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Crop yield prediction using MODIS LAI, TIGGE weather forecasts and WOFOST model: A case study for winter wheat in Hebei, China during 2009–2013

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ABSTRACT

Timely and reliable in-season forecasting of crop yield is crucial for regional and national agricultural management. To improve the winter wheat yield prediction accuracy at the regional scale, we developed a data assimilation scheme that assimilated the MODIS leaf area index (LAI) into the WOrld FOod STudies (WOFOST) model. The meteorological data of the WOFOST model include current weather data, 15-day THORPEX Interactive Grand Global Ensemble (TIGGE) forecast dataset and weather forecast data generated by TIGGE forecast and historical meteorological data (1979–2008) using the vectorial angle method. The WOFOST model was calibrated within 10 subregions of Hebei province based on field measured winter wheat growth data from each corresponding agrometeorological station to account for the spatial variability of crop and soil parameters to some extent, and the Savitzky-Golay (S-G) filtered MODIS LAI was then assimilated into the WOFOST model for regional winter wheat yield forecasting. We constructed a four-dimensional variational data assimilation (4DVar) cost function to account for the observations and model errors from Feb. 10th to Apr. 30th, and the Shuffled Complex Evolution-University of Arizona (SCE-UA) algorithm was used to minimize the cost function by reinitializing three WOFOST parameters. The winter wheat yield forecasting date was started from Apr. 30th, and the results showed that assimilating MODIS LAI into the WOFOST model substantially improved the accuracy of regional wheat yield predictions (R = 0.60, CCC = 0.53, RMSE = 619.73 kg/ha) compared with the unassimilated results (R = 0.35, CCC = 0.24, RMSE = 857.32 kg/ha), and the relative error (RE) between the averaged predicted yield and official statistics for most cities decreased after data assimilation. This demonstrated that assimilating MODIS LAI can optimize the simulation of LAI in the WOFOST model, thereby further reduce the uncertainty of yield forecasting. These promising results highlighted the potential of integrating remotely sensed data, crop model and weather forecasts for in-season prediction of crop yield at the regional scale.

1. Introduction

Information on crop yield estimates can be used to support government agricultural decision-making, assist in agricultural management practices and optimize resource use (Jin et al., 2017). Therefore, accurate and timely crop yield forecasting and estimations are becoming increasingly important for ensuring the world's food security and maintaining sustainable agricultural development (Lecerf et al., 2019; Wu et al., 2021). In recent decades, crop yield estimation and forecasting research have been developed from agrometeorological models, regression models using remote sensing data, to a more comprehensive method that integrates crop growth environment (e.g., weather data,

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soil and crop parameters), process-based models and remotely sensed data (Curnel et al., 2011; Dorigo et al., 2007; Huang et al., 2015a; Ma et al., 2008; Ma et al., 2013b; Pauwels et al., 2007; Zhao et al., 2013). The conventional method for estimating crop yield usually consists of establishing statistical models using agrometeorological data (e.g., precipitation, temperature or radiation) (Kandiannan et al., 2002; Qian et al., 2009; Scian 2004) or remotely sensed data (e.g., visible light, thermal infrared or microwave radiation) (Arshad et al., 2013; Chen et al., 2011; Kuri et al., 2014), and the principal deficiency of such methods is that a large number of field measured data are needed for statistical model calibration and the established statistical models are only suitable for specific crop varieties, crop growth stages or specific geographic areas (Doraiswamy et al., 2003; Fang et al., 2011; Huang et al.; 2015b).

In contrast, the crop growth model (CGM) is an effective way for crop yield estimation and forecasting by inputting a series of crop, soil, weather and management parameters, and it can simulate the whole growth process of various crop types. However, the CGM faces the problem that it is difficult to obtain accurate initial parameters at the regional scale when only field data are available (Doraiswamy et al., 2004). Along with the development of remote sensing technology, it is possible to obtain these parameters at the regional scale. Meanwhile, many empirical correlation methods have been conducted for crop yield forecasting (Arshad et al., 2013; Chen et al., 2011; Kuri et al., 2014; Lobell, 2013; Qian et al., 2009; Scian, 2004), however, these methods rely heavily on the accuracy of the field-measured data and lack mechanistic explanations. Therefore, the data assimilation method, which can integrate remote sensing observations and CGM, has been recognized as the most promising approach for crop yield estimation and forecasting at the regional scale (de Wit et al., 2007; Fang et al., 2008).

There are two main data assimilation methods for crop yield estimation. The first is the sequential strategy that corrects the trajectories and minimizes the uncertainties of crop state variables by combining CGM and remote sensing observations (Qin et al., 2009; Ines et al., 2013). The typical sequential data assimilation algorithm for yield estimation is the Ensemble Kalman Filer (EnKF), and several EnKF-based crop model data assimilation frameworks have been developed in the past few years. Ines et al. (2013) incorporated remotely sensed soil moisture (SM) and leaf area index (LAI) into Decision Support System for Agro-technology Transfer (DSSAT) model using EnKF method to estimate maize yield at an aggregate scale, and found that assimilating SM and LAI performed better than using only one of these two variables. Huang et al. (2016) improved the winter wheat yield accuracy significantly by assimilating a synthetic LAI time series remotely sensed data with 30-m resolution into the WOrld FOod STudies (WOFOST) model using EnKF data assimilation algorithm. Kang et al. (2019) developed a data assimilation scheme by assimilating LAI retrieved by Landsat satellite data into Simple Algorithm For Yield estimates (SAFY) model using EnKF method, and achieved a 30-m resolution yield map with high estimation accuracy. The second data assimilation method is the variational approach which improves the crop state variable simulation accuracy by reinitializing the crop model input parameters to optimize a given criterion (minimization of a cost function), such as Three-Dimensional Variational Data Assimilation (3DVar) and Four-Dimensional Variational Data Assimilation (4DVar) (Huang et al., 2019). Fang et al. (2011) assimilated MODIS LAI products into the CERES-Maize model using a simplified variational method based on the Powell optimization algorithm, and the results showed that the estimated corn yield agreed well with the statistical data. Huang et al. (2015b) developed a data assimilation procedure by assimilating scale-adjusted remotely sensed LAI into the WOFOST model using 4DVar cost function, and found that the winter wheat yield estimation accuracy was improved further. Jin et al. (2017) assimilated canopy cover (CC) and biomass data that were retrieved from HJ-1A/B and RADARSAT-2 into the AquaCrop model by constructing a relative error cost function, and the particle swarm optimization (PSO) algorithm was used for optimizing initial parameters. Results indicated that the estimated crop yields were in good agreement with the measured yields.

By summarizing these data assimilation (DA) researches, we found that most studies mainly focused on the crop yield estimation after harvest is completed, but not on forecasting within the season prior to harvesting. In the study of yield forecasts, the weather forecast data play a vital role when predicting crop yield within the season prior to the harvest (Basso and Liu, 2019). Several researchers have used different approaches, including using mean historical weather data (Dumont et al., 2014), weather generators (Dumont et al., 2015; Hansen and Indeje, 2004), and climate forecast models (Mishra et al., 2008; Singh et al., 2017), to synthesize weather data for crop yield forecasting. In a previous study (Zhuo et al., 2020), we developed an approach that assimilates the Moderate Resolution Imaging Spectroradiometer (MODIS) leaf area index (LAI) product into the WOFOST model to predict the maturity dates of winter wheat in Henan province of China, and the weather forecast data used for driving the WOFOST model was consist of THORPEX Interactive Grand Global Ensemble (TIGGE) weather forecast and historical meteorological data. The results showed promising regional maturity date prediction with the determination coefficient (R^2) of 0.94 and the Root Mean Square Error (RMSE) of 1.86 d. Moreover, we found that Apr. 30th, which corresponds to the stage from anthesis to grain filling, was the optimal forecasting starting time. These initial results were encouraging and demonstrated great potential of using data assimilation method in winter wheat growth forecasting.

However, there are still some issues that the previous research (Zhuo et al., 2020) has not yet fully addressed, and we would like to obtain further improvements in this article. First and foremost is that the crop model is driven by only one set of crop and soil parameters, and ignores the spatial differences of crop varieties and soil properties over large areas (Jin et al., 2018). Simulation region partitioning is a beneficial way to cause the crop model simulation results to be more reasonable at the regional scale by considering the spatial variations in crop varieties and soil properties (Guo et al., 2018, Miao et al., 2006; Thorp et al., 2008). A second potential issue is that the previous study optimized the cumulative temperature from emergence to anthesis (TSUM1), cumulative temperature from anthesis to maturity (TSUM2) and emergence date (IDEM), which are mainly related to the growth stage. In this study, the parameters that are sensitive to crop yield (e.g., TSUM1, SPAN (the lifespan of leaves growing at 35 °C, in days) and IDEM) should be considered. Third, the cost function used in the previous study was based on the idea of normalization that only considered the gap between remotely sensed observations and crop model simulations without taking the errors of observation and crop model into account. Constructing a cost function with 4DVar by considering the uncertainties in the crop model and remotely sensed observations could potentially be beneficial (Huang et al., 2019). Because the uncertainties of crop model and observation are treated as two variables in the 4DVar cost function, minimizing the cost function by reinitializing crop model input parameters could optimize the LAI simulation, and further improve the yield estimation.

Therefore, the objective of this study is to predict winter wheat yield at the regional scale and improve the accuracy by assimilating remotely sensed observations. Specifically, we conducted this research through: (i) dividing the winter wheat region of study area into 10 subregions based on agro-meteorology stations and calibrating WOFOST model in each subregion, (ii) constructing a 4DVar cost function based on MODIS S-G filtered LAI and WOFOST simulated LAI before Apr. 30th and using SCE-UA optimization algorithm to find the optimal parameter sets, (iii) using the vectorial angle method to generate a weather forecast dataset (WFD_{vec}) after May 15th based on TIGGE weather forecast and historical meteorological data, specifically, TIGGE weather forecast data was used in the WOFOST model from Apr. 30th to May 15th, and the WFD_{vec} was used after May 15th, (iv) driving the WOFOST model by using optimized parameters and the weather forecast dataset to predict winter wheat yield at the regional scale and validating the forecasting results by using

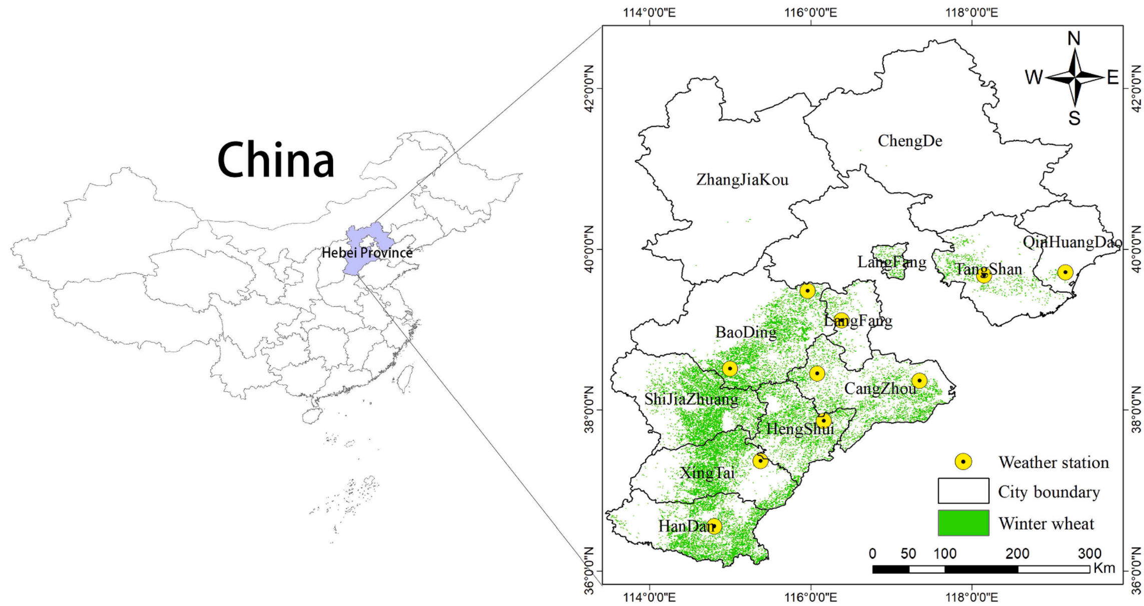

Fig. 1. Study area. (Green represents the winter wheat region (Huang et al., 2015b) and the yellow points show the agrometeorological stations).

official statistical yield.

2. Materials and methods

2.1. Study area

Hebei province is located in northern China and covers an area of 188,800 km^2 (Fig. 1). The climate of this region is a typical temperate monsoon climate, which is characterized by a hot and rainy summer and a cold and dry winter. The total annual sunshine hours are 2303.1 h, and the average annual temperature is 15 °C, with an average annual precipitation of 484.5 mm (http://www.hebei.gov.cn/hebei/14462058/14462085/14471224/index.html). Hebei province is one of the major winter wheat production areas in China and is dominated by a typical double cropping system of rotational winter wheat and summer maize cultivation. Winter wheat in this area is usually planted from late September to early October and usually harvested in late May to June (Wu et al., 2019).

2.2. Datasets

The 4-day Moderate Resolution Imaging Spectroradiometer (MODIS) LAI product (MCD15A3H) with 500-m spatial resolution were collected from January to April of 2009 to 2013 ((https://ladsweb.modaps.eosdis.nasa.gov/). Due to the influence of cloud and aerosol noise, the MODIS LAI time series curve is zigzag. An upper-envelope-based S-G filter was used to smooth the MODIS LAI curve (Zhuo et al., 2020).

The input data for the WOFOST model include weather, crop, soil and management parameters. The WOFOST weather parameters include six elements (irradiation, early morning vapor pressure, maximum temperature, minimum temperature, wind speed and precipitation). The daily weather data with spatial resolution of 0.1° during 1979–2013 were obtained from China Regional Surface Meteorological Elements Dataset produced by National Tibetan Plateau Data Center (TPDC, http://www.tpedatabase.cn/portal/MetaDataInfo.jsp?MetaDataId=249369) and were preprocessed to the WOFOST weather input format. Some crop and soil parameters, including the day of emergence (IDEM), initial total crop dry weight (TDWI), cumulative temperature from emergence to anthesis and from anthesis to maturity (TSUM1/TSUM2), were collected from the agrometeorological stations (measuring crop type, typical growth stages, biomass, LAI, soil moisture (SM), yield, irrigation and fertilization amount and date). We used the Chinese soil database (http://www.soil.csdb.cn) to derive soil moisture content at the wilting point (SMW), in saturated soil (SM0), and at field capacity (SMFCF). Overall, we regionalized the IDEM, TSUM1, TSUM2, SMW, SM0 and SMFCF of the crop and soil parameters, and the remaining parameters were obtained from three ways: (1) calibration using agrometeorological station record winter wheat growth data; (2) reference from previous researches and (3) set as default values. Ma et al. (2013b) and Huang et al. (2015b) provide details of the parameterization and calibration of the WOFOST model for winter wheat in the study area. Official government statistics on winter wheat yields were obtained at a county level from the 2009–2013 Hebei statistical yearbook.

The weather forecasts data came from the THORPEX Interactive Grand Global Ensemble (TIGGE) database that provides ensemble forecast results of seven operational Numerical Weather Prediction (NWP) centers (Bougeault et al., 2010; Roudier et al., 2016). The control forecast dataset of European Centre for Medium-Range Weather Forecasting (ECMWF) with a spatial resolution of 0.25° * 0.25° during 2009–2013 was used in this study (https://apps.ecmwf.int/datasets/data/tigge/levtype=sfc/type=cf/). We selected 7 elements (surface net solar radiation, 2-meter dewpoint temperature, maximum temperature at 2 m, minimum temperature at 2 m, 10-meter U/V wind component, total precipitation) to generate the WOFOST required weather parameters. The ECMWF forecast model does not include the water vapor pressure information, so we used Eq. (1) to calculate this parameter:

$$e_a = 0.61078e^{\frac{17.27T_{dew}}{T_{dew}+237.3}} \tag{1}$$

where e_a is the water vapor pressure, T_{dew} is the dewpoint temperature.

In this study, we conduct winter wheat yield forecasting scheme started from Apr. 30th and because the forecasting time period of TIGGE forecast data is 15 days, we used the historical weather data over 30 years (1979–2008) to generate the weather forecast data after 15 days. First, we regard the TIGGE 15-day irradiation forecast data of the current year as a vector and then calculate the vectorial angle that is formed by this vector and the vector of the same period in each year from 1979 to 2008 using Eq. (3) to find the similar year:

$$\theta = arccos\frac{\boldsymbol{a}\bullet\boldsymbol{b}}{|\boldsymbol{a}||\boldsymbol{b}|} \tag{3}$$

where θ is vectorial angle, $\boldsymbol{a}$ and $\boldsymbol{b}$ is the vector of current year and

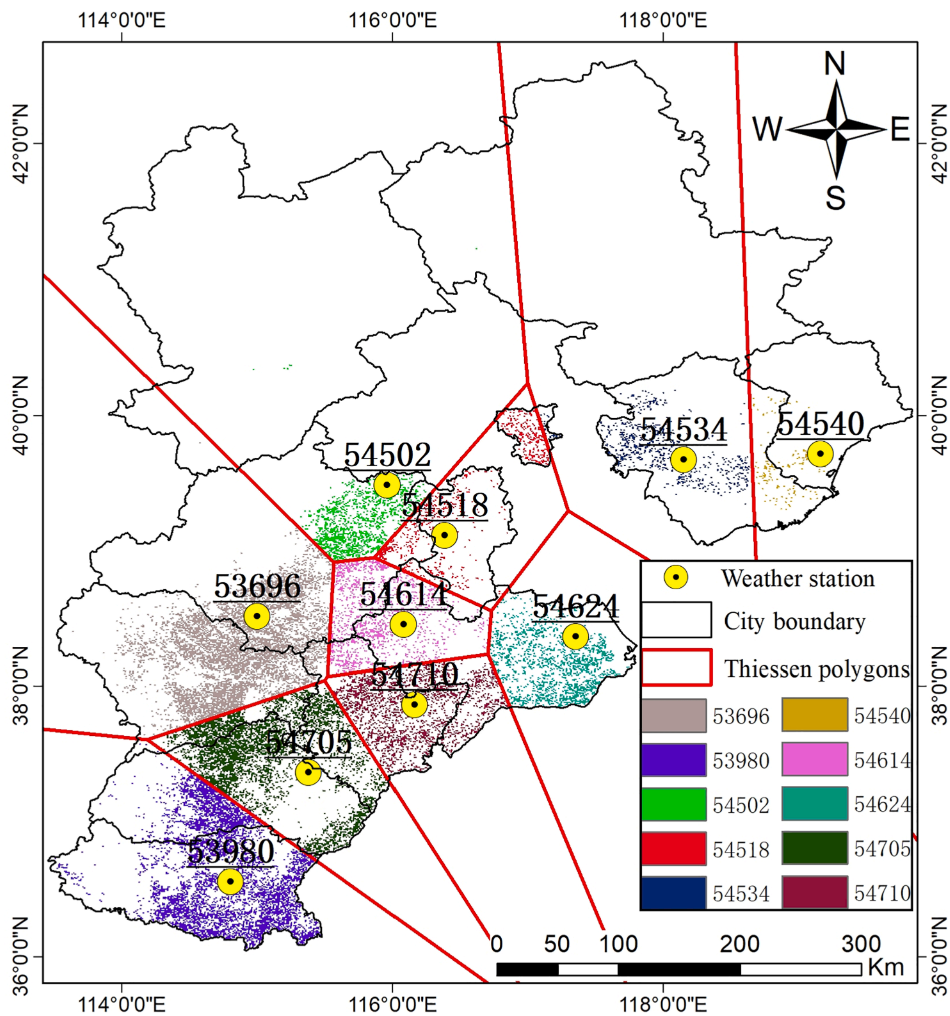

Fig. 2. Subregions of winter wheat in Hebei province.

historical year, respectively. In Eq. (3), $\boldsymbol{a} = (a_1, a_2, \cdots, a_{15})$, $\boldsymbol{b} = (b_1, b_2, \cdots, b_{15})$, thus the Eq. (3) can be described as Eq. (4):

$$\theta = arccos\frac{\sum_{i=1}^{n} a_i b_i}{\sqrt{\sum_{i=1}^{n} a_i^2}\sqrt{\sum_{i=1}^{n} b_i^2}} \quad (4)$$

Overall, the meteorological data of the WOFOST model consist of three parts. i) Before Apr. 30th, the WOFOST model is driven by real weather data from TPDC; ii) from Apr. 30th to May 15th, the TIGGE weather forecast data are used as the weather inputs; iii) after May 15th, we use the vectorial angles to generate the weather forecast data using TIGGE forecasts and historical meteorological data (1979–2008).

Besides, the relative error was used to evaluate the accuracy of the winter wheat yield forecasting with and without data assimilation. The relative error was calculated by Eq. (5):

$$RE = \frac{Yield_{pre} - Yield_{sts}}{Yield_{sts}} \times 100\% \quad (5)$$

where $Yield_{pre}$ represents the predicted winter wheat yield, $Yield_{sts}$ represents official statistical winter wheat yield.

2.3. WOFOST model

WOFOST model (de Wit, 1965) is a process based mechanistic model which can simulate daily crop growth by giving a set of soil, crop, meteorological and management parameters. The major processes are phenological development, CO_2-assimilation, transpiration, respiration, partitioning of assimilates among various organs, and dry matter formation. LAI is an important state variable of the WOFOST model that participates in many dynamic growth processes. Crop leaves participate in light interception, and the LAI in the WOFOST model represents the ability of crop leaves to intercept solar radiation for photosynthesis to generate potential gross primary production. Moreover, LAI is an essential parameter for calculating crop potential transpiration rate. Given the important role of LAI in the WOFOST model, LAI was adopted as the state variable in the presented data assimilation framework. The WOFOST model can run in three modes: potential mode, a water-limited mode, and a nutrient-limited mode. We used the water-limited mode in this study, and we followed Wang et al.'s (2013) research to add the irrigation into the WOFOST model. A detailed description of the WOFOST model can be found on its website (https://www.wur.nl/en/Research-Results/Research-Institutes/Environmental-Research/Facilities-Tools/Software-models-and-databases/WOFOST.htm). General structure of the WOFOST model is presented in supplementary.

The field measured data of winter wheat from 10 agrometeorology stations in Hebei province (Fig. 2) in 2011 were used for WOFOST model calibration, and we assumed that the winter wheat varieties, soil properties and management all remained unchanged during 2009–2013. We used only one set of parameters to represent the crop and soil conditions at the regional scale in our previous research (Huang et al., 2015b, 2016; Zhuo et al., 2019, 2020), whereas we divided the Hebei winter wheat area into 10 subregions based on the 10 agrometeorology stations using Thiessen polygons (Fig. 2) for WOFOST model calibration in this study.

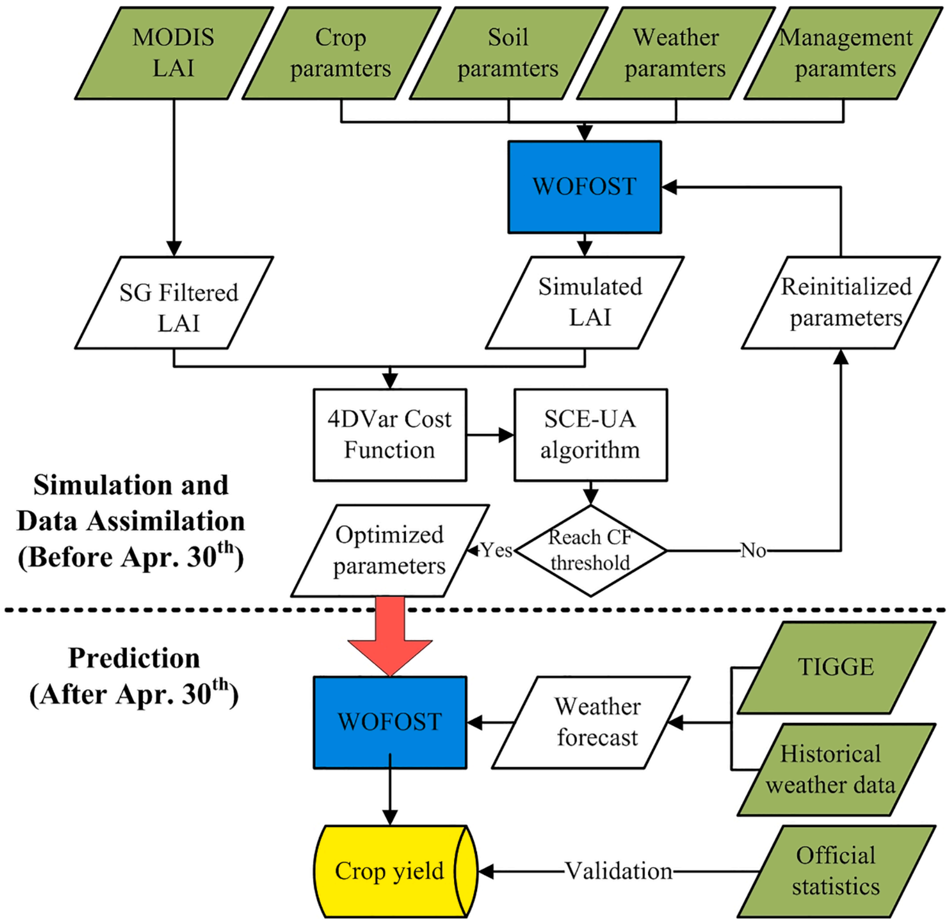

Fig. 3. Winter wheat yield forecasting framework (Note: CF represents cost function).

The WOFOST model was calibrated in each subregion separately using field measured data from the corresponding station. In each subregion, winter wheat assimilation units share the same set of calibrated parameters, which make the simulation more reasonable.

2.4. Data assimilation algorithm

In this study, the cost function was constructed by using the 4DVar method (Liang and Qin, 2008; Dente et al., 2008). The values of MODIS LAI are often much lower than the WOFOST model simulated LAI because of the mixed information and the impact of clouds and rain at the 500 m spatial resolution. Therefore, we used the normalized LAI value to construct the 4DVar cost function rather than the true LAI value.

$$LAI_{nor} = \frac{LAI_t - LAI_{min}}{LAI_{max} - LAI_{min}} \tag{6}$$

where LAI_{nor} represents normalized LAI, LAI_t represents MODIS or WOFOST simulated LAI on Day t, LAI_{max}andLAI_{min} represents maximum and minimum LAI of MODIS or WOFOST simulated LAI during the crop growing season, respectively.

The selection of parameters that need to be reinitialized is pivotal in a 4DVar procedure. In this study, the TSUM1, SPAN and IDEM were chosen as the reinitialization parameters, because these parameters are highly sensitive to LAI and crop yield (Ma et al., 2013a). Therefore, the cost function (J(x)) was constructed as Eq. (7):

$$J(x_0) = \frac{1}{2}\left[x_0 - x_0^b\right]^T B^{-1}\left[x_0 - x_0^b\right] + \frac{1}{2}\sum_{k=1}^{K}\left[H(x_k) - y_k\right]^T R^{-1}\left[H(x_k) - y_k\right] \tag{7}$$

where x_0 represents the vector of reinitialized parameters (e.g., TSUM1, SPAN, and IDEM); x_0^b represents the prior knowledge of these reinitialized parameters; B represents the error covariance matrix for the three parameters; K represents the total number of the observations (MODIS LAI); $H(x_k)$ represents the model simulated variable (normalized WOFOST simulated LAI); y_k represents the observations (normalized MODIS LAI); R represents the error covariance matrix for observations. In this study, the error covariance of TSUM1, SPAN, IDEM were defined based on our previous research (Huang et al., 2019), which used Markov Chain Monte Carlo approach to estimate the uncertainties; and the error covariance of MODIS LAI was set to 0.01 at the green-up stage (DOY 41–69), 0.02 at the jointing stage (DOY 70–100) and 0.04 at the flowering stage (DOY 101–120). Besides, the upper and lower values of TSUM1, SPAN, IDEM were set to 800–1500 °C, 21.9 d – 40.7 d and DOY 270–315, respectively. We used Shuffled Complex Evolution-University of Arizona (SCE-UA) algorithm to optimize the parameters, the implement of the SCE-UA is presented in the supplementary.

2.5. General framework

Fig. 3 shows the flowchart of the winter wheat yield forecasting by using MODIS LAI, TIGGE forecasts and WOFOST model. In this study, the prediction starting date is Apr.30th. Therefore, before Apr.30th, S-G filtered MODIS LAI time series was assimilated into the WOFOST model by using 4DVar data assimilation method to generate a set of optimal WOFOST input parameters; after Apr.30th, the WOFOST model was driven by optimal input parameters and weather forecast data (generated by TIGGE and historical meteorology data) to predict winter wheat yield at the regional scale. The official statistical winter wheat yield of

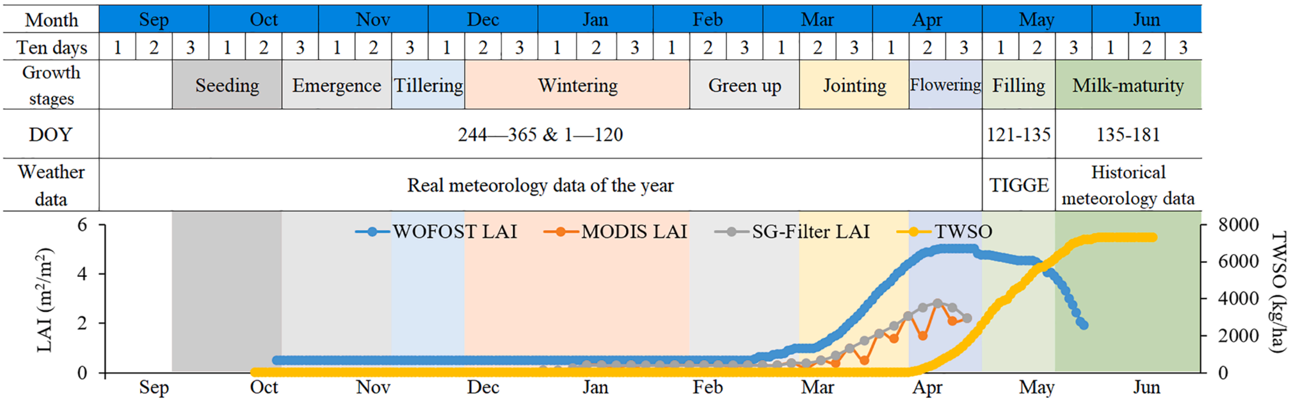

Fig. 4. General growth stages of winter wheat in Hebei province, and the comparison of MODIS LAI, S-G Filtered LAI, WOFOST simulated LAI and TWSO. (Note: TWSO represent Total dry weight of storage organs).

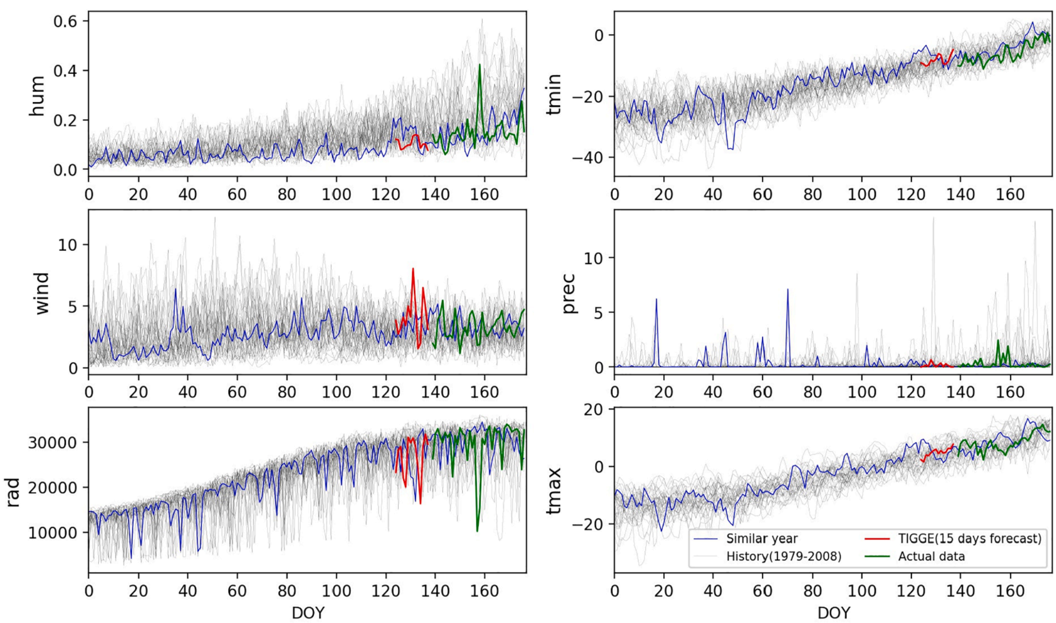

Fig. 5. Comparison of meteorological data for six elements (a sample assimilation unit in Xingtai city). (Note: hum represents humidity, wind represents wind speed, rad represents solar radiation, prec represents precipitation, tmin/tmax represent minimum and maximum temperature).

Hebei province during 2009–2013 were used to validate the regional-scale winter wheat yield forecasting results. In this study, the winter wheat pixel (assimilation unit) size was 500 m which was consistent with the spatial resolution of MODIS LAI, and the corresponding weather data were extracted from TPDC, TIGGE forecasts and historical meteorology data directly used the centroids coordinate of the assimilation units. In each subregion, the winter wheat assimilation units share the same set of calibrated crop and soil parameters, and we run the WOFOST model and conduct data assimilation scheme with MODIS LAI individually in each assimilation unit.

3. Results

3.1. Generation of the S-G filtered MODIS LAI and weather forecast data

The 4-day MODIS LAI used in this study extended from Jan. 1st to Apr.30th of each year (2009–2013). General growth stages of winter wheat in Hebei province, and the comparison of MODIS LAI, S-G Filtered LAI, WOFOST simulated LAI and TWSO are shown in Fig. 4. The MODIS LAI (red circles) is usually affected by cloud and aerosol so that the shape of MODIS LAI is serrated. We used the upper-envelope-based S-G filter method to remove the temporal gaps and low-quality pixels of the MODIS LAI, and some outliers of MODIS LAI were filtered (e.g., Mar. 30th, Apr. 15th) and a smoother S-G filtered LAI time series was generated (gray diamonds) which was then used to assimilate into the WOFOST model. Compared with the WOFOST simulated LAI, the MODIS LAI is generally low due to the coarse spatial resolution (500 m) that consists of a mixture information of land types. Fig. 4 also shows the general growth stages of winter wheat in Hebei province and the weather data that were used for the WOFOST model simulation. From seeding stage to flowering stage (day of year (DOY) 244–365, 1–120), the WOFOST model was driven by real meteorology data of the current year; the prediction starting date was May 1st, and the 15-day TIGGE forecast data were then used; from May 16th to the end of the growth period, the WOFOST model used similar historical year meteorology data to predict the winter wheat growth.

We used the vectorial angle method to generate the weather forecast data after May 15th, and Fig. 5 shows the meteorological data comparisons for six elements at a sample point. The blue line (weather data from similar historical year) has roughly the same trend as the green line (actual weather data for the current year), which means it can be used, to a large extent, for forecasting the current weather situation.

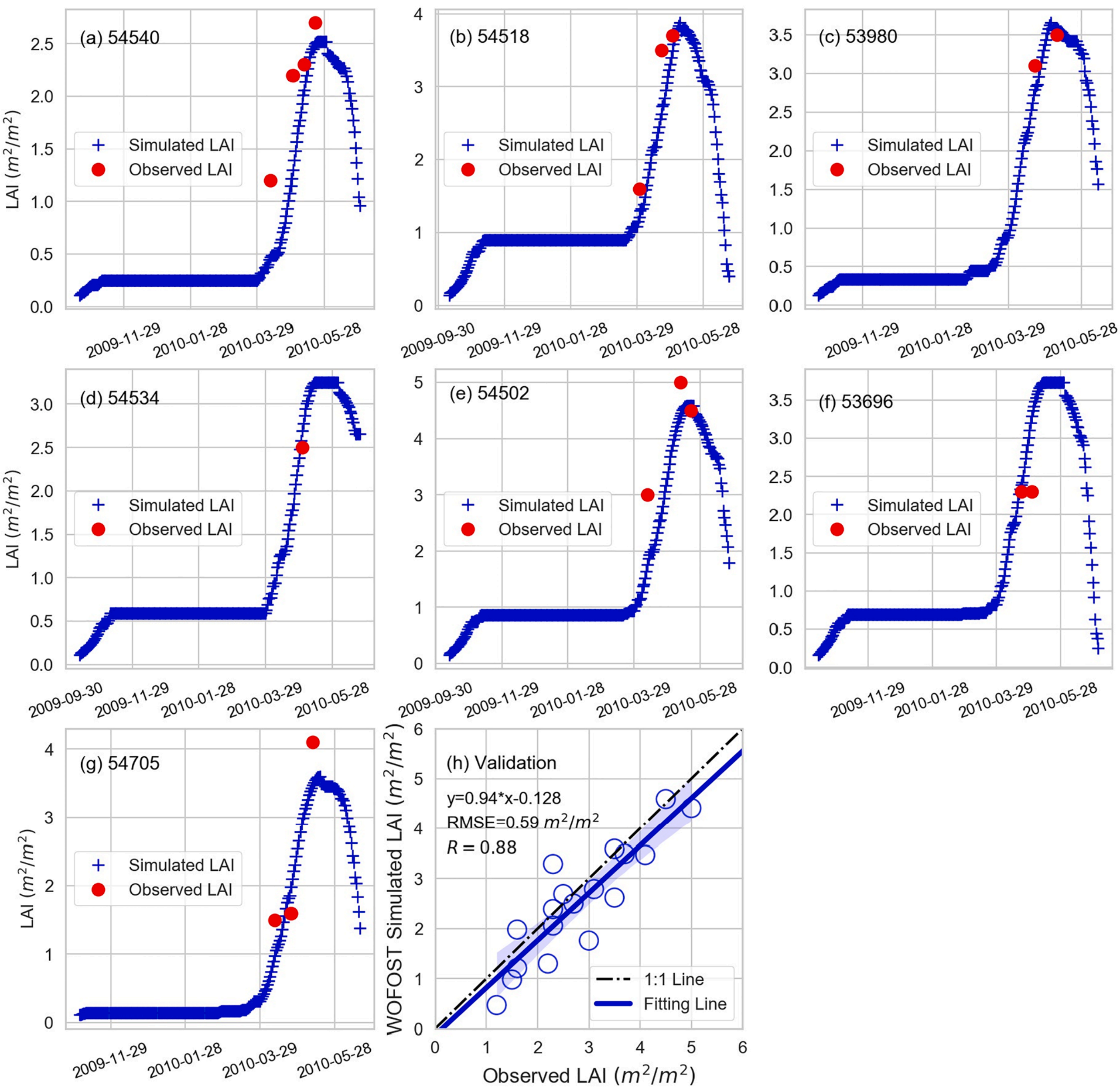

Fig. 6-1. WOFOST simulated and measured winter wheat LAI of agrometeorology stations.

3.2. *Calibration of the WOFOST model*

The winter wheat LAI and Total dry weight of storage organs (TWSO, equals to yield) during winter wheat growing stage of each agrometeorology station in 2010 were simulated by the calibrated WOFOST model, as shown in Figs. 6-1 and 6-2, and were compared with observed site-scale LAI and yield. After the green-up stage, the LAI value continually increased to its maximum value during flowering-heading stage, due to the rapid growth of the wheat leaves and stems in the jointing stage. Then, the LAI values decreased sharply as the leaves turned yellow and withered during maturity stage. Whereas, TWSO began to increase from flowering-heading stage. TWSO increased rapidly during grain-filling stage, and it was approximately stable in maturity stage. Thus, the simulated LAI and TWSO trajectories can effectively reflect the phenological characteristics of the LAI and TWSO during the winter wheat growing season. From the validation results (Fig. 6-1(h) and Fig. 6-2(i)), we found that the WOFOST simulated LAI and TWSO agreed well with the field measured LAI and yield. The correlation coefficient (R) and root mean square error (RMSE) of WOFOST simulated and field measured LAI were 0.88 and 0.59 m^2/m^2, respectively; and they were 0.92 and 672 kg/ha for WOFOST simulated TWSO and field measured yield. These results indicated that the WOFOST model was well calibrated and could simulate the winter wheat growth status in the study area properly.

3.3. *Assimilation of MODIS LAI into the WOFOST model for yield forecasting*

We compared the WOFOST simulated LAI (with and without data assimilation) with the field measured LAI and MODIS LAI. Fig. 7 shows the results of three sample agrometeorology stations. MODIS LAI are relatively low than field measured LAI and WOFOST simulated LAI due to the coarse spatial resolution. The WOFOST simulated LAI have been changed larger to some extent after data assimilation and were closer to field measured LAI than those without assimilation. The possible reason was that the SPAN was optimized to increase after data assimilation,

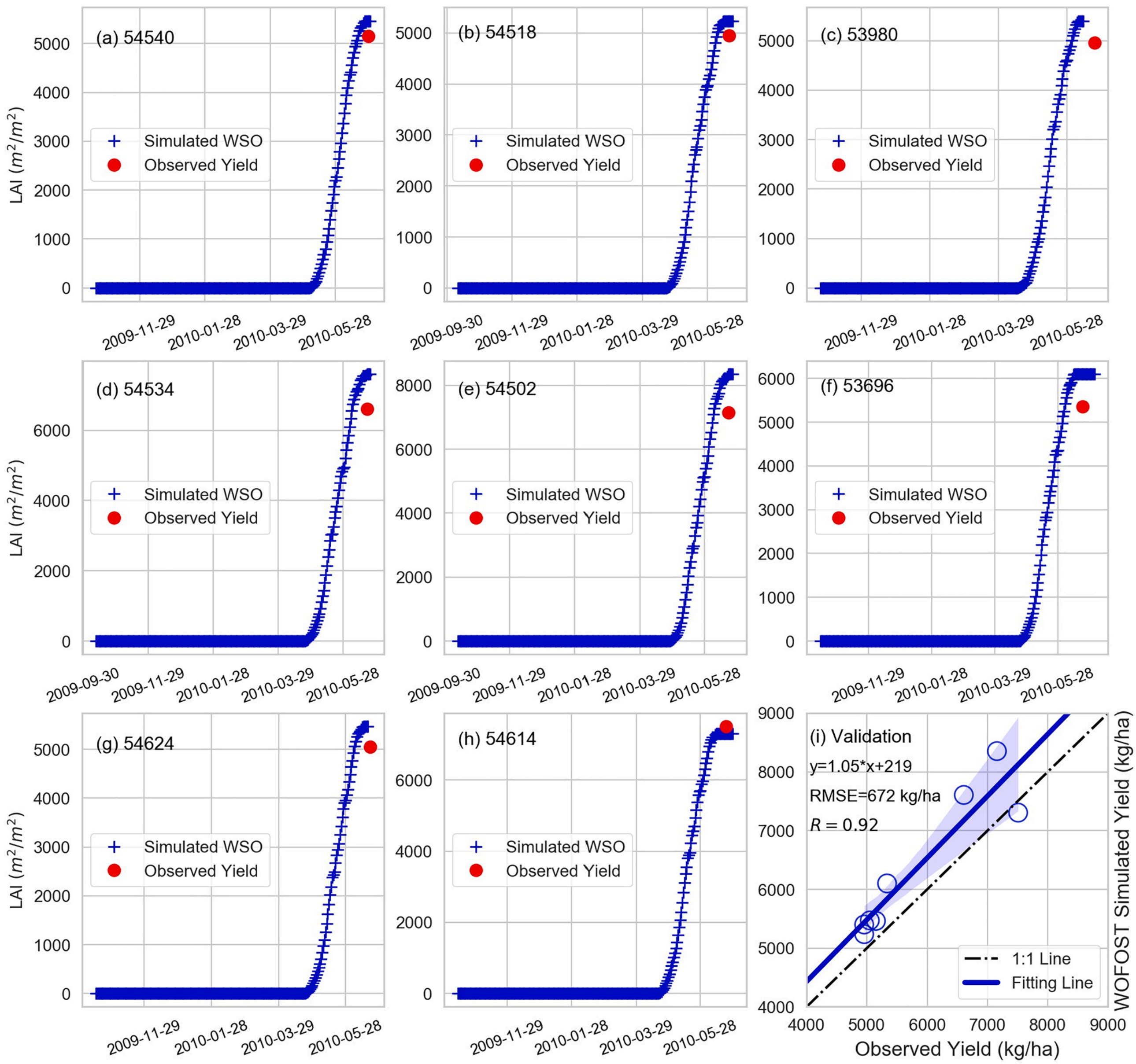

Fig. 6-2. WOFOST simulated TWSO and measured winter wheat yield of agrometeorology stations.

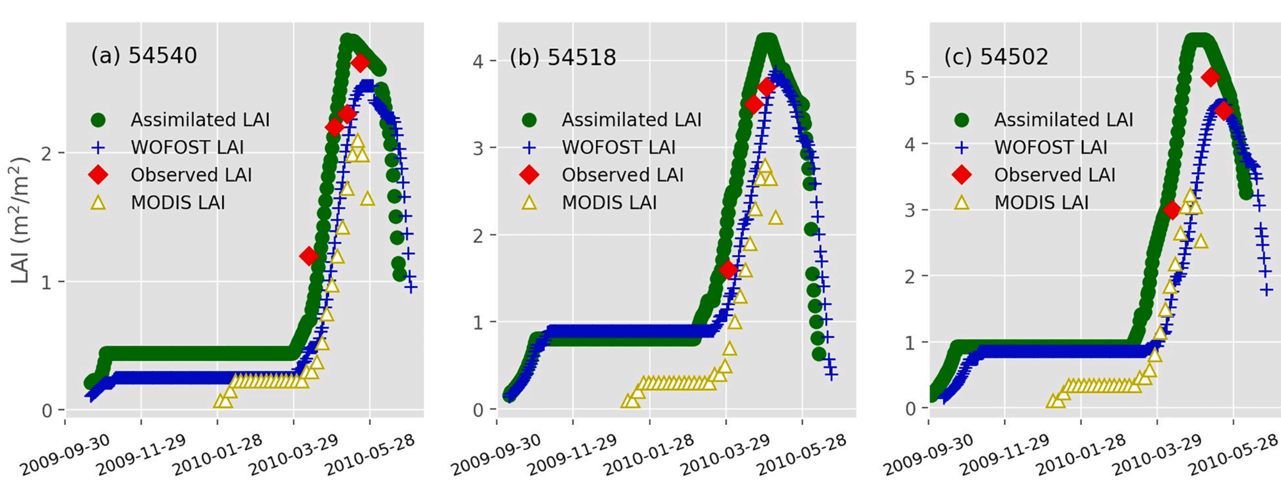

Fig. 7. Comparison of the WOFOST simulated LAI with and without data assimilation in agrometeorology station (a) 54,540, (b) 54,518 and (c) 54,502.

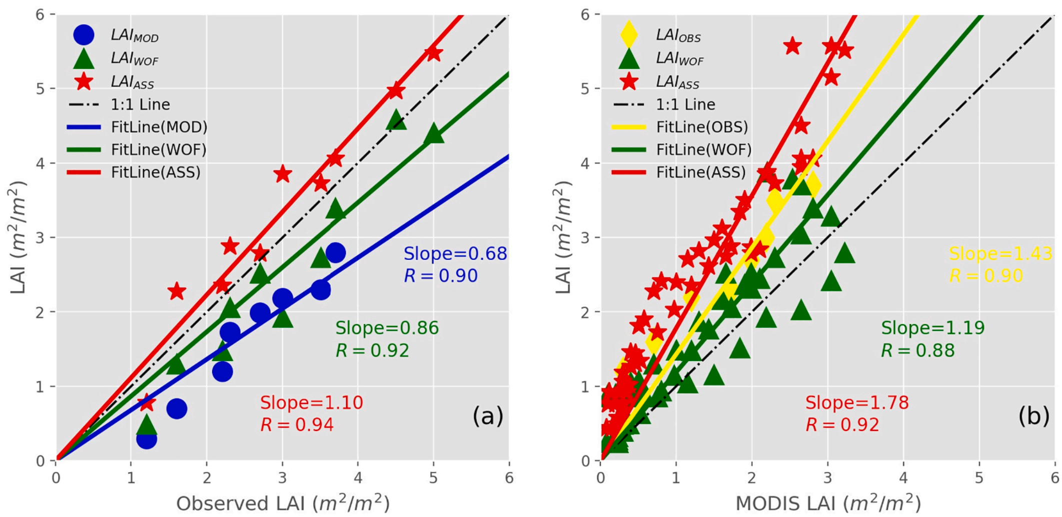

Fig. 8. Correlation between various LAI results at the site scale. (Note: LAI_{OBS} represents field measured LAI, LAI_{MOD} represents MODIS LAI product, LAI_{WOF} represents WOFOST simulated LAI, LAI_{ASS} represents WOFOST simulated LAI after data assimilation).

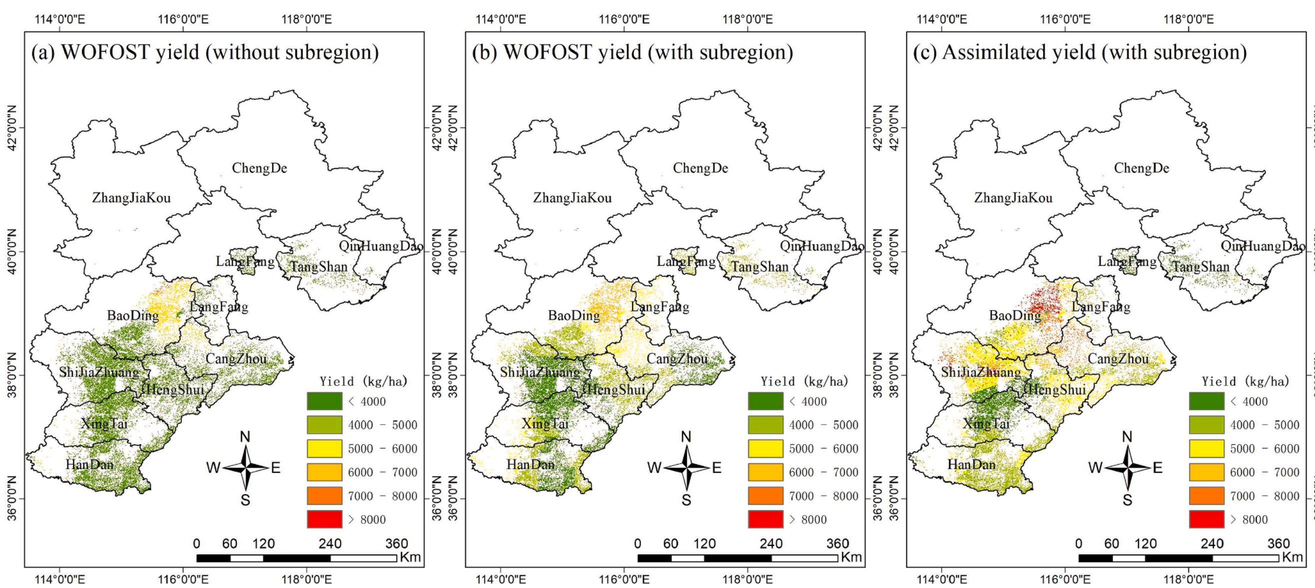

Fig. 9. Regional winter wheat yield estimation with and without data assimilation method in 2010. (a) WOFOST simulated yield using one set of parameters; (b) WOFOST simulated yield using 10 subregions parameters; (c) WOFOST simulated yield after data assimilation.

which can cause the LAI to increase. Fig. 8 shows the correlation between various LAI results at the site scale. MODIS LAI (LAI_{MOD}), WOFOST simulated LAI (LAI_{WOF}) and WOFOST simulated LAI after data assimilation (LAI_{ASS}) were both strongly correlated with the field measured LAI (LAI_{OBS}) with R equal to 0.90, 0.92 and 0.94, respectively (Fig. 8(a)), and the slope of LAI_{ASS} was the closest to 1, followed by LAI_{WOF} and LAI_{MOD}. From Fig. 8(b) we found that LAI_{OBS}, LAI_{WOF} and LAI_{ASS} were generally greater than LAI_{MOD} due to the scale effect that was caused by coarse-resolution of MODIS.

Fig. 9 shows the WOFOST simulation results of winter wheat yield at the regional scale. The spatial variance of the WOFOST simulated yield using calibrated subregion parameters (Fig. 9(b)) was enhanced compared with that when only one set of parameters was used (Fig. 9 (a)). The calibration method that uses subregions takes the spatial differences of crop varieties and soil texture for the study area into account, which causes the simulation results to be more reasonable. The spatial variations in the winter wheat yield results became obvious after data assimilation (Fig. 9 (c)) and showed more realistic spatial variations throughout the study area, which demonstrated the fact that using MODIS LAI data enabled us to account for local conditions and to reduce their uncertainty effects to some extent on the winter wheat yield simulation. However, there are still some boundary effects at the border of each subregion, which may lead to large differences in yield simulation between adjacent plots in these areas.

Fig. 10 displays the RE of the WOFOST simulated winter wheat yield with and without data assimilation for each city. It is clear from Fig. 10 that in most cities, the RE results of the WOFOST simulated yield are higher than those with data assimilation. All RE results of assimilated yield are lower than 30%, and in most cases (35 out of 45), are lower than 20%. However, there are two cases in which the WOFOST simulated yield without data assimilation for Qinhuangdao city in 2011 and for Xingtai city in 2012 exceeded 30%. By comparing the RE results, we found that there were 27 out of 45 cases in which the data assimilation method decreased the model error, and 9 out of 45 cases exhibited relatively similar RE results which indicated that data assimilation had an inconspicuous effect on the model error. However, there were still 9

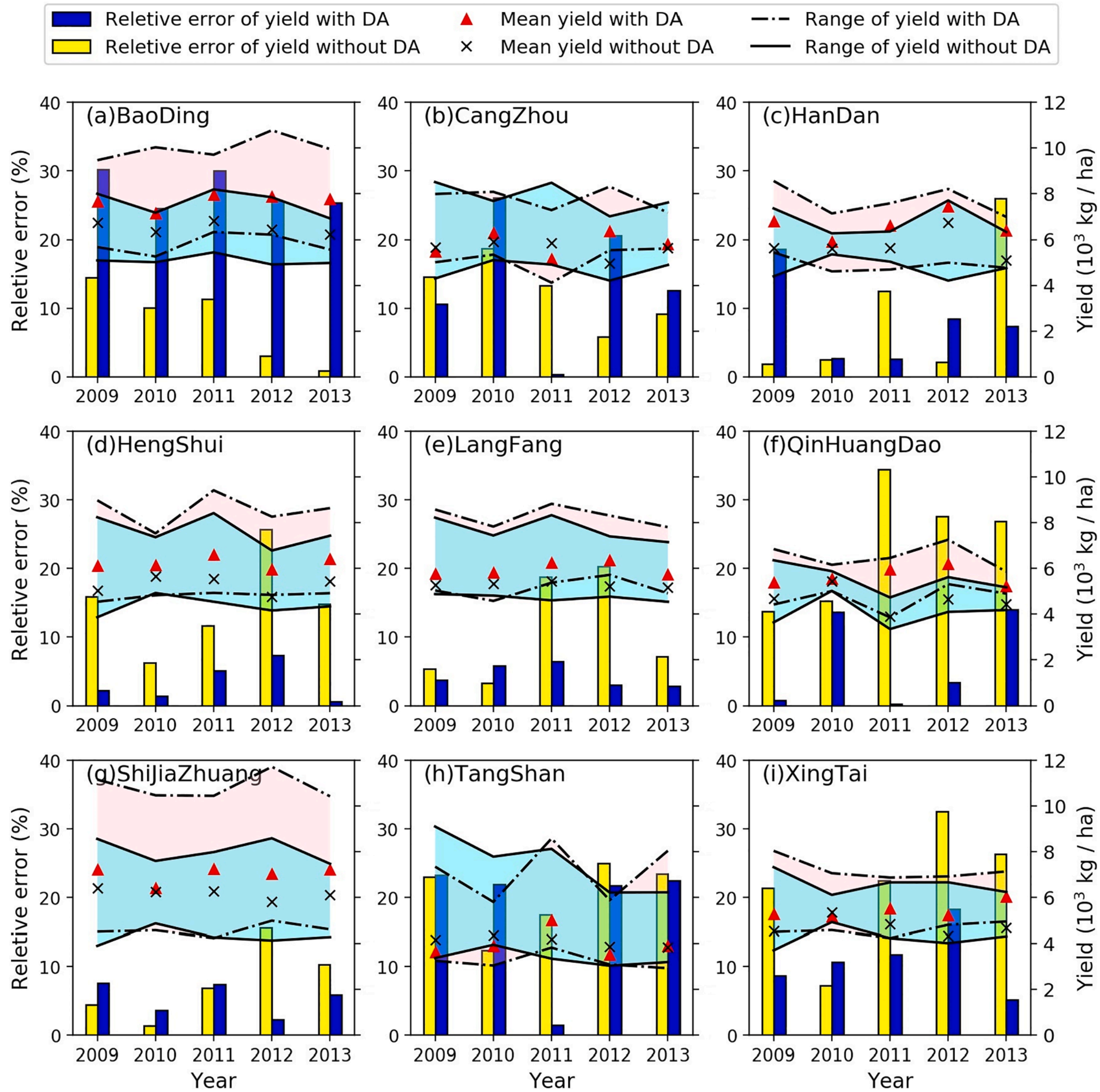

Fig. 10. Relative error of WOFOST simulated winter wheat yield with and without data assimilation during 2009–2013 in (a) Baoding city, (b) Cangzhou city, (c) Handan city, (d) Hengshui city, (e) Langfang city, (f) Qinhuangdao city, (g) Shijiazhuang city, (h) Tangshan city and (i) Xingtai city. (Note: DA represents data assimilation).

out of 45 cases in which the RE results of the assimilated yield were higher than the WOFOST simulated yield and were mainly concentrated in Baoding city. Overall, the results demonstrate the improved performance due to the data assimilation of the MODIS LAI for winter wheat yield forecasting.

The winter wheat yield forecasting results with and without data assimilation method at the city level during 2009–2013 are shown in Fig. 11. This study does not count the results of Chengde and Zhangjiakou, because the winter wheat planting areas are very small in these two cities, and the yield results of each city are the zonal mean values of the yield forecasting results with 500 m spatial resolution. In most cities, the assimilated yield results are generally higher than the WOFOST simulate yield. The general trend is that the northern cities showed lower yield results, especially Tangshan and Qinhuangdao city, and the spatial pattern of the assimilated yield agreed better with official statistical yield in most years when compared with the WOFOST simulated yield results.

We also compared the official statistical yield ($Yield_{Stat}$), WOFOST predicted yield without data assimilation ($Yield_{WOFOST}$) and WOFOST predicted yield with data assimilation ($Yield_{ASS}$) at the city level during 2009–2013 by using histogram (Fig. 12). Fig. 12 clearly shows that the yield results for most cities are in the range of 5000–7000 kg/ha, whereas the $Yield_{ASS}$ values for Baoding city are all greater than 7000 kg/ha and Tangshan city are all lower than 5000 kg/ha in each year. $Yield_{ASS}$ shows a wider yield range than $\mathrm{Yield}_{\mathrm{WOFOST}}$ and $\mathrm{Yield}_{\mathrm{Stat}}$ (Fig. 12(f)), which corresponds to the results of Fig. 9 that assimilating remotely sensed LAI increased the spatial variations for winter wheat yield. The validation results are shown in Fig. 13, and the circle size represents the variance of the pixel yield in each city, the larger the circle is, the greater the variance. The yields without assimilation had a low correlation coefficient and a large error (R = 0.35, RMSE = 857.32 kg/ha) whereas the yields with assimilation had a high correlation coefficient with a lower error (R = 0.60, RMSE = 619.73 kg/ha), besides, the concordance correlation coefficient (CCC) (Lin, 1989) of the yield with assimilation was higher than that without assimilation which indicated that assimilating MODIS LAI improved the accuracy of winter wheat yield forecasting and indicated that this is a feasible method for medium- and short-term winter wheat yield forecasting.

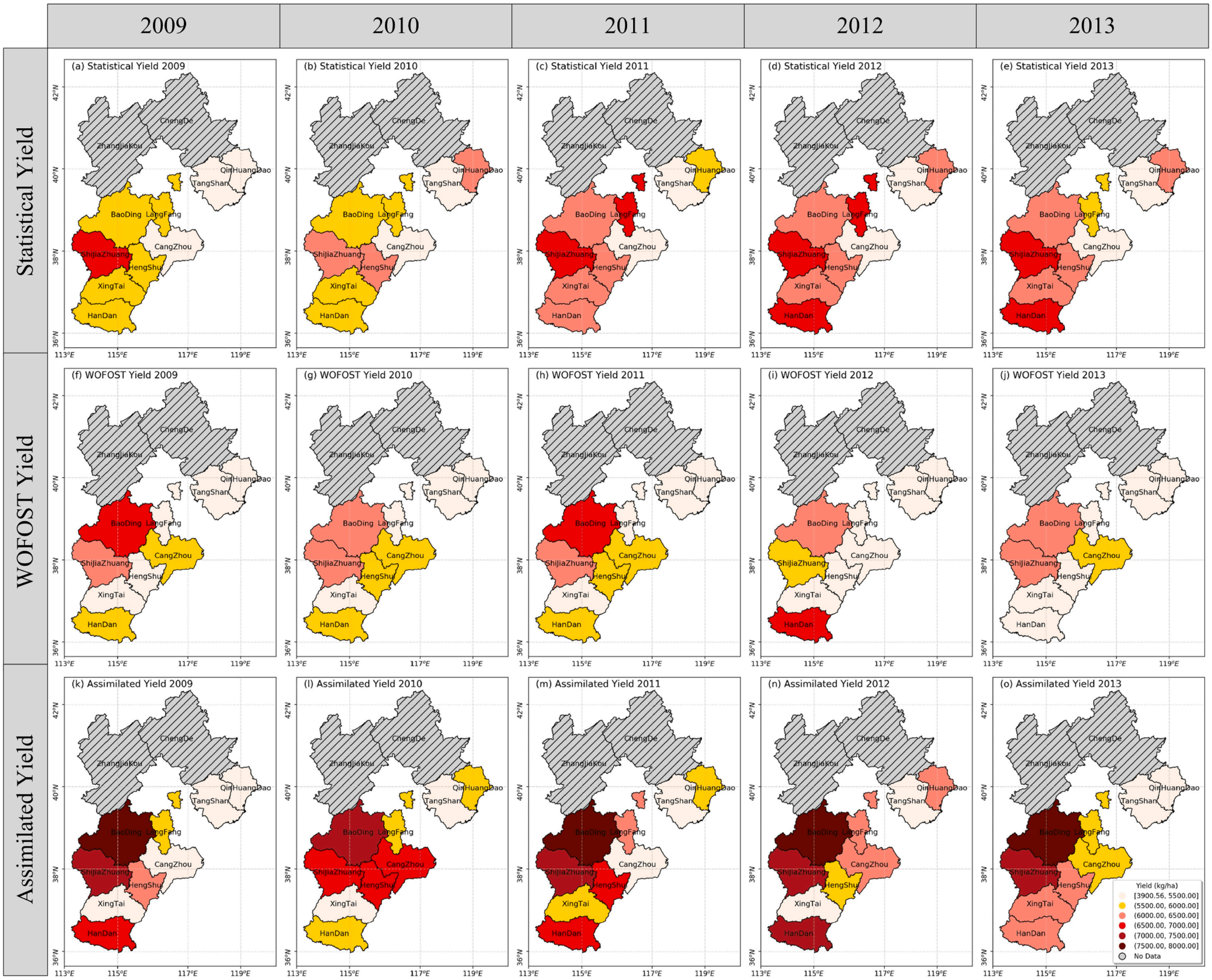

Fig. 11. Winter wheat yield forecasting results with and without data assimilation method at city level during 2009–2013.

4. Discussion

4.1. Accuracy of winter wheat yield forecasting

The winter wheat yield forecasting results were compared and validated by using the official statistical yield data in this study. Substantial cases indicated that the assimilated yields have lower REs than the simulated yields without data assimilation (Fig. 10), which demonstrated that data assimilation method can reduce the model errors in predicting winter wheat yield. These results are consistent with the conclusion of previous studies (Mishra et al., 2021; Xie et al., 2017; Wu et al., 2021). The main reason is that the remotely sensed LAI is a reflection of the real crop growth information, especially irrigation and fertilization which may not have been fully considered by crop models. However, there were still some cases in which the REs increased after assimilating MODIS LAI, especially in Baoding city. The possible reason may be that the winter wheat yield of the subregions in Baoding city were too high when the WOFOST was calibrated. Baoding city consists of 4 subregions: 54,518, 54,502, 54,696 and 54,614. As shown in Fig. 6-2, the WOFOST simulated TWSO of 3 agrometeorology stations in Baoding city were greater than 6000 kg/ha, moreover, the TWSO of 54,502 was higher than 8000 kg/ha (Fig. 6-2 (e)) which may cause the high winter wheat yield forecasting results within this subregion. Fig. 9 (c) clearly shows that the yield results of northeast Baoding were obviously higher than those of other regions. Taking all cities together, the assimilation results significantly improved the winter wheat yield forecasting accuracy compared with the results without assimilation. Overall, these results demonstrated the potential of data assimilation method for winter wheat yield forecasting.

4.2. Comparison of different methods in crop yield forecasting

Crop yield forecasting has been considered to be of profound significance to food security and sustainable agricultural development (Huang et al., 2015b), and there have been many related researches in the past few decades. An advantage of our approach over conventional studies (Dumont et al., 2015; Huang et al., 2020; Ines et al., 2011; Wang et al., 2020) that use crop growth models is that we integrated remotely sensed data and a process-oriented crop model by using data assimilation method, and it can produce more accurate estimates of model outputs. Furthermore, crop model is driven using weather forecast data, which, in this study, consist of TIGGE forecast and historical meteorology data. This method enables us to predict crop yield in advance in the medium- and short-term, which is very useful for agricultural policy makers or smallholders to adjust crop management in time.

Another benefit of our approach is that we divided the study area into several subregions, and each subregion had its own set of crop model input parameters, and this method made the regional crop yield

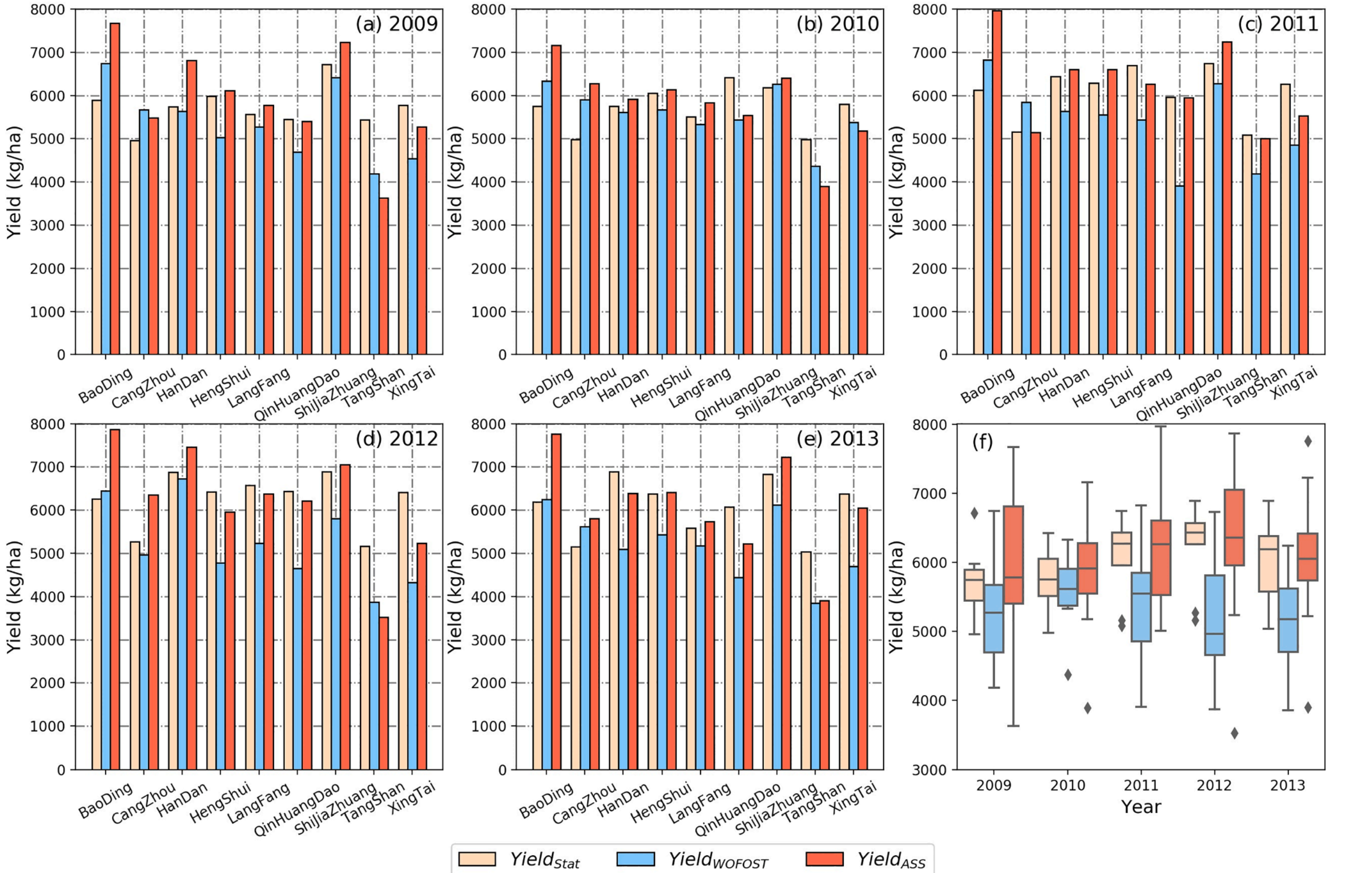

Fig. 12. Comparison of the winter wheat yield results among official statistical yield ($Yield_{Stat}$), WOFOST predicted yield without data assimilation ($Yield_{WOFOST}$) and WOFOST predicted yield with data assimilation ($Yield_{ASS}$) at a city level during 2009–2013.

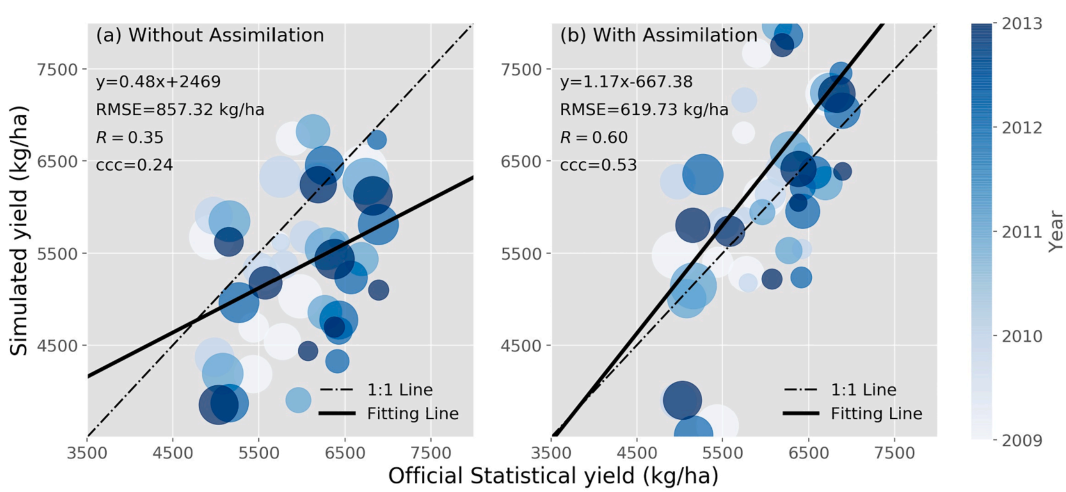

Fig. 13. Comparison between simulated yield ((a) without assimilation (b) with assimilation) and official statistical yield (Note: RMSE represent root mean square error, R represent correlation coefficient, CCC represent Lin's concordance correlation coefficient).

forecasting results more reasonable. Many previous studies on crop yield forecasting with crop model data assimilation methods have only used one set of parameters to drive crop model at the regional scale, they ignored the differences in crop varieties and soil properties over large regions, and the spatial heterogeneity of model outputs were mostly caused by meteorological data. Our regional winter wheat yield forecasting results showed that the spatial variations became obvious when using subregion parameters (Fig. 9(b)) compared with those obtained when using only one set of parameters (Fig. 9(a)), which demonstrated that the WOFOST model calibration can account for the spatial differences in crop varieties and soil properties to some extent by dividing the study area into subregions.

However, the drawback of the current study is obvious that the crop yield prediction accuracy is highly dependent on weather forecast data. On one hand, TIGGE forecasts data itself has uncertainty. On the other hand, the weather forecasts, which are generated by using historical meteorological data through the vectorial angle method, contain certain differences from the actual situation. In addition, the simple Thiessen polygon method for partitioning the study area into subregions needs further improvement to fully consider the spatial variations in crops and soils across the regional scale.

4.3. Sources of uncertainty and the future development

In this study, the MODIS LAI time series was assimilated into the WOFOST model by using a 4DVar cost function, and the SCE-UA was used as optimization algorithm. The selection of reinitialization parameters is crucial in a 4DVar assimilation strategy (de Wit et al., 2012), and we only chose TSUM1, SPAN and IDEM in this study. Other important crop and soil parameters all have great effect on crop LAI and yield, especially the total initial dry weight of the crop (TDWI) (Huang et al., 2019). Therefore, more important parameters may need to be considered within data assimilation scheme in future research for a more reliable crop yield simulation result.

Simulation region partitioning, which make crop model simulation results to be more reasonable at the regional scale by considering the spatial difference of crop varieties and soil properties, is used to separate and cluster a large area into subregions that have relatively consistent crop growth characteristics and environments (Guo et al., 2018). In this study, we divided the study area into subregions using agrometeorology stations based on simple Thiessen polygons. Although this method can account for some spatial variations in crop and soil at the regional scale to some extent, it still has shortcomings. It was essentially based on geographical distance division and using one set of crop and soil parameters of agrometeorological station to represent the corresponding subregion. A more reasonable method that fully consider crop and soil properties is needed for the next step research, which should be based on crop yield level, soil properties, climate conditions and planting structures to achieve simulation region partitioning using spatial clustering method (Guo et al., 2018; Miao et al., 2006; Thorp et al., 2008).

The weather forecast data played a key role in yield forecasting of this study. However, the accuracy of various prediction datasets varies (Zhao et al., 2016), and certain deviation still existed between the forecasting data (Fig. 5) and the real meteorological data. In the present study, we only used the control forecast dataset of ECMWF to test and verify the feasibility of this method for crop yield forecasting, while the 50 perturbed forecast ensembles may be more reasonable by generating 50 crop yield ensembles and using the average value of ensembles to represent the predicted yield (Bougeault et al., 2010). Meanwhile, improvement of weather prediction quality is also needed. Many studies have shown that, in most cases, the integration of the multicenter ensembles based on TIGGE has a better forecasting ability than the single center, and can significantly improve the operational ensemble forecasting accuracy (Bougeault et al., 2010; Johnson and Swinbank, 2009; Khan et al., 2014; Krishnamurti et al., 2009; Park et al., 2008).

The scale effect is always an issue for crop model data assimilation research. Agricultural landscapes in some other places are usually scattered and patchy, which means that low spatial resolution sensors (>250 m) may have large uncertainties in retrieving crop variables due to the mixed information of land surface (Jin et al., 2018). In addition, crop model, which is proposed at the field scale, also has a scale difference with remotely sensed observations. In this study, we used MODIS LAI with 500 m spatial resolution which have large scale issue at the field level, therefore, high spatial resolution observations (e.g., 5–30 m) are needed for the next step research to obtain crop parameters and can effectively reduce the spatial mismatch between crop models and observations.

5. Conclusions

In this study, we used the WOFOST model, TIGGE weather forecast and historical weather data to predict winter wheat yield at the regional scale, and assimilated the MODIS LAI into the WOFOST model by using the 4DVar cost function and the SCE-UA algorithm to improve yield prediction accuracy. Our results indicated that WOFOST model calibration can take into account the spatial differences of crop varieties and soil properties by dividing the study area into subregions, which enhanced the spatial variations and made the simulation results to be more reasonable. Assimilating MODIS LAI into the WOFOST model was able to reduce the errors in winter wheat yield forecasting for most cities in each year. Furthermore, taking all cities together, the assimilation results improved the winter wheat yield prediction accuracy (higher R and lower RMSE) compared with the simulation results without data assimilation. Overall, the assimilation of MODIS LAI into the WOFOST model showed promising results and highlighted the potential of combining TIGGE and historical weather data for medium- and short-term winter wheat yield forecasting, and this method may be adapted to improve other crop yield forecasting in other agricultural regions of the world.

CRediT authorship contribution statement

Wen Zhuo: Conceptualization, Methodology, Software, Writing – original draft. **Shibo Fang:** Conceptualization, Supervision, Resources, Writing – review & editing. **Xinran Gao:** Resources, Visualization. **Lei Wang:** Resources, Software. **Dong Wu:** Resources, Software, Formal analysis. **Shaolong Fu:** Data curation, Visualization. **Qingling Wu:** Writing – review & editing. **Jianxi Huang:** Conceptualization, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jag.2021.102668.

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