Study on Maize Yield Estimation Based on Unmanned Aerial Vehicle Remote Sensing

Yitong Bao [1], Meilin Li [2,*], Haoran Liu [3], Zirui Pan [4]

[1] Guangzhou Foreign Language School, Guangzhou, China

[2] Guanghua Cambridge International School, Shanghai, China

[3] Xuzhou No1. Middle School, Xuzhou, China

[4] Beijing Wenhui Middle School, Beijing, China

* Corresponding Author Email: limeilin20071007@gmail.com

Abstract. Accurately estimating crop yields is crucial for effective agricultural management, particularly with the continuous development of agricultural technology. However, traditional farmland survey methods are time-consuming and expensive. In recent years, there has been a growing interest in using UAV remote sensing technology for maize yield estimation. This study utilized UAV remote sensing technology and data assimilation methods to estimate maize yields. The study utilized UAV remote sensing to acquire ground remote sensing images and estimate maize yield by inverting the leaf area index (LAI). The WOFOST crop growth model was then employed to simulate the growth process of maize using meteorological data and soil property parameters. Finally, the ensemble Kalman filter (EnKF) method was applied to estimate and predict the growth status of maize based on the observed data and model simulation results. The experimental results indicate that the EnKF method can effectively integrate multi-source data, including UAV remote sensing data, meteorological data, and soil data, with the maize growth model for model state assimilation. As a result, it can accurately estimate the maize growth state and yield. This study provides a scientific basis for maize production management and has significant application value.

Keywords: UAV, remote sensing, maize, yield estimation.

1. Introduction

According to statistics from the Food and Agriculture Organization of the United Nations, maize is the largest food crop with the highest total yield in the world. In 2017, the total planting area was 198 million hectares, and it is estimated that the total production will reach 1.148 billion tons by 2022. Maize is a major food crop in China, with a planting area accounting for 30.3% and total production accounting for 33.7% of China's food crops, ranking first and second in China's food crop planting area and total output, respectively [1]. The North China Plain is the main maize-producing area in China, with the planting area and total production of summer maize accounting for 34.7% and 36.8% of the national maize production, respectively [2]. Maize is a crucial food crop, as well as a significant source of feed and industrial raw materials. Accurately estimating maize yield is essential for ensuring national food security, effective agricultural product supply, and market regulation. Therefore, it holds great value for food supply, market regulation, and the formulation of agricultural policies.

Traditional yield estimation methods mainly rely on field surveys and statistics, which have problems such as high survey costs, long cycles, and narrow coverage [3]. The continuous development of remote sensing technology, especially the application of unmanned aerial vehicle (UAV) remote sensing technology, provides new methods for agricultural production [4]. With the advantages of flexibility, low cost, and wide coverage, UAVs have great potential for farmland monitoring and management [5]. Currently, numerous scholars have researched maize yield estimation using UAV remote sensing data. Maize field images are obtained through drone remote sensing in some studies. Hierarchical classification based on image features is then performed to extract maize planting information. The differences between different features (texture, spectrum, etc.) of different ground objects are comprehensively utilized to accurately locate the approximate distribution of maize plots and extract the planting area of maize plots. Further studies have conducted in-depth extraction and analysis of key characteristics of maize growth [6]. They collected vegetation index (such as NDVI) and leaf area index (LAI) as indicators to estimate maize yield and growth status [7]. Maize yield was then evaluated and estimated.

This paper focuses on multiple maize field samples and their growth patterns. Different experimental areas were set up to cultivate maize with varying collection sizes and growth periods as variables. Regular use of UAVs to capture remote sensing images of the experimental areas was employed to invert LAI, which is an indicator for estimating maize yield and growth status. The ensemble Kalman filter (EnKF) assimilation method is used to preprocess the inverted LAI data. The cost function of the biophysical parameters, which are inverted by remote sensing, and the parameters simulated by the model are minimized by adjusting the initial state or input parameters [8]. The iterative technique of the optimization algorithm is used to reinitialize the crop growth model for continuous assimilation of LAI data. The images captured under different variables should be inputted into the data processing system. LAI should be used as the indicator and combined with the crop growth model (WOFOST) to create an EnKF assimilation time series LAI curve model. Finally, the current and future growth yield of maize should be analyzed based on the variable experimental group model obtained by the system and the crop growth model.

2. Methods

2.1. Inversion LAI with UAV remote sensing

LAI is the ratio of vegetation leaf area to ground area. It effectively reflects the degree of leaf cover of maize plants, which is closely related to their growth status and yield. Therefore, it is widely used to estimate maize yield [9]. In this paper, we use UAV remote sensing technology to obtain images of the ground and then invert the LAI. UAV remote sensing data can be used to obtain the spatial distribution of vegetation and the color of leaves through visible spectrum (RGB) images. Vegetated areas can be distinguished from non-vegetated areas using image processing and segmentation algorithms. As maizefields are typically situated in rural areas, debris such as open water pipes and tractors may be present in the images. It is necessary to remove this type of noise when performing calculations. The objective of the inverse LAI is to segment the green leaf region and open soil region of maize. To achieve this, the AP-HI algorithm is used in this paper to accurately segment the maizefield image. The algorithm converts the image into a binary map, where black pixels represent the land and white pixels represent the maize leaves. Additionally, there are usually aisles in each maizefield, so pixel points must be estimated and eliminated from each column. After obtaining the binary map of the land and maize leaves, it is necessary to partition the map into 50x50 pixel units to facilitate the calculation of LAI. The LAI is calculated by determining the proportion of white pixel points to the total pixel points, using the formula shown in equation (1). This paper examines various maize fields by creating different experimental zones with variables such as set size and fertility differences.

$$LAI = n / 250\text{-}x \tag{1}$$

Where n is the number of white pixel points, and x is the sum of pixel points occupied by various clutter in the block.

2.2. WOFOST crop growth model

WOFOST (World Food Studies) is a crop growth model widely used to simulate the growth, development, and yield of various crops. Developed by the University of Wageningen, it is used in agricultural production research and farmland management worldwide. The WOFOST crop growth model has specific parameters for different geographic regions, environments, and varieties, with each parameter playing a distinct role in the operation of the crop model. This paper utilizes LAI data acquired by UAVs as inputs to the WOFOST model. The model is then combined with meteorological data, soil properties, and other parameters to simulate the growth process of maize. The WOFOST crop growth model considers physiological processes such as photosynthesis, transpiration, and nutrient uptake, as well as environmental factors such as soil moisture, temperature, and precipitation (as shown in Table 1 and Table 2). This simulation allows for the growth status of maize at different stages to be determined. The parameter settings of the WOFOST crop growth model have a significant impact on the model run results. To analyze the influence of each parameter on the results, a commonly used method is parameter sensitivity analysis. This method is mainly used to analyze the output of the model results under different parameter conditions and explore the way and degree of influence of parameters on the results. If a parameter has a greater impact on the results, it is considered more sensitive; conversely, if it has less impact, it is considered less sensitive [10]. Less sensitive parameters are set as constants based on existing literature and a priori knowledge, while more sensitive parameters are calibrated and determined. This reduces the computational complexity of model parameter correction and optimization, resulting in better outcomes.

Table 1. Soil parameters and properties of the WOFOST model

Soil parameters	Corresponding names	Unit	Range of values	Digital
SMW	Apoptotic coefficient	cm^3*cm^3	0.01-0.35	0.11
SMFCF	Field water holding capacity	cm^3*cm^3	0.05-0.74	0.28
CRAIRC	Critical air content for soil aeration	cm^3*cm^3	0.04-0.1	0.075
K0	Saturated soil water content	Cm/d	0.1-100	18.1
SPADS	Deep seedbed first surface soil leakage parameters	-	0.02-0.8	0.8
SPODS	Parameters of second surface soil percolation in deep seedbeds	-	0.02-0.04	0.04
SPASS	Shallow seedbed first surface soil percolation parameters	-	0.05-0.9	0.9
SPOSS	Shallow seedbed first surface soil percolation parameters	-	0.03-0.07	0.07
WAV	Dehumidification of effective root soil water	cm	0-45	25
DD	Drainage depth	cm	20-300	20
SMLIM	Maximum water content of surface soil	cm	0.01-0.9	0.065
SM0	Soil saturated water content	cm^3*cm^3	0.3-0.90	0.34

Table 2. Crop parameters and properties of the WOFOST model

Crop parameters	**Corresponding name**	**Unit**	**Range of values**	**Digital**
TSUMEN	Accumulated temperature from sowing to emergence	°C* d^{-1}	0-170	100
TSUM1	seedling to flowering temperature	°C*d^{-1}	150-1050	900
TSUM2	Flowering to maturity temperature	°C* d^{-1}	600-1550	921
TDWI	gross initial dry weight	kg/ha	0.5-300	12
SLATB1	Specific leaf area (0 at growth stage)	kg/ha	0.0007-0.0042	0.0035
SLATB2	Specific leaf area (growth stage 1)	kg/ha	0.0007-0.0042	0.0016
PAN	Foliar life cycle at 35°C	days	17-50	40
TBASE	Leaf senescence offline temperature	°C	-10-10	10
EFFTB1	0°C single leaf light energy utilization efficiency	(Kg/ha*hr)(J/m^2*s)	0.4-0.5	0.5
EFFTB2	Light energy utilization efficiency of a single leaf at 40°C	(Kg/ha*hr)(J/m^2*s)	0.4-0.5	0.5
AMXTB1	Maximum CO_2 assimilation rate (growth stage 0)	Kg/ha*hr	1-70	70
AMXTB2	Maximum CO_2 assimilation rate (growth stage 1.25)	Kg/ha*hr	1-70	70
AMXTB3	Maximum CO_2 assimilation rate (growth stage 1.5)	Kg/ha*hr	1-70	63
AMXTB4	Maximum CO_2 assimilation rate (growth stage 1.75)	Kg/ha*hr	1-70	49
AMXTB5	Maximum CO2 assimilation rate (growth stage 2)	Kg/ha*hr	1-70	0

2.3. Ensemble Kalman Filter

Ensemble Kalman Filter is a method of data assimilation, which is widely used in maize yield estimation [11]. The EnKF method mainly consists of two parts: forecasting and updating. In the forecasting part, the model is used to simulate the state and yield estimates at future moments. In the updating part, the observed data are compared with the predicted results, and the parameters and state variables of the model are updated by calculating the covariance matrix and gain matrix to optimize the yield estimates. The accuracy and reliability of the model are gradually improved through multiple times of iterations of the prediction and update steps [12-13].

This paper applies EnKF to generate a simulation ensemble by model simulation based on a predefined set of initial state and parameter estimates. The observed data, including LAI data acquired by UAV and meteorological data, are then used to calculate the differences between observation and model by comparing the results with those simulated by the WOFOST crop growth model through the observation operator [14]. The EnKF updates the states and parameters in the ensemble by weighing the observations and models through Kalman gain, based on the differences between them. This allows for iterative data assimilation, gradually optimizing simulation results and maize yield estimation. By combining observation data with model simulation data and constantly updating model states and parameters, EnKF improves the accuracy of system state estimation. EnKF utilizes observation data to provide more accurate maize yield estimations. Unlike traditional statistical methods, EnKF does not rely on assumptions about data distribution and is better suited for nonlinear and non-Gaussian systems. Additionally, EnKF can handle incomplete data by adaptively adjusting update step weights based on available observations.

3. Result and discussion

Based on the yield simulation results, the yields of maize were 7889kg/ha, 8043kg/ha, and 8019kg/ha respectively, with relative errors of -6.4%, -4.6%, and -4.9%. The model results with set sizes of 50 and 90 are closer to the measured results, and the set size of 50 is the closest to the measured yield value. Fig. 1 illustrates the comparison of Enkf assimilation time series LAI curves with different set sizes. The impact of different set sizes on the LAI curve is reflected in the distance between the LAI and the observed data after assimilation. The assimilated leaf area index curve is further from the observed data with larger ensemble sizes. This is due to the calculation of the variance of the forecast ensemble. The errors of forecast ensembles with different ensemble sizes are similar. The assimilation results deviate more from the observation data as the ensemble size increases and the variance decreases.

Fig.2 shows a comparison of Enkf assimilation time series LAI curves during the same growth period. The figure indicates that the assimilated time series LAI curve is larger than the simulated value during the seedling stage to the jointing stage, and is closer to the observed value of remote sensing data. The curve's changing trend after the jointing stage is consistent with the original simulated value. The time series of leaf area index (LAI) from the jointing stage to the silking stage is significantly lower than the simulated value and is similar to the LAI curve observed through remote sensing. Additionally, the LAI curve from the silking stage to the maturity stage is also lower than the simulated value, which is more consistent with actual changes. Based on the yield simulation results, the maize yields are 9083kg/ha, 8606kg/ha, and 7834kg/ha respectively, with relative errors of +7.7%, +2.1%, and -6.9% respectively. The simulation results indicate that the assimilation from the jointing stage to the silking stage has the best effect.

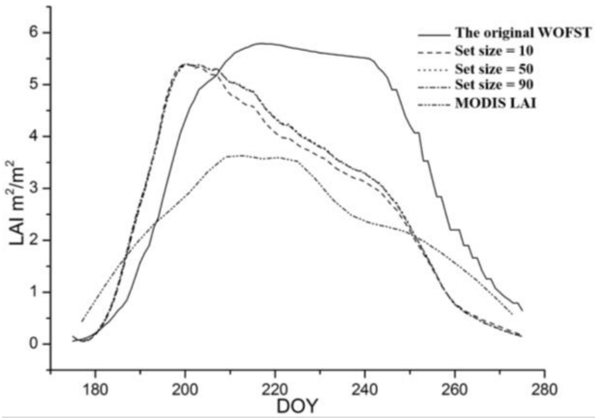

Figure 1. Comparison of Enkf assimilation time series LAI curves of different set sizes

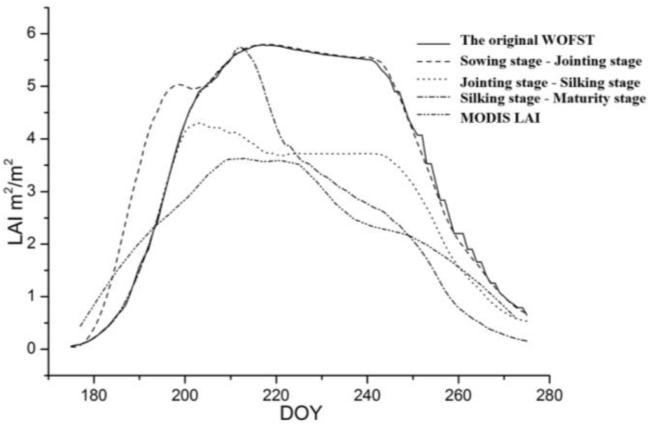

Figure 2. Comparison of Enkf assimilation time series LAI curves in different growth stages

This paper presents a method for monitoring maize fields using UAV remote sensing data. The method allows for the inversion and acquisition of high-resolution, spatiotemporally continuous LAI data. LAI provides detailed information on the growth status of maize, which can be used as a reliable basis for yield prediction. The potential application of other parameters, such as NDVI, requires further exploration. Additionally, this paper solely measured the sensitivity parameters that have the most significant impact on LAI and yield. The optimum values of parameters such as base temperature (TBASE), maximum assimilation rate (AMAXTB), cumulative temperature (TSUM), leaf inclination (SLATB), and SPAN were not explored. Although the EnKF method in this paper has some feasibility and the error is within a controllable range, it still requires multiple verifications due to the small sample size. Furthermore, when implementing the method, it is possible to decrease the variable gradient for data collection and analysis, resulting in reduced experimental data errors and improved relevance of experimental data. Additionally, future research could investigate the effects of alternative methods on maize yield estimations.

4. Summary

This study used UAV remote sensing data to invert LAI and estimate maize yield and growth status. The WOFOST model and ensemble Kalman filter data assimilation method were employed to achieve rapid and accurate yield estimation. The study drew the following conclusions based on field investigation and model verification:

(1) The correlation between leaf area index and maize yield is well-established, and UAV-imaged LAI data can effectively extract maize growth characteristics.

(2) The WOFOST model has demonstrated strong predictive capabilities in estimating maize yield, and this paper utilizes it to identify the crop and soil parameters that have the greatest impact on LAI and yield results.

(3) EnKF can improve maize yield estimation by assimilating multi-source data, including drone remote sensing data, meteorological data, and soil data, with the maize growth model. This improves the prediction of maize growth and estimation accuracy of yield and status. Ensemble Kalman filtering (EnKF) is a data assimilation method based on ensemble simulation. It can dynamically adjust model parameters and state variables to better adapt to different growth stages and environmental conditions, improving the model's adaptability. EnKF is widely used in agricultural research, including maize yield estimation.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

References

[1] Wang Zhanbiao, Wang Meng, Yin Xiaogang, et al. Temporal and spatial variation characteristics of water and heat in each growth period of summer corn in the North China Plain under the background of climate change. Chinese Journal of Ecological Agriculture, 2015, 23 (4): 473-481.

[2] Ge Yaning, Liu Luo, Xu Xinliang, et al. Spatiotemporal evolution characteristics of my country's corn production potential under the background of climate change in the past 50 years. Journal of Natural Resources, 2015, 30 (5): 784-795.

[3] Zhao Hu, Pei Zhiyuan, Ma Shangjie, et al. Leaf area index inversion using WOFOST model assimilation of time series HJCCD data. Chinese Journal of Agricultural Engineering, 2012, 28 (11): 158-163.

[4] Chen Yanling. Research on remote sensing yield estimation of winter wheat based on WOFOST crop model and leaf area index assimilation. Henan University of Science and Technology, 2015.

[5] Huang Jianxi, Li Xinlu, Liu Diyou, et al. Comparative study on winter wheat yield estimation by sequentially assimilating LAI with different spatial and temporal resolutions. Journal of Agricultural Machinery, 2015, 46 (1): 240-248.

[6] Xie Y, Wang P, Bai X, et al. Assimilation of the leaf area index and vegetation temperature condition index for winter wheat yield estimation using Landsat imagery and the CERES-Wheat model. Agricultural & Forest Meteorology, 2017, 246.

[7] Jiang Mingnuo. Research experiment on summer corn yield estimation in Shandong Province based on data assimilation method. East China Normal University.

[8] Chen Sining, Zhao Yanxia, Shen Shuanghe. Verification of the applicability of the WOFOST model based on ensemble Kalman filtering in corn yield estimation in Northeast China. Chinese Agricultural Meteorology, 2012, 33 (2): 245-253.

[9] Wang Laigang, Xu Jianhua, He Jia, et al. Corn leaf area index and yield estimation based on drone remote sensing. Corn Science, 2020 (006): 028.

[10] Han Wenting, Peng Xingshuo, Zhang Liyuan, et al. Summer maize yield estimation based on vegetation index derived from multi-temporal UAV remote sensing. Transactions of the Chinese Society for Agricultural Machinery, 2020, 51 (1): 8.

[11] Chen Sining. Research on combining remote sensing information and crop models based on ensemble Kalman filter. Nanjing University of Information Science and Technology, 2012.

[12] Xie Yi, Wang Pengxin, Liu Junming, et al. Winter wheat yield estimation based on four-dimensional variation and ensemble Kalman filter assimilation method. Chinese Journal of Agricultural Engineering, 2015, 31 (1): 187-195.

[13] Zhang Shuyu, Sun Huitao, Wang Pengxin, et al. Winter wheat yield estimation based on assimilated leaf area index and conditional vegetation temperature index. Agricultural Research in Arid Areas, 2017 (6): 266-271.

[14] Jin Huaan, Wang Jindi, Bai Yanchen, et al. Regional corn yield estimation based on crop growth model and remote sensing data assimilation. Chinese Journal of Agricultural Engineering, 2012, 28 (6): 162-173.