Paddock-scale yield estimation using fused PlanetScope and Sentinel-2 imagery and crop modelling

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Abstract

One of the major challenges in monitoring and managing food security is to provide reliable, consistent and scalable yield projections. For years, the trade-off between high spatial and temporal resolution coverage has limited remotely-sensed applications such as yield estimation at the paddock and sub-paddock scales. Recently, the availability of data from CubeSat satellites has opened the door to a new era of crop monitoring from space. This study aimed to improve in-season yield predictions by coupling crop modelling and satellite images with a focus on wheat in Australia. A new approach was developed to predict crop yield without ground-calibration data, making it broadly applicable across regions than currently available satellite-based methods. The method was effective not only for paddock-scale yield estimations, but also for yield map predictions at 3 m resolution up to three months before harvest.

Keywords

Remote sensing, data fusion, crop model, APSIM, sowing dates, leaf area index, yield map.

Introduction

Accurate yield estimations, as early as possible prior to harvest, are critical for market stability, farm management, grain companies and governments. Moreover, risks and uncertainties within the global food system are growing with the expected increase in extreme weather events owing to climate change. These may lead to food shortage and greatly affect food price in both short and long-term future. Importantly, studies have shown a linear relationship between (i) photosynthetic capacity estimated based on spectral responses from satellite remote sensing and (ii) crop phenology, which has been used to forecast wheat yields (e.g. Becker-Reshef et al. 2010; Franch et al. 2015). However, dependence upon a unique linear relationship can be problematic, particularly when crops experience highly variable environmental conditions, as in Australia, where crops are frequently stressed by heat waves, frosts and droughts (Chenu et al. 2013; Zheng et al. 2015).

Studies attempting to estimate crop yield using remote sensing have commonly depend heavily on detailed official crop statistics (e.g. Becker-Reshef et al. 2010) or on-farm measurements (e.g. Jin et al. 2017) to develop empirical prediction models. However, the applications of such models are mostly limited to the regions where they were calibrated, and have a low forecast accuracy in other regions. Although few studies have attempted to estimate yields without ground calibration (e.g. Azzari et al. 2017; Lobell et al. 2015), or to estimate yield at the paddock scale using remote sensing alone (e.g. Burke & Lobell. 2017; Donohue et al. 2018), their success has been limited.

Recent studies have suggested that improvement in crop yield prediction could come with more frequent high-temporal and high-spatial resolution satellite images within the growing season (Jain et al. 2016; Jin et al. 2017; Waldner et al. 2019).

Accordingly, the objective of this study was to develop a new approach to estimate crop yield at the paddock and sub-paddock scales without ground-calibration data, making it applicable across different environments.

Methods

First, a sowing date detection method using images from CubeSat satellites was developed to identify cultivated paddocks and the date when they were sown (Sadeh et al. 2019). Second, PlanetScope images (with a spatial resolution of ~3 m and a daily revisit time) and Sentinel-2 images (with a spatial resolution of 10 m and a 5-day revisit time) were fused to create daily leaf area index (LAI) datasets at 3 m resolution (Sadeh et al. 2021). Finally, the detected sowing dates and the field's LAI datasets were coupled with simulations from the APSIM-Wheat crop model (Holzworth et al. 2014) to estimate wheat yield at the paddock scale. As part of this process, ~2,000 simulations of APSIM were generated for each paddock, thus spanning a realistic range of possible environments and on-farm management practices (Figure 1). The weather data was taken from the nearest weather station and soil properties of four nearby soils (based on the APSoil database www.apsim.info/apsim-model/apsoil/) were considered. Each APSIM simulation produced yield estimation (kg/ha) as well as daily crop traits including LAI output. In order to choose the simulations which best reflected the studied crop, and thus project the likely final yield, an automatic rule-based algorithm was developed. The accuracy of the estimated yield was evaluated against 28 paddock-scale yield data reported by farmers, including 21 paddocks sourced from the National Paddock Survey (Lawes et al. 2018). These selected paddocks were located in the different growing regions of the Australian wheat-belt, and had various weather conditions, soils, farm management and cultivars.
The 3 m LAI maps were also used to estimate yield at a sub-paddock scale. The LAI map when the paddock's remotely sensed LAI was at its maximum during the growing season was converted to a yield map using the ratio between the estimated paddock-scale final yield and the paddock-average LAI when LAI was maximum. The accuracy of these yield maps was compared (RMSE and R^2) against yield maps generated by combine harvesters at harvest.

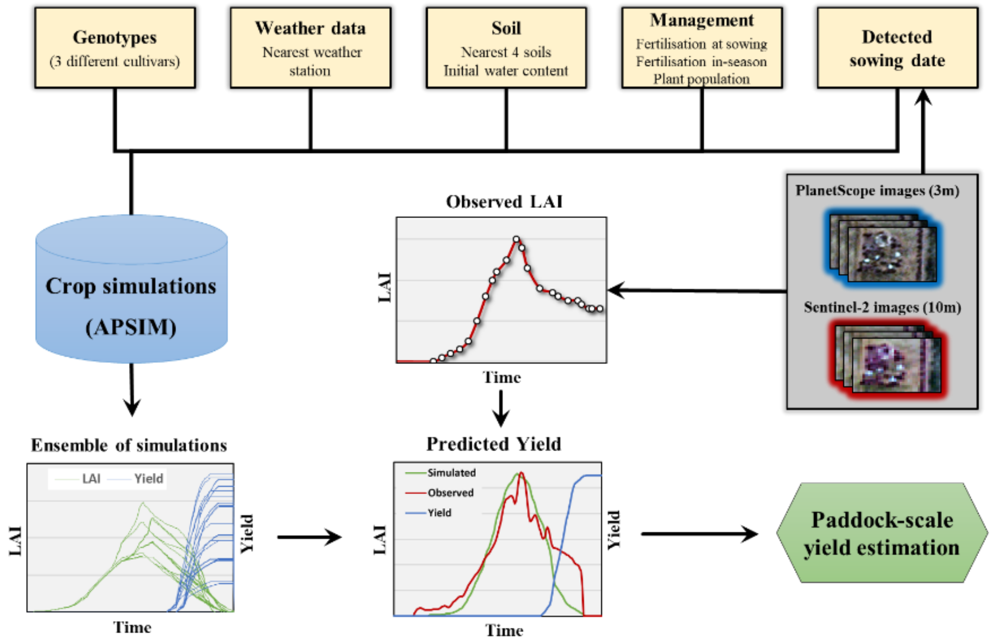

Figure 1. Workflow to estimate paddock-scale yield.

Results

The sowing date detection method managed to detect the sowing dates of 95.4% of the analysed paddocks with an average error of 1 day and the RMSE of 2.7 days.
The proposed fusion method enabled consistent, cloud free, surface reflectance RGB-NIR images and crop LAI to be generated at a 3 m resolution. Overall, the results demonstrated that the new fused time-series data combined the spatial, temporal and spectral advantages of sensors from both PlanetScope and Sentinel-2 satellites, allowing wheat LAI to be monitored on a daily basis (Sadeh et al. 2021).

The preliminary results of the 28 paddocks analysed using the proposed method are very promising with an RMSE of 870 kg/ha, a R^2 of 0.8 and a median error of -459 kg/ha between the reported and estimated yield at the paddock-scale (Figure 2 and Table 1).

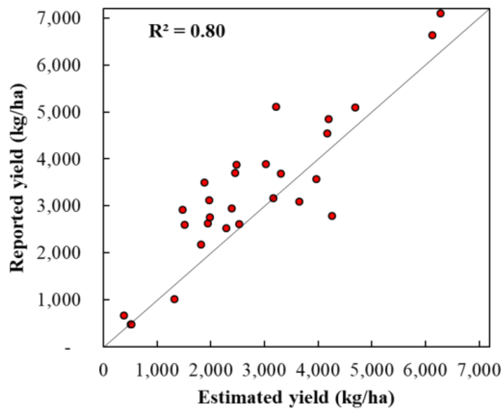

Figure 2. Relationship between reported and detected sowing dates. The black line represents the 1:1 line.

Table 1. Accuracy assessment of estimated yield for the 28 paddocks studied.

Average error	-500 kg/ha (13.7%)
Median error	-459 kg/ha (12.5%)
RMSE	870 kg/ha

An attempt to generate a yield map with a spatial resolution of 3 m, presented in Figure 3, produced using the field's maximum daily median LAI of the season on 4 October 2017 which was about two and a half months before the harvest date of 18 December 2017. The accuracy at the pixel level of these two yield maps (Figure 3) reached R^2 = 0.5 and RMSE = 1,125 kg/ha between the estimated and the harvester driven yield maps.

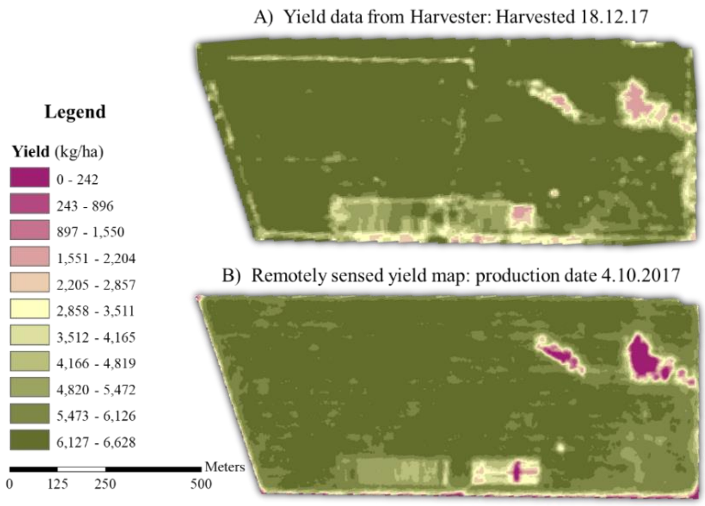

Figure 3. Comparison between a yield map generated by the harvester (A) and the yield map generated using the proposed methodology (B), for a wheat paddock near Kapunda, South Australia.

Conclusion

For decades, scientists have tried to assess yield combining remote sensing and crop models with only limited success. By combining the advantages of both high spatio-temporal remote sensing and crop model simulations, the method proposed in this study managed to overcome the need of in crop statistics or on-farm measurements to estimate wheat yield. The method not only enables detection of sowing dates from space, but also overcomes the historical trade-off between high spatial and temporal resolutions for remotely sensed estimations of crop yield at the paddock and sub-paddock scales. This method was found effective for both paddock-scale yield estimations (RMSE of 870 kg/ha, a R^2 of 0.8) and yield maps (R^2 = 0.5 and RMSE = 1,125 kg/ha) generation at a 3 m resolution up to three months before crop harvest.

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