Coupling Fused High Spatio-Temporal Resolution Remote Sensing Data and Crop Modelling to Predict Wheat Yield at the Field Scale

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Abstract
Providing reliable, consistent and scalable crop yield data is one of the major challenges in monitoring food security. This study aims to improve in-season wheat yield prediction by coupling crop modelling and satellite images. We have developed a nano satellites-based method to detect crop sowing date of grower's fields, as well as a technique to fuse PlanetScope images (with a spatial resolution of ~3m) and Sentinel-2 images (10m) to create high-resolution datasets of spatio-temporal variation in crop Leaf Area Index (LAI). Finally, we will attempt to use the detected sowing dates and the LAI datasets with the APSIM-Wheat model to predict wheat yield within fields. We shall attempt to predict yield without ground calibration, in a bid to develop a method that is applicable broadly across environments.

Key Words
Yield prediction, nano satellites, sowing dates, LAI, crop modelling, image fusion.

Introduction
With a gross value of $7.3 billion, wheat is the main winter crop grown in Australia, covering more than 11 million ha of Australian farmland (Australian Bureau of Statistics, 2019). However, risks and uncertainties within the global food system are growing with the projected increase in extreme weather events due to climate change. These uncertainties may affect the variability of food prices in the short and long term. One approach to address these uncertainties is the development of new technologies and techniques for precision agriculture, along with improved approaches and tools for crop yield prediction over large regions. Many studies have shown a linear relationship between photosynthetic capacity estimated from spectral responses and crop phenology, relationships that can be used to predict wheat yields using satellite remote sensing (Becker-Reshef et al., 2010). Using a unique linear relationship is not ideal, especially when crops experience highly variable environmental conditions, as in Australia, where crops are frequently stressed by heat waves, frost and drought (e.g. Chenu et al., 2013). Numerous studies have attempted to predict wheat yields using remote sensing. However, most of them heavily relied on detailed official crop statistics (e.g. Becker-Reshef et al., 2010) and in-situ measurements (e.g. Jin et al., 2017) to develop empirical forecasting models. Such models typically have applications limited to the regions where they were calibrated (using ground data), and a lower prediction accuracy when applied to other situations. Only a few studies have attempted to predict yields without ground calibration (e.g. Azzari et al., 2017; Lobell et al., 2015). Similarly, only a few studies have tried to predict yield at a field scale using remote sensing (e.g. Burke & Lobell, 2017; Donohue et al., 2018). Their success has been limited.
Over the last decade, the number of companies developing nano satellites (also known as CubeSats) has increased. These new satellites, such as PlanetScope, which typically are as big as a shoe box and weigh less than 10 kg, are relatively inexpensive to mass produce, thereby enabling the creation at low cost of large image collections with a high level of spatial (<5 m) and temporal resolution (<1 week) (Jain et al., 2016). However, contrary to outputs from larger and expansive satellites such as Sentinel-2 or Landsat, the images obtainable from nano-satellites constellations frequently suffer from inconsistency in the data collected by different satellites in the constellation (Houborg & McCabe, 2016). Such inconsistencies may limit the accuracy of surface reflectance-based applications such as estimation of vegetation indices and LAI.
The objective of this study is to predict wheat yield in grower's fields by coupling fused high spatio-temporal resolution remote sensing data and crop modelling.

Methods
In this study, space-borne remote sensing data will be combined with crop modelling to predict in-season wheat yield in three stages. While the first two stages have already been completed, the methodology of the third one is under development. First, a nano satellites-based method was developed to detect sowing date of grower's fields (Sadeh et al., 2019). The method detects changes between consecutive PlanetScope (PS) nano-satellite images (from Planet Labs Inc.) and assumes that sowing corresponds to the first detectable field-scale

change in the surface after the harvest of the previous crop, as expected for the widely-used no-tillage farming practice (Figure 1). In the next stage, PlanetScope images (daily revisit time with a spatial resolution of ~3m) and Sentinel-2 (S2) images (5-days revisit time with a resolution of 10 m) were fused to create daily surface reflectance images (Figure 2). This enabled us to calculate different remotely-sensed vegetation indices, which were then used to estimate daily leaf area index (LAI) datasets at a spatial resolution of 3 m. In the third stage, the detected sowing dates will be used as inputs for the crop model simulations, as well as the weather data from the considered field (from SILO), a combination of nearby soils (based on grid data), a combination of representative local management practices, and genotypes contrasting for their maturity. As APSIM outputs crop characteristics daily, the different simulated LAI patterns will be compared to the remotely-sensed LAI for each pixel of the field image to choose the most-suited simulation (i.e. best combination of soil x fertilisation x genotype). Using short-term climate forecast, the selected simulations will be pursued up to the end of the season to forecast grain yield with a 3 m resolution in the studied field for the current season (Figure 3).

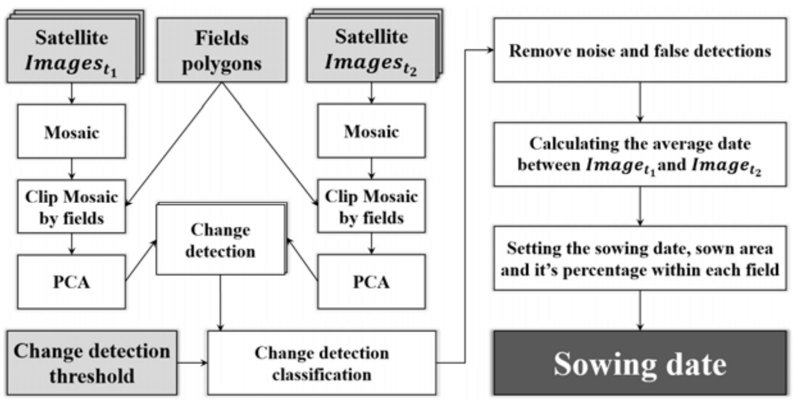

Figure 1. Sowing-detection workflow. Inputs are in light-grey boxes. Adapted from Sadeh et al. (2019).

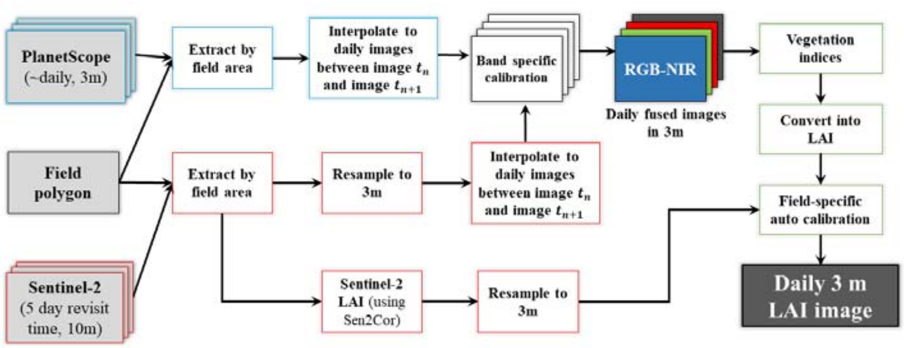

Figure 2. Data fusion of PlanetScope (with a spatial resolution of ~3 m) and Sentinel-2 (10 m) imagery.

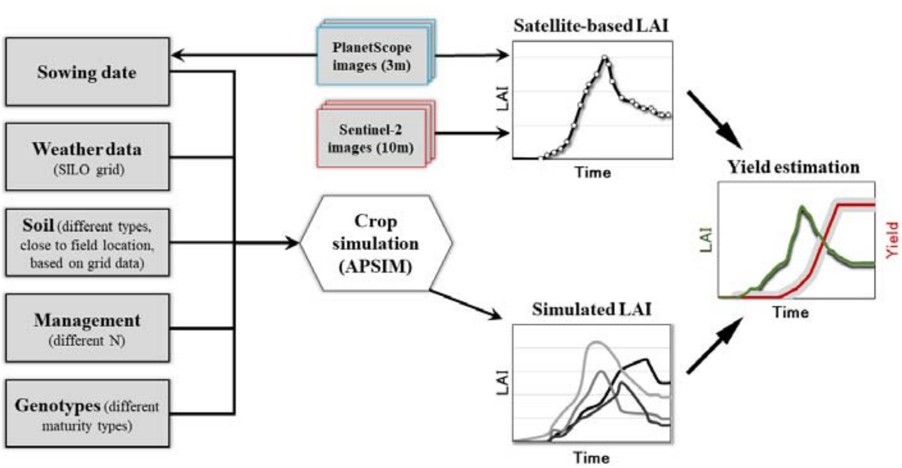

Figure 3. Framework of the proposed methodology that combines satellites data and crop model to predict yield.

Discussion and Results

Predicting crop yield from space is challenging, which is mainly hindered by the spatial and temporal resolutions satellites, and also by the ability to translate reflected radiation from the crops to biophysical data. Our study aims to overcome some of these limitations by coupling fused high spatio-temporal resolution remote sensing data and crop modelling. As sowing dates of individual fields greatly influence yield (Flohr et al., 2017), their accurate identification from the high spatio-temporal PlanetScope data can reduce the uncertainty of simulating yield with crop modelling. The method to detect sowing dates (Figure 1) was found to be robust and simple, and could be applied over a wide range of soil types, atmospheric conditions, crop types and sensors (Figure 4). The method detected 85% of the sown fields with $R^2 = 0.99$ (Figure 5) and succeeded in identifying the actual sowing dates of individual fields with a median gap of 0 days and an unparalleled RMSE of 0.9 and 1.9 days in a set of national trials and in 55 fields of one commercial farm, respectively.

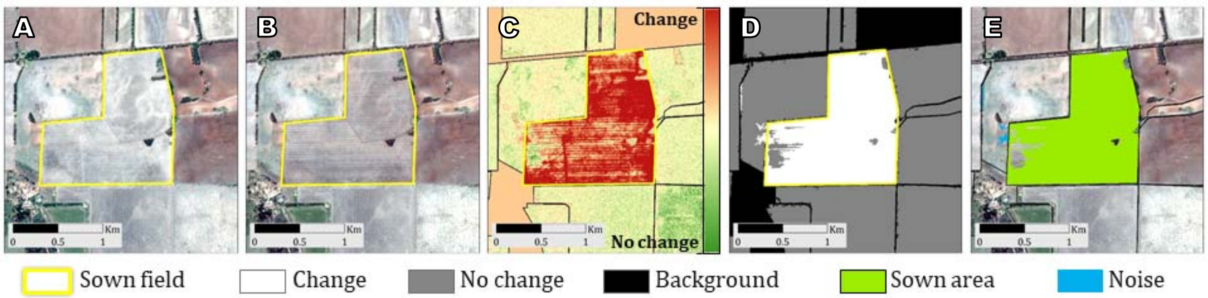

Figure 4. Sowing detection of a field (boundaries in yellow) using two satellite images from different dates (A and B). Significant changes (red) between the images found based on a PCA approach (C). These changes were used to classify the image into change/no-change classes (D) and estimate the sown area (green, E). Adapted from Sadeh et al. (2019).

Preliminary results from the PlanetScope and Sentinel-2 data fusion have shown that the method (Figure 2) is able to produce daily surface reflectance images with a 3 m resolution. This new dataset was used to calculate 13 selected vegetation indices known to be highly correlated with LAI, and convert them to LAI estimates. A linear regression between the different vegetation indices was used to resize LAI time-series, and produce daily LAI images with the quality of Sentinel-2 which has a lower spatio-temporal resolution (Figure 6).

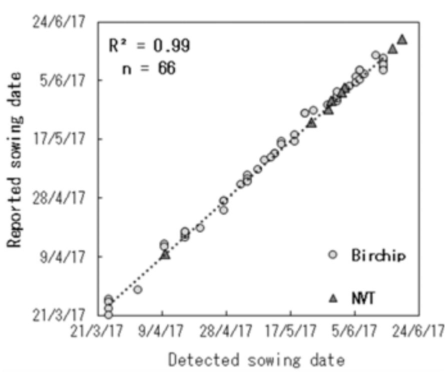

Figure 5. Correlation between the reported and detected sowing dates of 16 NVT fields and 50 fields from a farm at Birchip, Victoria.

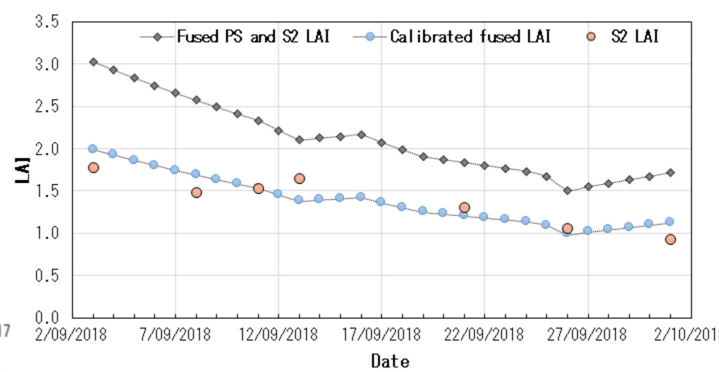

Figure 6. Daily 3 m LAI estimates created by fusing PlanetScope (PS) and Sentinel-2 (S2) data. The initial fused PS and S2 LAI is presented in black, while the blue line corresponds to the data after performing the auto field-based calibration. The S2 LAI values are in orange**.**

The method for fusing PlanetScope and Sentinel-2 data combines the advantages of both sensors and enables us to create daily vegetation-index images in a spatial resolution of 3 m, and with the accuracy of Sentinel-2 data. The fused datasets can be used to monitor crops on a daily basis and create high spatio-temporal resolution LAI images with the quality of Sentinel-2, which have a strong correlation with the crop LAI (e.g. Herrmann et al., 2011; Nguy-Robertson et al., 2014). Finally, this study will use the APSIM-Wheat model in a bid to predict wheat yields during the season in surveyed fields located in different locations across Australia. APSIM provides outputs on daily crop attributes, including LAI and yield. Predicting grain yield will be conducted by choosing the most-suitable combination of genotype x soil x fertilisation, based on the correlation between the remotely sensed LAI and APSIM-simulated LAI. This type of approach has already been tested by a number of studies (e.g. Azzari et al., 2017; Jin et al., 2017; Lobell et al., 2015), but their yield estimations did not achieved high accuracy, including when focusing at the field-scale (e.g. Burke & Lobell, 2017; Jain et al., 2016). However, our study will narrow the possible range of conditions by (1) using sowing dates identified for the considered crop, (2) focusing on the weather data from the nearer station, and (3) focusing on soil characteristics found nearby the field of interest. Furthermore, we will use more frequent LAI images per growing season, a strategy pointed out by a number of studies as a promising way to improve the accuracy of the yield predictions (e.g. Burke & Lobell, 2017; Jain et al., 2016; Jin et al., 2017). These studies suggested that the long revisit time of the satellites, in addition to the presence of clouds in the images, may cause them to miss the peak LAI of the season, and therefore increased the bias from the reported yield. Our approach (Figure 3) will increase the chances to have more clear-sky images by using the daily-fused LAI images. We believe that this proposed method, which does not rely on ground data, has the potential to improve in-season yield predictions at the field scale.

Conclusion

In-season yield predictions at a field scale could be improved by combining fused PlanetScope and Sentinel-2 data, with crop modelling. To reduce part of the uncertainties in simulating yield for a specific field, new methods were developed to (i) detect when this field is sown, and to (ii) fuse data from different satellites to enable daily monitoring of LAI at field and sub-field scales. Outputs of these methods will be used to narrow down the ensemble of possible yields simulated with a crop model. Overall, the approach is designed to be more accurate and applicable more broadly than previous methods (i.e. without ground calibration data).

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