Optimising Rice Crop Management: Harnessing Near-Real Time Growth Curves

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Abstract

Optimising rice crop yield and input use efficiency relies on timely and informed decision making, especially regarding fertiliser and water application. In this study, we present an approach to deliver near-real time crop growth curves at the paddock level, which are benchmarked against historical crop growth trajectories.

Growth curves were based on vegetation indices (VIs), which are sensitive to leaf area index (NDVI), water status (LSWI) and chlorophyll content (CIRE). These were derived from Sentinel-2 satellite imagery. We created a database of growth curves from > 6,600 Riverina rice fields in 6 seasons (2018-2023). Poor quality observations due to cloud were removed from the time-series data, and a Savitzky-Golay smoothing filter was applied. The data were grouped into variety, region and sowing-method subsets, from which the quantiles (10, 50, 90%) were derived over 2 time axes: day-of-season, and days after flowering. These growth curves were sensitive to growth stage, applied nitrogen, mid-season drain events, grain moisture dry-down, and were predictive of crop yield.

We provide growers and agronomists with access to online dashboards that include growth curves of each of their rice crops, which are compared to the historical trajectories of crops of similar variety, region and sowing method. The dashboards also include weather, prediction of growth stages, nitrogen status and grain moisture dry-down. Challenges remain however, including imperfect cloud masks, data gaps, atmospheric and satellite view angle effects. We suggest possible avenues to ameliorate these issues.

Keywords

Remote sensing, rice crop yield, crop monitoring, agricultural decision support.

Introduction

The productivity and sustainability of rice cropping in Australia relies on good management of inputs, particularly water and nitrogen (Dunn et al. 2014).

Abundant free remote sensing data collected by satellites offers potential to monitor crop spatial variability, and development over time. Sentinel-2 imagery from the European Space Agency captures imagery every 5 days or less. Images include reflectances at many wavelengths including optical, red edge, near infra red and shortwave infrared. These data have applications in predicting crop parameters, such as leaf area index, nitrogen and water status.

While much research has demonstrated high correlations between crop nitrogen status and vegetation indices derived from canopy reflectances (Schlemmer et al. 2013), models that are stable over sites and seasons have proved elusive (Colaço and Bramley, 2019). Consequently, while the quest for robust models continues, there is significant value in providing remote sensing information in ways that can augment current decision-making processes.

Many existing software platforms show snapshots of crop spatial variability from individual image dates, and these tools have been widely adopted by growers and agronomists. Our work, however, is focused on delivering complementary time-series information, which describes the trajectory of crop growth and performance. By integrating this temporal perspective with growers and agronomists expert knowledge of individual fields, we anticipate decision-making and understanding of historical crop performance will be enhanced.

Methods

We obtained a dataset of more than 6,600 rice crops grown in the Riverina, New South Wales from 2018-2023. The data included field boundaries, sowing date, sowing method and rice variety. We used previously developed models to derive the dates that permanent water was applied to each field (Brinkhoff et al. 2022), and the panicle initiation (PI) and flowering dates of each field (Brinkhoff et al. 2023).

Satellite imagery (Sentinel-2 L1C) over each field was processed using Google Earth Engine. Clouds were masked using the new Cloud Score+ algorithm (Pasquarella et al. 2024). For each image, the median of all pixels within each field for all image bands were calculated and the results stored in a database. The time-series of image bands for each field was then interpolated to a daily time step, and Savitzky-Golay filtering was applied to smooth the trajectories, resulting in a dataset with more than 2 million rows. Three important vegetation indices (VIs) were calculated, the normalized difference vegetation index (NDVI=(NIR-R)/(NIR+R)), which is related to green biomass and leaf area index, the land surface water index (LSWI=(NIR-SWIR1)/(NIR+SWIR1)), which is sensitive to the presence of surface or crop canopy water and the chlorophyll index red edge (CIRE=NIR/RE2-1), which is linearly related with chlorophyll content and hence to nitrogen status (Schlemmer et al. 2013).

In order to compare each crop's growth against historical characteristics of similar crops, we computed the 10th, 50th and 90th percentile of the time-series trajectories of the VIs across grouped sets of the data. Groups included the different sowing methods (drill sowing with delayed ponding vs aerial and dry broadcast) and regions (Murrumbidgee, Coleambally, Eastern and Western Murray Valleys). Additionally, two varieties that have quite different growth characteristics to the other varieties had their own groups (Koshihikari, a tall lodging-susceptible variety, and Viand, a short season variety). Within each of these groups, the percentiles were calculated across two time axes and at each time point. The first axis was simply the day of season (DOS, days since July 1). The second axis was the days after flowering, which normalized the VI trajectories to phenological stage, rather than calendar date (compensating for early/late sowing for example). The VIs of individual fields in new seasons are then compared to these grouped trajectories, providing near real-time benchmarking of crop progress.

Results

Tracking field progress with VI time series

Figure 1 shows an example of the time-series of VIs for a rice crop. The management and phenology dates are listed in the caption. LSWI is a good indicator of the presence of water, and it can be seen that it rises and falls as permanent water was applied, drained and refilled. NDVI experienced a small dip during the time of the mid-season drain in December, indicating a reduction in vigour. The VIs (and particularly CIRE) peak just before flowering, which is commonly observed. This example demonstrates how time-series growth curves of rice fields can provide information on crop management and status for in-season monitoring and historical analysis. The trajectories of rice crops are very dynamic, and indicate that commonly adopted generic curve-fitting methods that assume a consistent rise at the start of season, and fall at the end of season (such as the double-logistic) are not suitable for rice crops. Local fitting methods such as the Savitzky-Golay algorithm used here however, can describe the dynamics, while still smoothing noise in the observations.

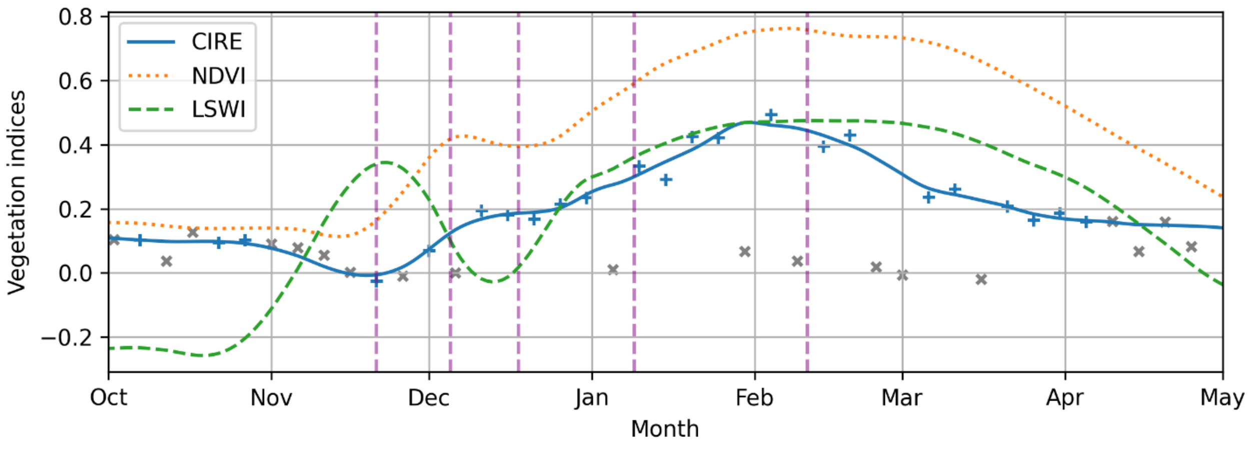

Figure 1. Vegetation indices for a V071 variety rice crop, planted on 26 September. Following dates are indicated by vertical lines, including permanent water application on 22 November, mid-season drain on 5 December, and refilling on 18 December, PI on 9 January and mid flowering on 11 February. CIRE observations marked as clear are denoted with a blue +, and cloudy observations with a grey x.

Industry-wide time-series benchmarks

We calculated the 10th, 50th and 90th percentile of vegetation indices, per time point, for all fields (n>6,600) from the 2018-2023 harvest seasons. 2019 and 2020 seasons were omitted as they had only 10% of usual rice area due to drought and resulting high water prices. The 50th percentiles for each year are shown in Figure 2. CIRE vs month (middle chart) shows that the 2023 crop was on average about 2 weeks later than other years. 2021 saw typical establishment, but the decline of CIRE was delayed, most probably due to cool conditions during the reproductive and ripening growth stages.

When CIRE is plotted against days after flowering (right chart in Figure 2) instead of calendar date, the peaks align. This allows a comparison of the growth curves relative to phenology date. 2023 had significantly lower VIs, probably due to both cold conditions and difficulty in applying nitrogen because of flooding during the early part of the season. These results demonstrate the usefulness of these growth curves in comparing between seasons, and may provide additional understanding of factors driving yield variability between seasons (Brinkhoff et al. 2024).

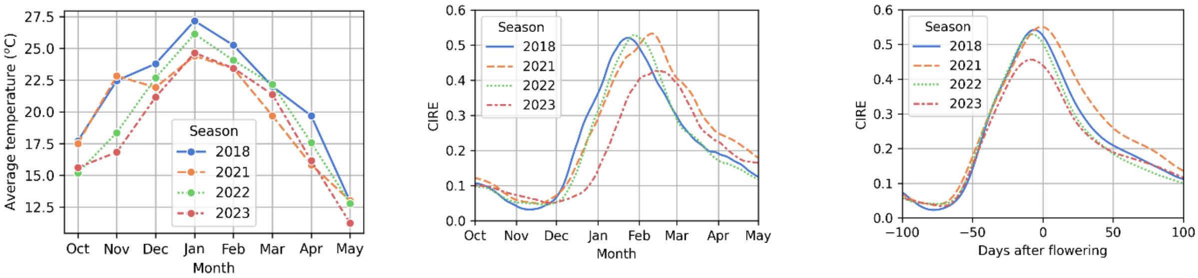

Figure 2. Average temperatures per month and season (left), and corresponding industry-wide median CIRE against the calendar date (middle) and days after predicted flowering (right).

Growth curves indicating nitrogen status

The time-series vegetation indices are useful to manage crop inputs in season. For example, the CIRE index is linearly related to nitrogen uptake (Schlemmer et al. 2013). Figure 3 shows the time-series of CIRE for a nitrogen rate trial, with plots large enough to be distinguished by the 10/20m pixels of Sentinel-2 imagery. The low nitrogen plots are below the industry median, and the rate of increase of CIRE is slow, whereas the high nitrogen plots show the opposite trend. This indicates how near-real time growth curves can help growers decide on mid-season nitrogen applications.

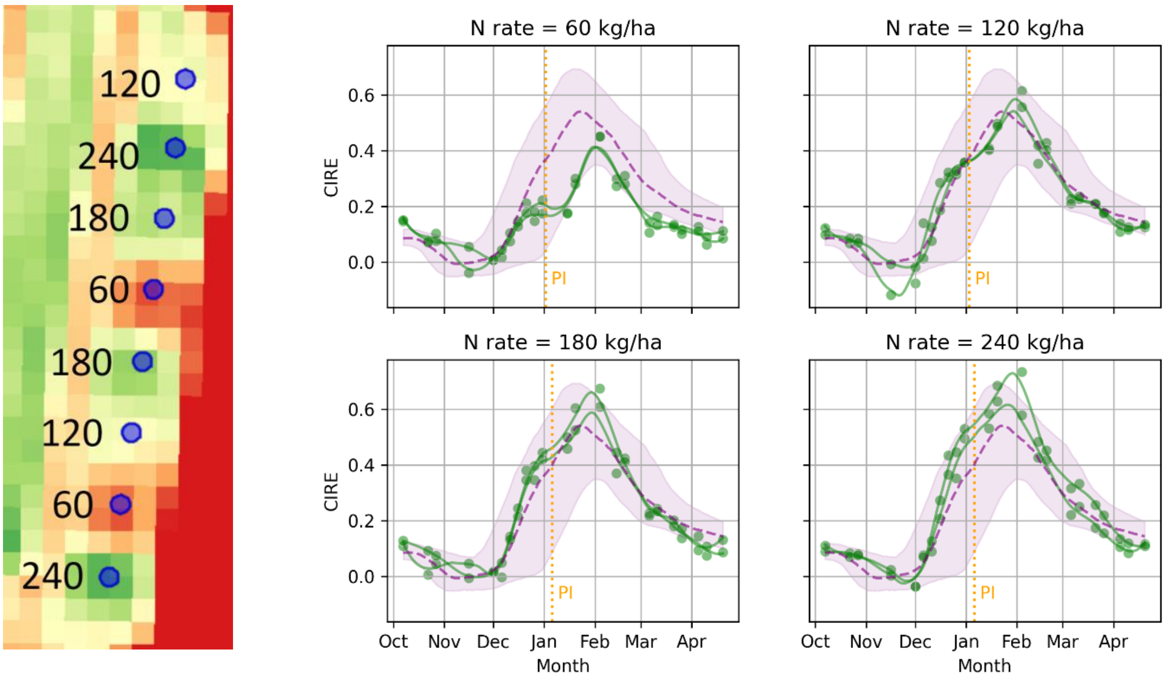

Figure 3. Large plot trial with 2 replicates of 4 nitrogen rates (kg N/ha). The image shows CIG (NIR/G-1), from 31 December 2022. The time series charts show CIRE for each of the plots, compared with industry 10th-90th percentile (purple shaded area) and 50th percentile (purple dashed line).

Discussion and conclusion

Provision of near-real time time-series growth curves to growers has the potential to be an additional powerful source of information for making in-crop decisions, as well as benchmarking previous crops to understand causes of yield and quality variability. Such data can be aggregated across entire industries in order to provide a benchmark to compare in-season crop performance in near real-time.

However, there are challenges to providing quality and timely data. When growth curves are provided at scale, robust algorithms to determine the quality of pixels are needed, marking pixels affected by cloud, haze and shadows for example. Cloud masks are improving all the time, for example, the recently released Cloud Score+ (Pasquarella et al. 2024) is providing excellent performance in filtering pixels that are obscured by either cloud or cloud shadow. However, there are tradeoffs in the thresholds used to determine the strictness of the filtering, a higher threshold will ensure only very clear observations are retained, but this also reduces the frequency of usable observations, which may cause issues if a slightly hazy image is removed at a critical time, such as rice PI. While revisit of satellite data has improved (for example the 5-day revisit of Sentinel-2), if multiple consecutive observations are cloudy during a critical crop management time, this can frustrate the use of such data. Additionally, indices such as CIRE are very sensitive to satellite look angle effects, bias between the multiple satellites in a constellation and atmospheric effects.

There are efforts to mitigate many of these adverse effects. These include integrating data from multiple satellite constellations to provide high frequency observations, correcting image imperfections to provide high quality observations (Claverie et al. 2018) and forecasting and filling gaps in growth curves caused by cloud (Farbo et al. 2024).

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