Developing an integrated approach for estimation of soil available nutrient content using the modified WOFOST model and time-series multispectral UAV observations

Zhiqiang Cheng[1, 2, 3] Jihua Meng [1] Jiali Shang[2] Jiangui Liu[2] Budong Qian[2] Qi Jing[2]

1 Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences, Beijing China

2 Ottawa Research and Development Centre, Agriculture and Agri-Food Canada, Ottawa, Ontario, Canada

3 University of Chinese Academy of Sciences, Beijing, China

[*] Corresponding author. Jihua Meng (mengjh@radi.ac.cn) and Jiali Shang (Jiali.Shang@agr.gc.ca)

A paper from the Proceedings of the
14th International Conference on Precision Agriculture
June 24 – June 27, 2018
Montreal, Quebec, Canada

Abstract. *Soil available nutrient (SAN) plays an important role in crop growth, yield formation, and plant-soil-atmosphere system exchange. Nitrogen (N), phosphorus (P) and potassium (K) are recognized as three primary nutrients in crop production. Accurate and timely information on SAN conditions at key crop growth stages is important for developing beneficial management practices. While traditional field sampling can obtain reliable information for limited number of sites, it is infeasible for spatially intensive sampling across an extended area at frequent temporal intervals. With recent advancements in Earth observation (EO) technologies, both hardware and software, spatial-temporal information on soil nutrients and crop growth conditions can be successfully captured. Conventional methods to link EO data with SAN conditions rely heavily on statistical models. The robustness and accuracy of these models require further improvements. In this study, we developed a new approach to improve model performance by integrating the World Food Studies (WOFOST) model and time series EO data. First, the WOFOST model was modified to simulate the daily nutrient-limited crop growth. Then the Ensemble Kalman Filter (EnKF) method was used to assimilate the time-series data acquired by an unmanned aerial vehicle (UAV) into the modified WOFOST model to simulate crop growth. Through comparison of the above two simulations, errors in the nutrient-limited crop growth caused by inaccurate SAN input were obtained. By eliminating these errors, a method was developed to estimate the SAN status. Finally, a field experiment was conducted on spring maize to assess the SAN estimation performance of the proposed method. The results demonstrate that, in addition to providing improved spatial details, the accuracy of the SAN estimation also improved through the synergy of the UAV data and WOFOST model.*

Keywords. *Soil available nutrients, WOFOST, UAV, data assimilation*

1 Introduction

As an important component in precision agriculture (Robert 2002), variable rate fertilization (VRF) is a management practice to optimize soil nutrient utilization. Studies have demonstrated that VRF is beneficial to boost yield and protect the environment (Basso et al. 2013&2016). With the advancement of mechanized farming and control technologies, the operability and accuracy of the VRF have been significantly improved through a reasonable prescription map derived from timely soil nutrient content (Reyes et al. 2015). However, conventional methods for soil nutrient content measurement, include field surveys (Janik et al. 1998) and ground soil reflectance spectroscopy (Leon et al. 2003), can hardly meet the need for VRF application because they are time consuming, costly and with low application value (Lamsal 2009). Alternative methods are needed for operational applications over large areas.

A number of remote sensing based models have been proposed to address the issues, including a direct estimation model using soil spectrum (Leon et al. 2003) and an empirical model based on crop growth status (Meng et al. 2015). Soil reflectance spectrum can be successfully exploited to predict soil nutrients (Leon et al. 2003; Tian et al. 2012; Zheng et al. 2016). However, as reflectance information is only acquired for bare soil surface, it cannot capture the nutrient information below the surface or the surface with any coverage (crop, snow or water); hence, its application is limited (Meng et al. 2015). Using an indirect method to replace the direct spectroscopy has been a research hotspot. Statistical models can be built by combing soil available nutrient (SAN) contents and crop growth parameters estimated from multispectral remote sensing (RS) data. Such models can overcome the limitations of the direct estimation model and field surveys by estimating the real-time available nutrient contents with low cost and high efficiency (Meng et al. 2015; Cheng et al. 2018). However, the disadvantages of the statistical models, including low stability and accuracy, should be addressed before VRF application.

Crop models are able to simulate crop growth and provide reliable information on crop status throughout the growing season (Gerakis et al. 1998; Ma et al. 2013), therefore provide a feasible alternative to replace the statistical methods. Furthermore, as soil nutrient is usually an important input variable to crop models, and the changes in soil nutrient content can be easily revealed in crop growth simulations, a more stable relationship between the crop growth status and soil nutrient content can be established using a crop model. However, simulating crop growth at the field or regional scale requires calibration of additional parameters, which is difficult to conduct through field sampling. This has led to the development of time-series remote sensing (T-RS) data assimilation into crop models (Ma et al. 2013; Boogaard et al. 2013; Chen et al. 2014; Dong et al. 2013; Huang et al. 2015). Among them, the ensemble Kalman filter (EnKF) assimilation method is a widely used method based on variable updating (Meng et al. 2007; Huang et al. 2016; Cheng et al. 2016). Crop growth parameters can be accurately simulated by assimilating T-RS into a crop model.

In this study, we proposed a new method to estimate SAN contents of a spring maize field in Hongxing Farm. The World Food Studies (WOFOST) model was modified and calibrated to simulate nutrient-limited crop growth. The EnKF was used to assimilate time-series remote sensing data acquired by an unmanned aerial vehicle (UAV) into the modified WOFOST model (UAV-WOFOST). Through comparison of the two different simulations, the SAN contents can be estimated. The estimation accuracy was assessed using field data and complete details of the SAN estimation method and accuracy analysis are presented in the following sections.

2 Materials and methods

2.1 Study area and field campaign

This study was conducted in an experimental plot located in the southeast of Hongxing Farm

(48°09' N, 127°03' E), Heilongjiang Province, Northeast China. Hongxing Farm is within a mid-temperate monsoon climate zone characterized by an average annual precipitation of 548.8 mm and an average annual cumulative temperature (base 10°C) of 2293°C (2014). The growing season of spring maize extends from the beginning of May until mid-October. The experimental plot is about 15.7 hectare (ha), and the soil is black soil with a depth of 0.9–1.2 m. The experimental plot is named as 5-1-2 in this study. The location of the experimental plot is shown in Fig. 1.

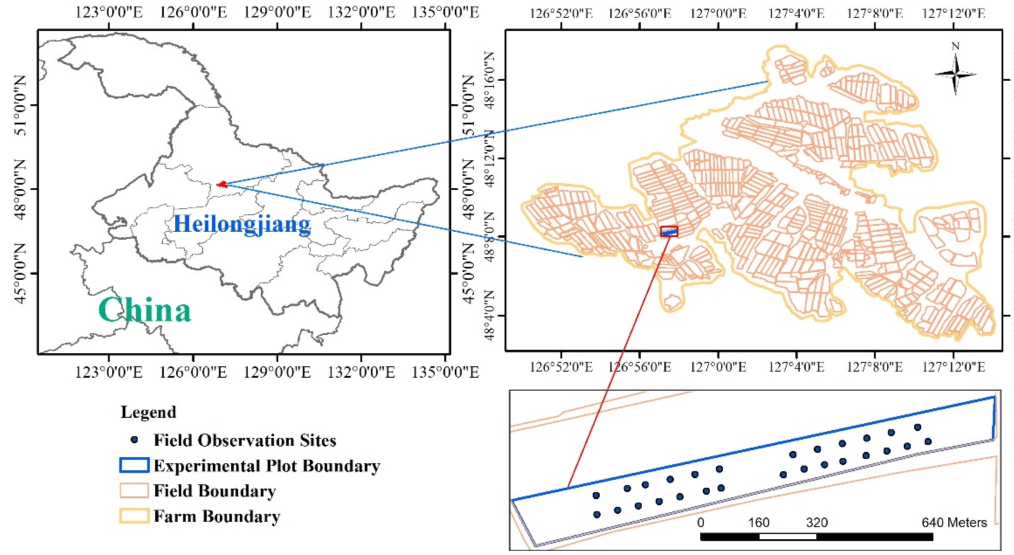


Fig. 1. Location of study area and the field observation sites in 2015

Experiments were conducted in 2015. Basic SAN content was collected from May 10 to 15. Totally 27 sampling quadrats (shown in Fig. 1.) were established in the plot using the isometric sampling method (Cheng et al. 2018) (with fixed distance of 100 m). Each quadrat was 10 m × 10 m, and data was collected at three sampling points along the diagonal (shown in Fig. 2.). At each sampling point, a soil sample to a depth of 40 cm was obtained by using a soil auger. After drying and pulverizing the samples, the basic N, P and K contents were tested in the lab. The mean value of the three points as the SAN content of the quadrat. Leaf area index (LAI) was measured on June 29 and 30 using an LAI-2000 (Li-Co 1992). Totally 34 LAI sampling quadrats were established using similar approach as SAN acquisition, but with a quadrat of 6 m × 4 m (shown in Fig. 2.). Yield was measured on October 5 and 6 using the same LAI quadrats. For each quadrat, three plants along the diagonal were selected for grain yield determination.

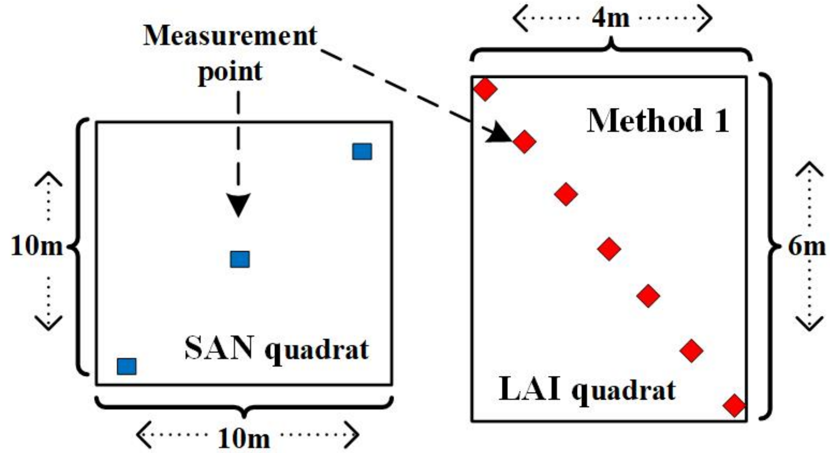


Fig. 2. The layout of and samples in different quadrats

2.2 WOFOST model calibration and modification

The WOFOST model was selected to simulate crop growth in this study. The model, as a primary member of the Wageningen crop models (van Ittersum et al. 2003) and a core component of the Crop Growth Monitoring System (CGMS) (Boogaard et al. 1998), can provide reliable crop growth simulations because of its comprehensive mathematical formulations of key physical and physiological processes, simulation of soil processes, and ability to overcome issues such as abnormal weather conditions and natural disasters (Ma et al. 2013). Calibration is required to use the model under different meteorological, soil and management conditions. Farm and field data were collected to calibrate the core parameters in this study. Farm data included historical field and management data, such as historical yield and daily meteorological data. Field data included yield, LAI, biomass, soil nutrients, and crop phenological stages for calibration.

As the nutrient module in the original crop model is only used at the end of a growing season, modification must be performed to conduct nutrient-limited crop growth within the growing season. The modification included three aspects: the reintegration of modules to adjust the calling sequence of modules, formulation of the daily nutrient uptake, and combination of SAN content and fertilizer amounts. The detailed introduction of the modifications and the two calibration methods can be found in our previous papers (Cheng et al. 2016 &2018)

2.3 UAV data assimilation

The Earth observation (EO) data used in this study were acquired using an UAV, with a five-band mini multiple camera array (MCA) system. The camera provides images of 1280 × 1024 (1.3 M) pixels in five bands centred at 470 nm (blue), 550 nm (green), 690 nm (red), 710 nm (red edge) and 810 nm (near-infrared). Three flights were conducted in 2015, and the detailed specifications are listed in Table 1.

Table 1. UAV acquisitions

Date	Orbit altitude (m)	Spatial resolution (m)	Flight line length (km)	Flight line overlap (%)	Number of Images
June 30	100	0.054	6.4	50% (longitudinally) 35% (laterally)	208
July 29	100	0.054	7.4	55% (longitudinally) 40% (laterally)	226
August 30	100	0.054	7.8	60% (longitudinally) 40% (laterally)	237

LAI was selected as the state variable to be derived from NDVI calculated from the EO data for assimilation：

$$NDVI = (NIR-RED) / (NIR+RED) \tag{1}$$

where NIR and RED are the reflectance of the near-infrared band (800-820 nm) and the red band (680-700nm), respectively. A simple regression model (listed in Table 2) was built to estimate LAI from NDVI. The model is represented by a piecewise linear function, with two different equations separated at DVS = 1 (peak LAI). The statistical model was built using data collected in 2014 (Cheng et al. 2018):

Table 2. The regression models for LAI calculation.

Time	Model
DVS = 0–1	LAI = 5.828NDVI − 0.784
DVS = 1–2	LAI = 4.564NDVI + 0.026

The EnKF method was used to assimilate the time-series UAV data into the WOFOST model. The method (Burgers et al. 1998) is based on Monte Carlo ensemble generations and performs a model forecasting where the state variables are propagated forward in time based on the model dynamics and a filter update in which the ensemble of the model state is adjusted through incorporating available observations (Ma et al. 2013). EnKF is a major assimilation method that can be easily applied to the WOFOST model (Cheng et al. 2013&2018; De Wit et al. 2007). The core algorithm is shown in the following equation:

$$A_a = A_f + A_c H^T (HA_c H^T + D_c)^{-1}(D_t - HA) = A_f + K (D_t - HA) \quad (2)$$

where Aa is the optimal estimated ensemble, A_f is an ensemble of forecast, K is the Kalman gain matrix, D_t is an ensemble of observation, and HA is typically equal to 1. For each pixel (0.5 × 0.5 m), the EnKF algorithm integrates the UAV-based LAI and model-simulated LAI to generate the forecast ensemble (Ma et al. 2013). The resulted ensemble was used as the input LAI in the next step for crop growth simulation.

2.4 SAN estimation

In this study, we proposed a new method for SAN content estimation. This method was designed based on the influence of the mid-season SAN absorption amounts on crop growth. To express the SAN estimation procedure clearly, the procedure of crop growth simulation was divided into two stages: growth simulation stage and SAN estimation stage. At the growth simulation stage, crop growth was simulated using the WOFOST model with EnKF assimilation method to ensure the accuracy of the input crop growth status variable (Biomass, soil water content, and LAI). Then, the SAN content was estimated at the second stage. Using the similar crop growth simulation method at the first stage, the UAV-WOFOST based short-term crop growth (LAI) was simulated. Additionally, the nutrient module in the WOFOST model was used to simulate the nutrient-limited LAI. Because the inadequate calibration of soil nutrient parameters at the pixel scale, the two types of LAI simulation yield different results. Nevertheless, the nutrient-limited LAI can be calculated at different levels by varying the input nutrient within a large range. Then the target SAN contents were determined via a comparison with the UAV-WOFOST based LAI. In this study, the N, P and K were estimated separately. For example, when N was estimated, the mean values of P and K for the plot were calculated and used in the nutrient module. The processes of crop growth simulation and SAN estimation are shown in Fig. 3.

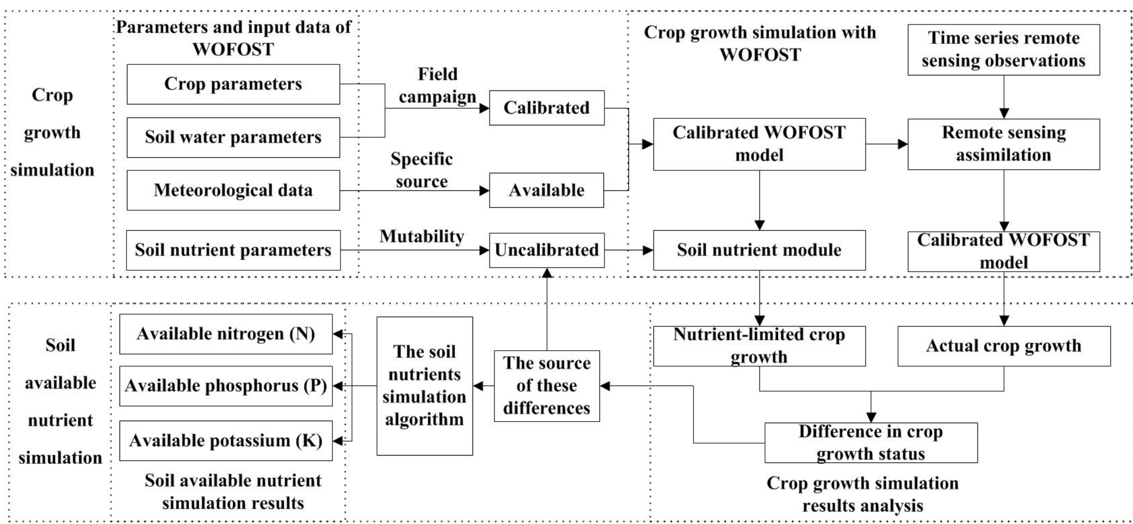


Fig. 3. The processes of soil nutrient estimation.

3 Results and discussions

3.1 Calibration of the WOFOST Model

The input parameters of the WOFOST model include meteorological, soil, and crop parameters. Daily meteorological data were obtained from the weather station in Hongxing Farm. The soil and crop parameters needed to be calibrated through field data collection. Based on sensitivity analysis (referred in the previous work (Cheng et al. 2018), 21 parameters significantly sensitive to LAI were calibrated in this study. The values of the calibrated parameters are listed in Table 3.

Table 3. Crop and soil parameter calibration results of the WOFOST model.

Parameters	Description	Values	Unit
TSUM1	Temperature sum from emergence to anthesis	890	°C*d

TSUM2	Temperature sum from anthesis to maturity	710	°C*d
CVL	Conversion efficiency of assimilates into leaf	0.64	kg/kg
CVO	Conversion efficiency of assimilates into storage organ	0.81	kg/kg
CVR	Conversion efficiency of assimilates into root	0.70	kg/kg
CVS	Conversion efficiency of assimilates into stem	0.66	kg/kg
FRTB	Fraction of total dry matter to root	0–0.40	kg/kg
FOTB	Fraction of above ground dry matter to storage organs (DVS = 0.1–1.7)	0–0.74	kg/kg
FLTB	Fraction of above ground dry matter to leaves (DVS = 0.1–1.7)	0.20-0.75	kg/kg
FSTB	Fraction of above ground dry matter to stem (DVS = 0.1–1.7)	0.06–0.57	kg/kg
NBASE	Mean basic soil nitrogen content	388	mg/kg
PBASE	Mean basic phosphorus content	32	mg/kg
KBASE	Mean basic potassium content	137	mg/kg
NF	Quantity of nitrogen fertilizer	261.5	kg/ha
PF	Quantity of phosphorus fertilizer	138	kg/ha
KF	Quantity of potassium fertilizer	150.5	kg/ha
SMTAB	Volumetric moisture content (pF = −1–6)	0.084–0.41	cm^3/cm^3
SMFCF	Soil moisture content at field capacity	0.289	cm^3/cm^3
SMW	Soil moisture content at wilting point	0.081	cm^3/cm^3
SM0	Soil moisture content of saturated soil	0.39	cm^3/cm^3
RDMCR	Maximum root depth allowed by soil	0–1.7	m

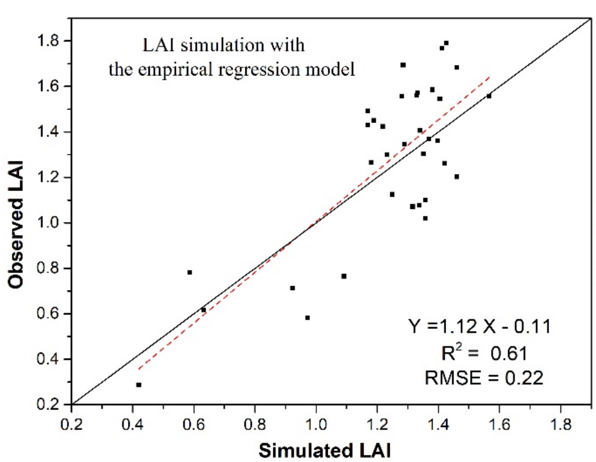
The calibrated WOFOST model was used to simulate spring maize growth of the experimental plot in 2015. Nutrient-limited LAI (WOFOST based LAI) and yield were selected as the indices to assess the parameter simulation accuracy. The analysis results (listed in Table 4) indicate that, compared with the original model, the calibrated model showed an improved simulation accuracy and reduced RMSE for both LAI and yield.

Table 4. The LAI and yield simulation accuracies of WOFOST model.

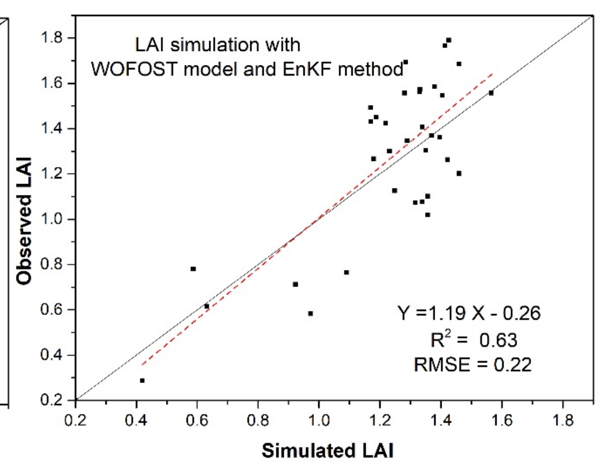
Index	Method	R^2	RMSE
LAI	Original model	0.31	0.31
	Calibrated model	0.44	0.28
Yield	Original model	0.21	618.23
	Calibrated model	0.37	576.55

3.2 Results of LAI simulation and assimilation

Using the linear regression model and the time-series UAV data, time-series LAI was estimated. LAI derived from the UAV data were then assimilated into the WOFOST model to update the model simulated LAI and generate UAV-WOFOST based LAI for SAN estimation. The accuracies of the LAI derived from the two methods were assessed using field LAI. The results (shown in Fig. 4.) indicate that the linear regression model can provide accurate LAI simulation (R2 = 0.61; RMSE = 0.22). Benefit from the mechanism of the WOFOST model, the accuracy of the UAV-WOFOST LAI was improved slightly (R2 = 0.63; RMSE = 0.22). Furthermore, compared with results of Table 4, the UAV-WOFOST based LAI has an obvious higher accuracy than WOFOST based LAI (R2 = 0.44). The difference of the UAV-WOFOST based and WOFOST based LAI simulation accuracy means the input SAN values are inaccurate, which is important for us to design the SAN estimation method by adjusting the WOFOST based LAI to be close to UAV-WOFOST based LAI by varying the input SAN and then determine the target SAN contents.



(a)



(b)

Fig. 4. Analysis results of UAV based (a) and UAV-WOFOST based LAI (b) simulations.

3.2 Results of SAN estimation

The proposed SAN estimation algorithm was applied to create a connection between the UAV-WOFOST based and nutrient-limited crop growth for SAN content estimation. The ranges of N, P and K were set to 0–800, 0–250, and 0–600 mg/kg, respectively. The mean values of the experimental plot for N-P-K are 388-31-137 mg/kg. The start of SAN estimation stage is on June 10 and the three end dates are June 30, July 31 and August 30 to include the three acquired UAV images. Then the SAN estimation method was repeated to estimate the SAN contents (new method based SAN contents) on the three dates. Additionally, a common statistical method was applied to estimate the SAN contents (statistic model based SAN contents) using NDVI and SAN contents. The estimation accuracies of the proposed method (the new approach) and the statistical method were also assessed using field data. The analysis results of N, P and K are listed in Table 5. The results show that the new approach can provide SAN estimations with higher accuracy than the statistic model. Applying the new method on June 30 for N and on July 29 for P and K can obtain SAN estimations with highest accuracy.

Table 5. The SAN estimation accuracies of new approach and statistical model.

Nutrient	Time	Method	R^2	Method	R^2
N	June 30	New approach	0.51	Statistic model	0.24
	July 29		0.34		0.13
	August 30		0.16		0.05
P	June 30	New approach	0.25	Statistic model	0.09
	July 29		0.39		0.15
	August 30		0.09		0.03
K	June 30	New approach	0.17	Statistic model	0.06
	July 29		0.21		0.11
	August 30		0.11		0.02

Meanwhile, the results also show that the K estimation accuracy was lower than the other two nutrients. The low stability of K in soil could be an important reason for its lower estimation accuracy. The potassium ion is the main form of K in soil, which means that it can be easily influenced by soil water flow. To analyze the K's stability, we calculated the coefficient of variance (CV). The CV of field K, N, P were calculated as K 11.31%, N 8.59%, and P 9.81%. The low stability brings difficulties in K estimation, and optimizing the K uptake action mechanism in both crops and soil can be a feasible method to improve the estimation accuracy of K.

Conclusions

In this study, we proposed a SAN content estimation method based on the modified WOFOST model and time-series UAV data. In this approach, the UAV-WOFOST based LAI is simulated by assimilating the UAV derived LAI into the modified WOFOST model, and the nutrient-limited LAI of the same period is estimated by integrating the nutrient module and the water-limited crop growth simulation results. By comparing the LAI derived from the two simulations, the SAN content can be estimated. The accuracy analyses indicate that the new approach is an effective method to improve the SAN estimation accuracy by addressing problems, including time consuming, costly, low stability and with low application value, associated with the existing SAN content monitoring method.

Acknowledgements

We acknowledge the DLO Winand Staring Centre, Wageningen, for providing the original WOFOST code and necessary parameter documentations, the Hongxing Farm for providing their database to calibrate WOFOST parameters and offering us the experimental field and laboratory for field campaigns. We are grateful to the China Scholarship Council (CSC) for providing a scholarship to pursue Zhiqiang Cheng's study in Agriculture and Agri-Food Canada as a joint PhD. student.

References

Basso, B., Dumont, B., Cammarano, D., Pezzuolo, A., Marinello, F., Sartori, L. (2002). Environmental and economic benefits of variable rate nitrogen fertilization in a nitrate vulnerable zone. *Science of the Total Environment*, 545, 227–235.

Basso, B., Cammarano, D., Fiorentino, C., Ritchie, J.T. (2013). Wheat yield response to spatially variable nitrogen fertilizer in Mediterranean environment. *European Journal of Agronomy*, 51, 65–70.

Basso, B., Diepen, C., Rötter, R. P., Cabrera, J. M. C. A., Laar, H. H. V. (1998). WOFOST 7.1: User's Guide for the WOFOST 7.1 Crop Growth Simulation Model and WOFOST Control Center 1.5. Wageningen: DLO Winand Staring Centre.

Boogaard, H., Wolf, J., Supit, I., Niemeyer, S., van Ittersum, M. (2013). A regional implementation of WOFOST for calculating yield gaps of autumn-sown wheat across the European Union. *Field Crops Research,* 143, 130–142.

Burgers, G., van Leeuwen, P.J., Evensen, G. Analysis scheme in the ensemble Kalman filter. Mon. Weather Rev. 1998, 126, 1719–1724.

Chen, Y., Cournède, P.H. (2014). Data assimilation to reduce uncertainty of crop model prediction with convolution particle filtering. *Ecological Modelling,* 290, 165–177.

Cheng, Z., Meng, J., Wang, Y. (2016). Improving spring maize yield estimation at field scale by assimilating time-series HJ-1 CCD Data into the WOFOST model using a new method with fast algorithms. *Remote Sensing*, 2016, 8, 303.

Cheng Z, Meng J, Qiao Y, Wang, Y., Dong, W., Han, Y. (2002). Preliminary Study of Soil Available Nutrient Simulation Using a Modified WOFOST Model and Time-Series Remote Sensing Observations. *Remote Sensing*, 10(1):64.

Gerakis, A., Ritchie, J.T. (1998). Simulation of atrazine leaching in relation to water-table management using the CERES model. *Journal of Environmental Management*, 52, 241–258.

Dong, Y., Zhao, C., Yang, G., Chen, L., Wang, J., Feng, H. (2013). Integrating a very fast simulated annealing optimization algorithm for crop leaf area index variational assimilation. *Mathematical and Computer Modelling,* 58, 877–885.

Huang, J., Tian, L., Liang,S., Ma, H., Inbal, B.R., Su, W., et al. (2015). Improving winter wheat yield estimation by assimilation of the leaf area index from landsat TM and MODIS data into the WOFOST model. *Agricultural and Forest Meteorology*, 204, 106–121.

Janik, L.J., Merry, R.H., Skjemstad, J.O. (1998). Can mid infrared diffuse reflectance analysis replace soil extractions? *Australian Journal of Experimental Agriculture*, 38, 681–696.

Lamsal, S. (2009).Visible near-infrared reflectance spectrocopy for geospatial mapping of soil organic matter. *Soil Science*, 174, 35–44.

Leon, C.T., Shaw, D.R., Cox, M.S., Abshire, M.J., Ward, B., Wardlaw, M.C., et al. (2003). Utility of remote sensing in predicting crop and soil characteristics. *Precision Agriculture*, 4, 359–384.

Li-Cor. (1992). LAI-2000 Plant Canopy Analyser: Instruction Manual, LI–COR, Inc.: Lincoln, NE, USA.

Ma, G., Huang, J., Wu, W., Fan, J., Zou, J., Wu, S. (2013). Assimilation of MODIS-LAI into the WOFOST model for forecasting regional winter wheat yield. *Mathematical and Computer Modelling*, 58, 634–643.

Ma, H., Huang, J., Zhu, D., Liu, J., Su, W., Zhang, C., et al. (2013). Estimating regional winter wheat yield by assimilation of time series of HJ-1 CCD NDVI into WOFOST-ACRM model with ensemble Kalman filter. *Mathematical and Computer Modelling*, 58, 759–770.

Huang, J., Sedano, F., Huang, Y., Ma, H., Li, X., Liang, S., et al. (2016). Assimilating a synthetic Kalman filter leaf area index series into the WOFOST model to improve regional winter wheat yield estimation. *Mathematical and Computer Modelling*, 216, 188–202.

Meng, J., You, X., Cheng, Z. (2015). Evaluating soil available nitrogen status with remote sensing. In Proceedings of the ECPA 10: The 10th European Conference on Precision Agriculture, The Tel Aviv-Yafo, Israel, 12–16, pp. 681–696.

Reyes, J.F., Esquivel, W., Cifuentes, D., Ortega, R. (2015). Field testing of an automatic control system for variable rate fertilizer application. Comput. *Computers and Electronics in Agriculture*, 13, 260–265.

Robert, P. (2002). Precision agriculture: A challenge for crop nutrition management. Plant Soil, 247, 143–149.

Tian, Y., Zhang, J., Yao, X., Cao, W., Zhu, Y. (2013). Laboratory assessment of three quantitative methods for estimating the organic matter content of soils in China based on visible/near-infrared reflectance spectra. *Geoderma*, 202-203, 161–170.

van Ittersum, M., Leffelaar, P., van Keulen, H., Kropff, M., Bastiaans, L., Goudriaan J. (2003). On approaches and applications of the Wageningen crop models. *European Journal of Agronomy*, 18 (3-4), 201–234.

Zheng, G., Ryu, D., Jiao, C., Hong, C. (2016). Estimation of organic matter content in coastal soil using reflectance spectroscopy. *Pedosphere,* 26 (1), 130–136.