A comparison of remote-sensing vegetation indices for assessing within-field variation of wheat yield

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Abstract
Within-field yield variation has become a crucial issue in wheat productivity. Data from satellite imageries such as vegetation indices might provide useful information to understand the variability pattern from multiple years better. This work compared several vegetation indices calculated from images at different stages of the growing season and assessed the most appropriate index to represent the within-field variation of wheat yields. The study also investigated the potential improvement from combining these indices. Results indicated that these combinations of indices gave little improvement over a single well-known index such as NDVI during vegetation peak biomass. Also, we investigated average yield predictions over multiple years, in comparison with predictions of yield for a single year. The results showed that predictions of the spatial pattern of longer-term average yield were more accurate than those for single years. This is important because in our validation dataset we had a maximum of four years of yield monitor data from the same field to test this; therefore we might reasonably expect the agreement to be better again when remote-sensing data from a large number of years are used (e.g. Landsat historical data from over 20 years). This study's findings will guide the development of decision-support systems that can be used for crop management by farmers and advisors, especially to investigate the within-field yield variation and their cause, such as soil constraints.

Keywords
Satellite imagery, indices combination, long-term average yield.

Introduction
In Australia, wheat is the major crop produced and has the highest export value of all the grain crops (Cai et al. 2019). However, the challenge faced in wheat production is how to reduce yield gaps even at very fine scales, like within a paddock. Vegetation indices calculated from satellite imagery have become an important tool to help develop crop yield indicators, such as biomass, to map field-specific productivity (Cai et al. 2019). However, determining a suitable vegetation index is crucial in any study seeking to develop yield indices. However, determining a suitable vegetation index is crucial in any study seeking to develop yield indices. Not only the index types, but also imagery selection based on crop biomass should be considered. In some cases, a combination of more than one vegetation index might improve analysis results.

This work aimed to derive a reliable indicator of within-field yield variation in Australia's northern grain-growing region (as defined by the Grains Research and Development Corporation of Australia, GRDC), encompassing Queensland and New South Wales. We were interested in how well we could assess spatial patterns of yield variation, rather than absolute yield variation. We also investigate predictions of average yield over multiple seasons and predictions of yield for a single season with an expectation that a long-term average might be more accurately predicted than any single year.
Many studies have focused on crop yield analysis using a single vegetation index (Lai et al., 2018; Yang et al. 2007) and multiple vegetation indices (Jurečka et al. 2018; Lobell and Asner 2003). However, studies integrating multiple vegetation indices in one model for predicting within-field yield variation are still limited.

Therefore, the questions addressed in this work were;
(i) Which vegetation indices perform best for predicting wheat yields in Australia's Northern grains region? Can combinations of vegetation indices provide improvements compared to a single index?
(ii) Which stages are best? Can data from multiple stages help predictions?
(iii) How does the accuracy of long-term average yield predictions compare with that of yields from a single year?

Methods

Datasets

Yield monitor data were collated (cleaned and block kriged to 30-m pixels) from 48 wheat crops, from a total of 23 fields across the Northern Region of the grain cropping region of Australia (Queensland and New South Wales). Remote-sensing data were also acquired from Landsat-5 Thematic Mapper (TM), Landsat-7 Enhanced Thematic Mapper Plus (ETM+), and Landsat-8 Operational Land Imager (OLI). Only images with at least 75% coverage of each yield map's pixels were included; images with cloud coverage of more than 25% of a yield map were excluded.

Selection of vegetation indices and set of covariates

This study tested eight vegetation indices, including structural (VI_{STR}) and chlorophyll-related (VI_{CHL}) indices. The structural-related indices included were NDVI (Normalized difference vegetation index), EVI (Enhanced Vegetation Index), EVI2 (Enhanced Vegetation Index 2), RVI (Ratio Vegetation Index), VARIgreen (Visible Atmospherically Resistant Index Green), and DVI (Difference Vegetation Index). They are positively correlated with leaf area index (LAI) and biomass, and thus provide a better representation of crop canopy structure. Chlorophyll-related indices, such as CVI (Chlorophyll Vegetation Index) and GCVI (Green Chlorophyll Vegetation Index), are suitable for describing crop photosynthetic activities (Zhao et al. 2020). We also specified vegetation index stages based on how dense the biomass of the wheat was. They are classified into three classes; pre-peak, peak and post-peak biomass with a 25-day interval for every stage.

The covariates investigated were;

(i) A single index, one stage (e.g., NDVI – pre-peak stage)
(ii) Two indices from different VI groups, one stage (e.g., a combination of NDVI and CVI in pre-peak stage)
(iii) A single index, two crucial stages (e.g., a combination of NDVI in peak and post-peak stages)

The linear mixed-effect model and cross-validation

This work used the linear mixed model framework (Pinheiro and Bates 2004) to assess covariates and yield relationships. We choose this method since it is appropriate to limit errors influenced only in distinct yield maps using a random-effects component for each specific yield map. Then, predictions from the linear mixed model approach were assessed using leave-one-yield-map-out cross-validation. To determine the relationship between observed and predicted values, we used the concordance correlation coefficient (CCC; Lin 1989). But since a primary objective of this work was to determine how well the predictions represent the spatial patterns of within-field variation of yield, the CCC was calculated based on the agreement between ranked predicted and ranked observed data referred to here as CCC_{Rank}. Also, an approach to investigate predictions of longer-term average yields was applied on fields with more than one year of yield data. For a given field with yield maps from T years, a total of P pixels were present in all T yield maps. The withheld data and predictions for this field were labeled as y_{pt} and $\hat{y}_{pt}$ (for p in 1,…,P and t in 1,…,T), respectively. Then the predictions (for each of the P pixels) of the T-year average yield were calculated as the average of $\hat{y}_{pt}$ over the T years and compared with the average of the data, y_{pt}, over the T years.

Results and Discussion

The best covariate for developing relevant yield index

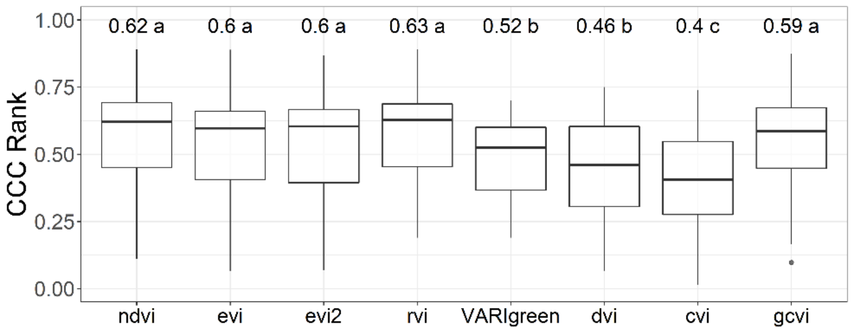

Figure 1. The concordance correlation coefficients of ranks for single vegetation indices from a single stage. Values show the median CCC_{Rank} for each treatment. For better visualization, the figure excluded negative CCC_{Rank}. Vegetation indices with the same letters are not significantly different.

Figure 1 depicts the CCC_{Rank} of all vegetation indices at the peak stage, when most vegetation indices had the highest median CCC_{Rank}. NDVI, EVI, EVI2, RVI, and GCVI performed reasonably similarly to each other and gave the largest median CCC_{Rank} values (0.59–0.63). Of all combinations of indices from two vegetation index groups (from the time of peak biomass), NDVI-CVI gave the highest CCC_{Rank} (0.63) but did not show any notable improvement over the best of the results based on a single vegetation index. Moreover, this work also assessed a combination of both peak and post-peak biomass stages. Compared to single-stage analysis, again the improvements were marginal, the best multi-stage results coming from RVI at peak and post-peak biomass (a CCC_{Rank} of 0.64).

In terms of vegetation index groups, it is difficult to compare the performance of canopy structural-related indices (VI_{STR}) and chlorophyll-related indices (VI_{CHL}) because there is no unique pattern that indicates each group's strength and weakness. The analysis showed that both the median CCC_{Rank} of VI_{STR} and VI_{CHL} differ from low to high. Also, in terms of stages, both gave the best performance during peak stage and in the multi-stage analysis.

Comparing multi-year average prediction and single year prediction

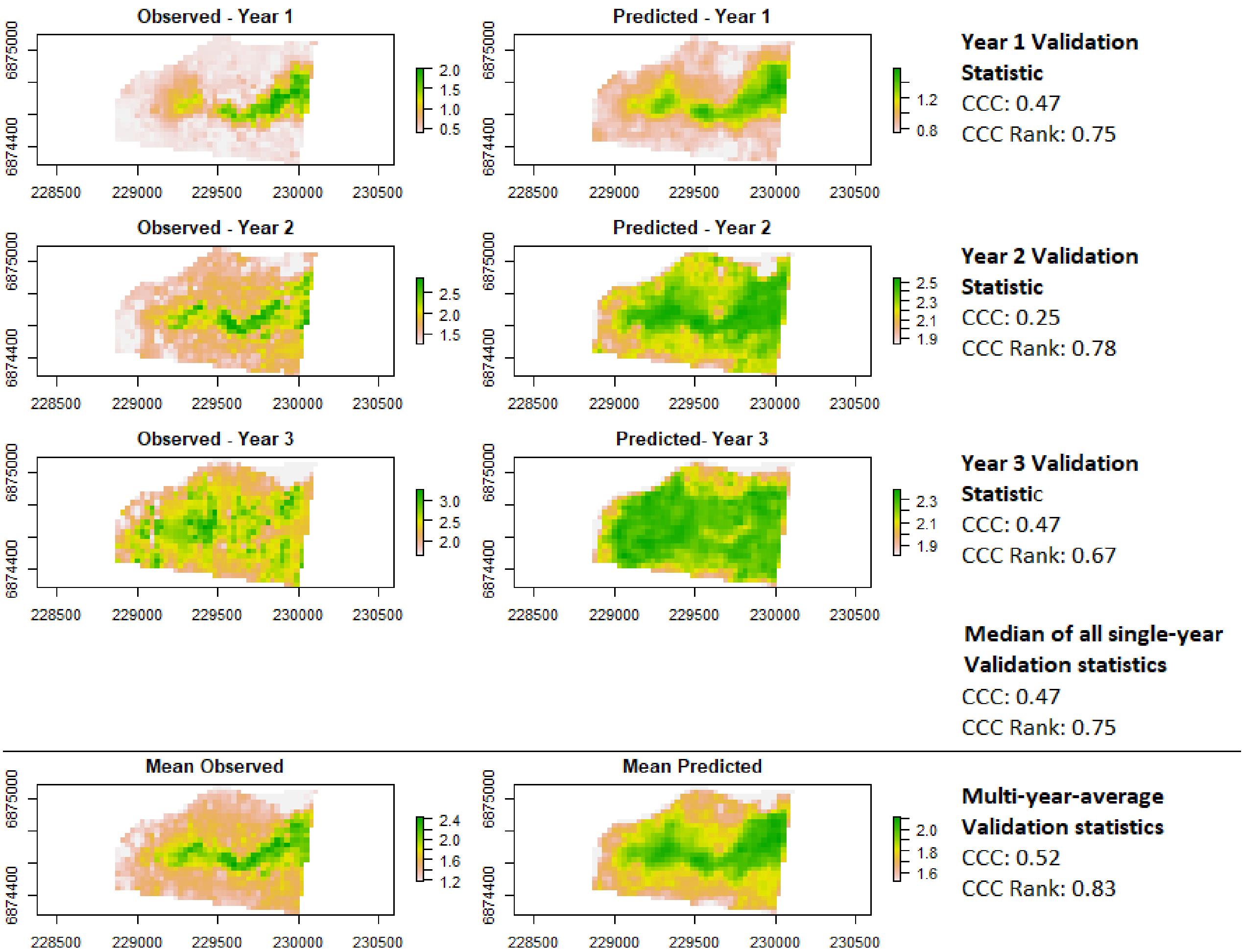

Figure 2. Single and multi-year yield maps (model of NDVI peak)

Figure 2 illustrates the multi-year analysis, showing observed and predicted data for a field with yield monitor data from three years. The validation statistics for a single year mainly showed variable performance and large differences in CCC and CCC_{Rank} between years. It is possible that there could be issues with the yield monitor data in some years or the remote-sensing data might have failed to capture the information most relevant to yield variation. Figure 2 shows that the single year CCC values were relatively low (0.47, 0.25, 0.47), giving a median CCC value of 0.47. In terms of the CCC_{Rank}, the best agreement occurred for the second-year data (0.78), followed by the first and third-year results (0.75 and 0.67), giving a median CCC_{Rank} value of 0.75 over the three years. These median values (0.47 for CCC and 0.75 for CCC_{Rank}) indicate the performance we might expect from predictions of yields for individual years in this field.

An indication of how well longer-term average yields prediction is provided by directly comparing the three-year-average maps (those on the final row of Figure 2); the CCC and CCC_{Rank} for the three-year-average maps were 0.52 and 0.83, respectively. The result showed that a multi-year-average gave a better validation statistic (a CCC_{Rank} of 0.83) than the median of all single-year analyses (a CCC_{Rank} of 0.75). This result suggests that validation for a single year might provide a conservative assessment of how well long-term average yields prediction. Similar analyses were repeated for all 15 fields where yield monitor data from multiple fields were available, and in all of the 15 cases, the CCC_{Rank} for the multi-year average was larger than the median of the CCC_{Rank} values that of the single year (by an average of 0.11).

Conclusion

This work concluded that there were only marginal differences between the performances of the different vegetation indices tested. The CCC_{Rank} values (a median of around 0.6) showed that well-known indices, such as NDVI, RVI, EVI and EVI2, showed a good prediction of within-field patterns of yield variation. A combination of multiple indices or data from multiple stages showed only marginal improvements. Moreover, the results showed that longer-term average yield predictions were generally more accurate than those of yield for single years.

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