Towards incorporating remote sensing in crop modelling for precision agriculture purposes

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Abstract

Understanding soil variability at field scale can be an important step towards precision agriculture as soil can be one of the main causes of the paddocks' variability. Remote sensing data can detect the variability and, if adequately parameterised, crop models can model it. Our goal is to present a methodology to integrate remote sensing data into a crop model to provide improved local model parameterisation of soil properties. The methodology incorporates remotely sensed LAI to parameterise APSIM soil characteristics, Crop Lower Limit (CLL) and Drained Upper Limit (DUL), to simulate different points in a field sown to wheat. Results show that an improved local model parameterisation with remote sensing data is possible. Our framework is the first step to auto-calibrate the different soil properties in different parts of the field that allows high-resolution runs of APSIM. When combined with weather forecasting, the approach can also provide yield forecasts and, thus, N fertilizer recommendations.

Keywords

model calibration, soil, optimisation, Future Farm project

Introduction

Paddocks' crop yields spatial variability is a function of local variations in weeds, pests, diseases, and soil attributes. Precision agriculture (PA) recognises such variability, i.e. that the land is heterogeneous (Cook and Bramley, 1998). The variability of soil texture can alter soil characteristics such as the crop lower limit (CLL), drainage upper limit (DUL), rooting depth and, consequently, the Plant Available Water Capacity (PAWC). By incorporating remote sensing in crop modelling, such spatial heterogeneity can be identified and managed accordingly (Basso and Antle, 2020). Crop modelling can be used as a tool to understand where the heterogeneity comes from and improve the likelihood that a sound decision about in-crop management is made. For example, crop modelling can help to optimise wheat nitrogen management (Lawes et al., 2019). Although crop modelling is a powerful tool, models, such as APSIM, require extensive and careful calibration to produce reliable simulations of crop growth across diverse management scenarios (He et al., 2017). Such problems can potentially be addressed by incorporating optical remote sensing in the calibration/modelling framework. There is potential to use remotely sensed variables to predict PAWC (He et al., 2020) and to calibrate crop models even when in situ ground data is not available (Richetti et al., 2019). Therefore, the aim of this study is to present a scale-neutral methodology to incorporate remote sensing data of leaf area index (LAI) into a crop model to provide local model calibrations for soil properties. This study presents the use of an optimisation algorithm to identify a soil parameter profile and calibrate its CLL and DUL in APSIM for each measured point in a field with different soil types and nitrogen treatments. It is hypothesised that the presented framework is able to calibrate the different soil properties in different parts of the field taking into account the land variability.

Methods

Study Area and Remotely Sensed LAI

A paddock in the Kalannie region of WA with soil textures ranging from sand to medium clay from diverse soil types was monitored for the 2019 winter wheat season. The average annual rainfall is 294 mm, but 2019 was drier than the long-term average, with 206 mm of rainfall between January and December and 187mm during the April to October growing season. The paddock was sown to wheat (*Triticum aestivum* cv Scepter) on 7 May 2019 with row spacing of 300 mm and seed depth of 20 mm. Three nitrogen (as liquid N fertiliser) treatments (low 5.8 kg N/ha, farmer 30.3 kg N/ha, rich 54.8 kg N/ha; Figure 1) were applied at sowing in 30 m wide strips across the paddock. Seven points were sampled within each strip. Samples consisted of pre-sowing soil and mid-season plant. Extra nitrogen application occurred on 30 June 2019 with 21.4 kg N/ha for the whole paddock.

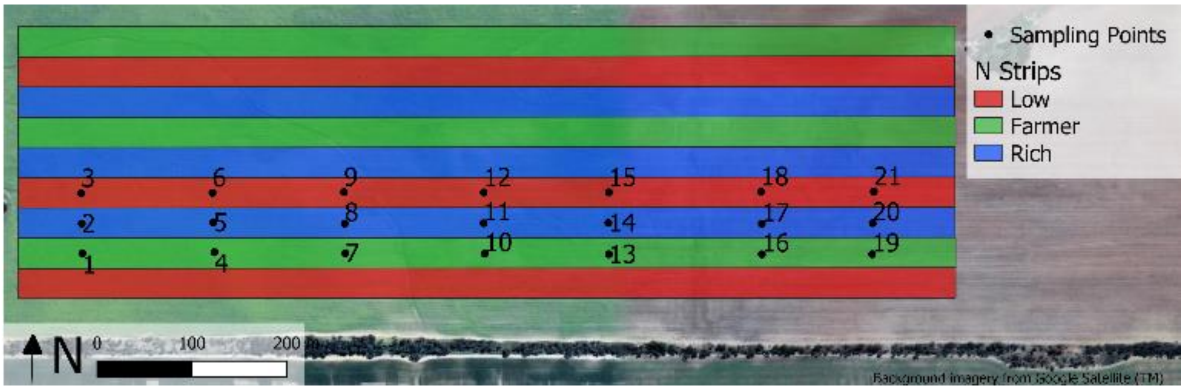

Figure 1. Monitored paddock in WA with low, farmer, and rich N treatments (5.8 kg N/ha, 30.3 kg N/ha, and 54.8 kg N/ha) and sampled points.

Normalized Vegetation Difference Index (NDVI) was measured 105 days after planting on 20 Aug 2019 at each point around growth stage 32 (Zadoks, Chang and Konzak, 1974) with a commercial proximal crop sensor system (Crop Circle Phenom; Crop Circle ADS-430 combined with a DAS43X unit; Holland Scientific). LAI values were derived from NDVI based on the Beer-Lambert law of light extinction (Monsi and Saeki, 1953; Monsi et al., 2005) ($LAI = -\ln(1 - NDVI)/k$ (Eq.1)). As there is only one measurement, k value of 0.25 was used (Tan et al., 2020); if measurement occurred on a different date, then a different value for k should be used.

Crop modelling and Optimisation Framework

The Agricultural Production Systems Simulator – APSIM (Holzworth et al., 2014) was used for the wheat simulations. The wheat simulations with cv. Scepter were started on January 1. The cv. Scepter is already present in the calibrated APSIM database. Weather information was obtained from the SILO database (Jeffrey et al., 2001) and to identify a soil profile and calibrate its parameters for each point, ten Western Australian generic soils from Oliver & Robertson (2009) (available at the APSoil database) were used. An optimisation scheme using Nelder-Mead algorithm (Nelder and Mead, 1965) was implemented by selecting one of the 10 soils and sequentially running APSIM simulations varying the soil parameters using a multiplier factor for CLL and DUL as presented by (Wu et al., 2019).

Results

Across all the points in the field, the observed LAI (remotely sensed LAI obtained with Eq. 1) at Z32 varied from 0.79 to 2.68. The algorithm converged for all points. The errors between observed and optimised simulated LAI were low (Table 1) with root mean squared error (RMSE) of 0.02 and mean error (ME) of 0.01. The method provided different soil properties in different parts of the paddock, where the soil types ranged from gravel to shallow sandy duplex and PAWC varying from 33.6 to 142.4 mm (Table 1) including points 16 to 21 where the soil texture changed from first (0 to 10 cm) to second (10 to 30 cm) layer and the methodology correctly identified four out of six of those points.

Table 1. Observed and selected optimised soil profiles with respective Crop Lower Limit multiplier (CLL_M), Drained Upper Limit multiplier (DUL_M), error (absolute difference between observed and simulated LAI), and Plant Available Water Capacity (PAWC) for each point.

Point	Observed Soil Type*	Optimised soil profile***	CLL_M	DUL_M	Error	PAWC (mm)
1		Gravel	1.00	1.05	0.01	75.0
2	Sand earth or	Gravel	1.00	1.03	0.00	64.5
3	Deep sandy duplex**	Shallow soil	1.00	1.00	0.00	33.6
4		Gravel	1.00	1.00	0.00	56.7

5		Gravel	1.01	1.08	0.02	80.9
6		Sand	1.05	0.90	0.00	64.0
7		Gravel	1.00	1.00	0.00	54.9
8		Shallow soil	1.00	1.05	0.06	49.3
9		Shallow soil	1.00	1.00	0.01	33.6
10		Sand	1.03	0.95	0.05	79.8
11		Sand	1.03	0.95	0.03	79.8
12	Sand	Shallow soil	1.00	1.05	0.01	49.3
13		Sand	1.03	0.95	0.00	79.8
14	Sand earth or Deep sandy duplex[**]	Sand	1.03	1.19	0.00	142.4
15		Sand	1.03	0.95	0.00	79.8
16		Shallow Sandy Duplex	1.01	1.06	0.01	85.4
17		Shallow Sandy Duplex	1.00	1.11	0.00	116.9
18	Shallow sandy duplex	Shallow soil	1.00	1.05	0.02	49.3
19		Shallow Sandy Duplex	1.00	1.00	0.00	66.8
20		Shallow Sandy Duplex	1.01	1.09	0.00	106.9
21		Shallow soil	1.00	1.03	0.04	41.1

[*] Observed soil type were determined from texture samples [**]A deeper soil sample is required, if clay layer occurs within 80cm then it is a deep sandy duplex, gravel was not recorded at the site [***] Optimised soil profile is from the generic APSoil profiles

The ME between the uncalibrated model and observed yield was 353 kg/ha, and the RSME was 558 kg/ha, while ME between optimised simulated and observed yield was -43 kg/ha, and RMSE was 453 kg/ha. Characterising the soil improved the overall simulation efficiency, reducing the mean error by 310 kg/ha and the RMSE by 105 kg/ha. The differences in LAI were translated into soil differences with PAWC from optimised soil profiles varying from 30 - 140 mm (Table 1). Previous studies have used remotely sensed LAI with other parameters to calibrate crop models, e.g. focusing on the crop parameters for the whole field (Richetti et al., 2019). Nevertheless, this provides an important step for using crop models to understand the soil variability within a field. Once calibrated, the lowest errors are observed with different soil profile and parameters for each point, resulting in different performances across the field, nonetheless simulating the field's heterogeneity. Also, the importance of proper soil parametrization is highlighted. As pointed by Beven (2006), even when concentrating on the search for an optimum solution, the issue of equifinality is present. In this study, this means that more than one suite of soil profile and parameters could be an optimum solution for each point. However, we aimed to understand and present a solution on how to incorporate remote sensing data into a crop model to provide local model calibrations about soil properties, and we do not deny that it could have more than one optimal solution. Sand and sandy earth and even loamy earth are similar in shape of PAWC; therefore, depending on the multiplier value (CCL_M and DUL_M values) this could end up with the same soil properties in terms of simulation. This means that even if the algorithm converged to different soil type, its profile could be very similar. The selected soil types from the clay on points 16, 17, 19, and 20 matched well the observed soil types (Table 1) while the gravels should have been a sandy earth and the shallow soils could be sands, for example. Ultimately, this suggests that LAI can be used to capture soil variability throughout the field, corroborating with previous studies using remote sensing and historical yield to predict PAWC (He et al., 2020). Nonetheless, more research is needed in all aspects of this proposed framework. More sites and seasons are needed as well as different sources of LAI and faster and better optimisations algorithms.

Conclusion

Therefore, the presented framework is the first step to auto-calibrate the different soil properties in different parts of the field. By minimizing differences between observed and simulated data using an optimisation algorithm, we provided a methodology to incorporate remotely sensed LAI data into a crop model (APSIM), providing a local model calibration about soil properties in different points of a heterogeneous paddock. Further research is needed to deploy the method and explore its limitations, especially regarding optimisation equifinality. Ultimately, this modelling framework will allow more precise yield forecasts and more precise and targeted N management strategies.

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