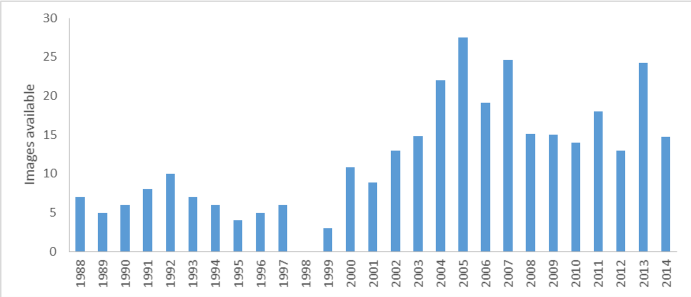

Figure 2. Mean number of Landsat samples available per year (1988 to 2014) for the Merriwa Pastoral paddocks.

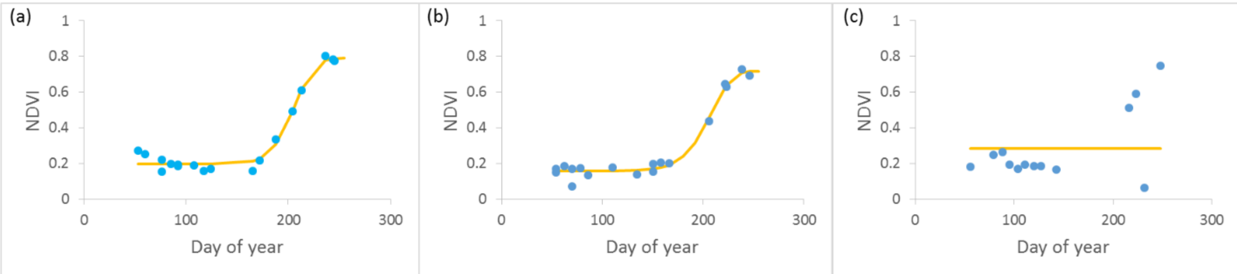

Figure 3. Examples of 5PL curves fitted to NDVI of Merriwa paddocks (a) good spread of Landsat samples (n=18) for (Paddock 10, 2011, sowing DOY = 136, DOY with rain over 3 days = NA); (b) poor density of Landsat samples (n=18) across key green-up period (Paddock 1, 2006, sowing DOY = 133, DOY with rain over 3 days = 118); (c) A failed 5PL fit (Paddock 10, 2012, sowing DOY = 119, DOY with rain over 3 days = 191).

3.2 Merriwa paddocks

Individual paddocks sowing records were available for 177 Merriwa paddock-years between 1988 and 2014.

Table 2. Comparison of estimated green-up dates from valid 5PL fits (out of a possible total 177) against recorded paddock sowing DOY and 'expected green-up' DOYs for 7 vegetation indices (VIs).

	NDVI	gNDVI	SAVI	OSAVI	SR	DVI	PV
All available valid fits							
# valid fits	139	116	140	131	141	142	130
R^2 fit vs sowing DOY	0.049	0.025	0.048	0.055	0.069	0.103	0.166
R^2 fit vs expected green-up DOY	0.079	0.009	0.120	0.086	0.220	0.180	0.091
Valid fits with >15 samples							
# valid fits	54	41	56	48	54	53	44
R^2 fit vs sowing DOY	0.183	0.190	0.325	0.370	0.122	0.323	0.322
R^2 fit vs expected green-up DOY	0.111	0.181	0.414	0.341	0.222	0.388	0.514
Valid fits with >20 samples							
# valid fits	36	21	36	28	34	33	28
R^2 fit vs sowing DOY	0.348	0.216	0.297	0.553	0.023	0.213	0.339
R^2 fit vs expected green-up DOY	0.552	0.330	0.663	0.737	0.157	0.441	0.763

Table 2 demonstrates the range of suitability of the different VIs tested, and highlights that estimation of the expected green-up date is more successful than estimation of an actual sowing date. However, none of the VIs performed well when all paddock-years of valid fitted 5PL functions were included. By restricting analysis to valid fits for paddock-years with more than 15 samples during DOY 50 to 250, the PV performed best, especially when compared against the expected green-up DOY rather than the sowing date. This number of fits reduced successful analysis to only 7 years (2004-7, 11, 13, 14). When examining valid fits for paddock-years with at least 20 samples between DOY 50 to 250, all VIs performed better but PV and OSAVI performed especially well. However, this reduced analysis to only 4 separate years (2004, 2005, 2007, 2013). Again, the fits of estimated green-up DOY against expected green-up DOY were better than against actual sowing DOY.

The Merriwa paddocks provided a long time-series, but with co-located paddocks. The NPS paddocks were therefore included to test the methods using geographically distributed locations. The PV index which gave the best fit against the Merriwa paddocks, was fitted against recorded sowing dates. Using all fitted paddock-years (17 paddock-years) gave a poor result ($R^2 = 0.02$), selecting only those with more than 15 samples (14 paddock years) achieved an R^2 of 0.03, and with more than 20 samples an R^2 of 0.55 but only captured 6 of 17 paddock years.

3.3 Sowing date and green-up trends

Sowing of Merriwa Pastoral paddocks has started an average of 0.8 days earlier each year (1988 to 2013). The end of sowing has occurred 0.3 days earlier each year, suggesting that the duration of sowing has also increased over this time by approximately 0.5 days per year. Opening rains on the other hand, appear to be occurring 0.56 days later per year over that period.

In most cases the trends in VI estimated green-up dates were negative (results not shown), suggesting the VI method could detect crop green-up occurring earlier each year, in line with the recorded sowing dates and expected green-up dates. However, these comparisons resulted in low R^2 values and the slope of trends do not consistently match. This suggests that the 5PL estimates are not an accurate predictor of trends in actual sowing dates.

4 Discussion

We have evaluated a method to use Landsat imagery to estimate crop green-up by fitting a logistic growth function to VIs. This investigation has included a group of co-located paddocks with long history of crop management, as well as several widely distributed paddocks with shorter sowing records. Determining sowing date on the basis of crop emergence or green-up to is complicated by the reliance of crop growth upon early season rainfall which can be spatially variable. Furthermore, the practice of dry-sowing is recommended as another way of increasing crop yields (Fletcher et al. 2015) which further weakens the relationship between time of sowing and crop green-up. The use of more refined opening-rains rule, or perhaps modelled soil moisture datasets may improve the estimation of green-up however.

The predictive value of VIs is dependent on an adequate number of remotely sensed samples (i.e. cloud free satellite image coverage) during the critical crop green-up period. Landsat revisit intervals of 8 to 16 days means this has been an important constraint in this study. More frequent satellite acquisitions at the key time would increase the likelihood of cloud free images around the time of early crop growth, and would improve detection of crop green-up. The incorporation of satellite imagery from other sources such as MODIS, Sentinel 2 might partially alleviate this issue. MODIS has been used to map crop timing at global scale (Whitcraft, Becker-Reshef, and Justice 2014), but whether the coarser pixel resolution works well for capturing sowing or crop emergence requires further validation. A possible confounding effect in analysing trends, is that years in which there are higher levels of cloud free imagery may also be years of lower rainfall, and therefore may not be representative of other years.

This application of remote sensing to detecting crop green-up has also tested the sensitivity of remote sensing at the resolution of sources such as Landsat to detect very low levels of vegetation cover (or LAI). There are a number of factors which affect the sensitivity of remotely sensed data to crop vegetation, which include leaf optical properties, atmospheric perturbations, solar zenith angle and leaf inclination angle (Liu, Pattey, and Jégo 2012). However, the main issue in this case is that the objective is to sense the very low LAI of newly emerged crops. This may be beyond the capability of such sensors, but we identified the OSAVI and the PV fraction of the FC25 product) as being most suited to this task.

Scaling up this assessment of crop green-up to national scale would require access to mapped paddock boundaries and assessment of which crops have been grown each year. For most of the grain cropping zone, paddock boundaries and crop types are not widely available. Additionally, the high computational requirements and long times taken to perform this analysis are also a constraint on scaling up to national coverage. The input of specialised programming expertise would be needed to improve performance of the analysis across larger extents.

The ability of this approach to monitor trends in actual sowing dates practiced by farmers appears limited to years and locations where cloud cover does not prevent successful image capture at key crop growing times, and the application of the method is unlikely to deliver reliable and consistent results across broad areas. However, the method applied here does shows promise in detecting crop green-up, and could potentially be applied to other phenological studies. With access to additional compatible remotely sensed imagery, the method could be used to assess historic and ongoing changes in timing of crop emergence, which is a function of both farmer management, and climatic influences such as timing of opening rains. Furthermore, this study is an early demonstration of the value of the AGDC infrastructure in enabling access to national coverage of time-series remotely sensed data.

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