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# Winter Wheat Yield Estimation Based on 4D Variational Assimilation Method and Remotely Sensed Vegetation Temperature Condition Index

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**Abstract**: Vegetation temperature condition index (VTCI) combines the main parameters of normalized difference vegetation index (NDVI) and land surface temperature (LST), and is applicable to a more accurate monitoring of droughts in the Guanzhong Plain, Shaanxi, China. VTCI also provides a scientific basis for drought relief and crop yield estimation by using remotely sensed data. This study chose Guanzhong Plain as the study area, and was to combine the remote sensed VTCI and simulated soil surface moisture by the CERES - Wheat (Crop environment resource synthesis for wheat) model to get a high regional yield estimation accuracy by using the four-dimensional variational (4D - VAR) data assimilation approach. The improved analytic hierarchy process, the entropy method and the joint the two weighting methods were used to establish winter wheat yield estimation models by using the monitored VTCI and the assimilated ones respectively. The optimal model for estimating winter wheat yields in the study area from 2008 to 2014 was selected, and the measured wheat yield of the year 2011 was used to validate the accuracies of the optimal model. The results showed that no matter at the sampling sites or at the regional scale, the assimilated VTCIs were all better able to respond the monitored VTCIs and the surface moisture data, and the texture of assimilated VTCI images was better and more consistent with the regional drought distribution. Compared the yield estimation models with the monitored VTCIs, the accuracies of the yield estimation models with the assimilated VTCIs were improved, and the correlation coefficients of the optimal yield estimation model with the weighted VTCIs of 0.784 ($P < 0.001$). The optimal yield estimation model was applied to estimate wheat yields in 29 counties of the Guanzhong Plain, and the results showed that except for the Pucheng County, the estimated yields' relative errors of other 28 counties in Guanzhong Plain were less than 15%, and the errors were less than 10% in 16 counties of Guanzhong Plain. In general, the average relative error of the estimated yields was 8.68%, and the root mean square error was 421.9 kg/hm$^2$, indicating the optimal yield estimation model had a better performance. The yearly estimated yields from 2008 to 2014 were in an increasing trend with fluctuation in Guanzhong Plain. For the spatial distribution of the yields, the yields were the highest in the central of Guanzhong Plain, and the yields in the west were higher than those in the east.

**Key words**: winter wheat; vegetation temperature condition index; 4D - VAR; assimilation; crop growth model; yield estimation

## 0 Introduction

Winter wheat is one of the most important food crops in China. It is a great significance to the effective control of food production and agricultural production and to guide government departments to develop a scientific and rational food policy for crop yield estimation and forecasting timely and accurately[1-2]. Recently, the combination of remotely sensed data and crop growth model becomes one of the current crop yield estimation research topics and an important part of the research trends. On the one hand, remotely sensed data can monitor crop growth status over a large area, on the other hand, crop growth models can reflect the dynamic crop growth and development by computer simulation, and data assimilation methods are capable of combining remotely sensed information and crop growth models, which can solve the problem encountered in the application of crop growth models from a single point to a large area[3-7]. Variational

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data assimilation algorithms and sequential assimilation algorithms are the commonly used data assimilation methods[8]. Compared with the three-dimensional variational (3D – VAR) algorithm, the four-dimensinal variational (4D – VAR) algorithm considers the background field of information changes over time, therefore, the 4D – VAR algorithm is better reflect the complex non-linear constraints[9-11]. XIE et al.[12] applied the 4D – VAR and the ensemble Kalman filter (EnKF) algorithm to assimilate leaf area index (LAI) using both the simulated LAI by the CERES – Wheat (Crop environment resource synthesis for wheat) model and the retrieved LAI by remotely sensed data, and extended the scale from a single point to a regional level. Their results showed that the assimilated LAI values were more accurate and closer to the real ones after combining the advantages of both the remotely sensed LAI and simulated LAI. A 4D – VAR data assimilation system was developed for assimilating ocean observations with the navy coastal ocean model by NGODOCK[13], and the assimilation system was tested in a series of twin data experiments to assess its ability to fit assimilated and independent observations by controlling the initial conditions and the external forcing while assimilating surface and subsurface observations. It was shown that the assimilation system generally fitted the assimilated and non-assimilated observations well in all experiments, and improved the observation accuracy and reduced the prediction errors.

WANG et al.[14], developed the vegetation temperature condition index (VTCI) for drought monitoring based on the assumption that the scatter plot of the land surface temperature (LST) versus the normalized difference vegetation index (NDVI) falls into a triangular shape over a large area. It was testified that the VTCI can be used to effectively monitor the droughts of an area in the real time, and successfully applied to the drought forecasting and impact assessment and crop yield estimation and prediction[15-16]. Most previous studies of crop yield estimates using the data assimilation approaches often only used a given year remotely sensed data for crop yield estimates, which was lack of analysis with remotely sensed data and assimilation algorithms between crop yields in years and annual yield differences in the role of estimates[17]. Combination forecast is based on information contribution of each model, giving different weights, and then a combination of a single prediction was applied, thereby the prediction errors were reduced and the prediction accuracy was improved[18]. The weights were often determined by using objective or subjective weighting methods[19], and cannot reflect the subjective wish and objective regulation at the same time. This study took the Guanzhong plain as the study area and the years from 2008 to 2014 as the study period. The retrieved VTCIs were selected as the assimilation system state variable. The 4D – VAR data assimilation approach was applied for assimilating the retrieved VTCI and the simulated soil surface moisture by the CERES – Wheat model. The improved analytic hierarchy process, the entropy method and joint the two weighting methods were used to establish winter wheat yield estimation models by using the monitored VTCIs and the assimilated ones respectively, and the measured wheat yields of the year 2011 was used to validate the accuracy of the developed models.

## 1 Materials and methods

### 1.1 Study area

The Guanzhong Plain is located in the central Shaanxi Province, China (106°22′E to 110°24′E and 33°57′N to 35°39′N). With Baoji City in the west, Tongguan City in the east, Qinling Mountains in the south, and the northern Shaanxi Plateau in the north, the plain includes Xi’an, Baoji, Xianyang, Weinan and Tongchuan Cities and Yangling Demonstration Zone (Fig. 1). This region has flat terrain, fertile soil, high wheat production and it is a key grain production area in Shaanxi Province. The prevailing cropping pattern is winter wheat in rotation with summer maize. The plain has a continental monsoon climate, and is located in the transition zone between the semi-humid climate and semi-arid climate in warm temperate. The average annual rainfall ranges from 500 mm to 700 mm. Since the 1990s, the climate becomes warming and drying significantly in overall, and warm spring, warm winter, spring drought and summer drought become even more significant[20], and it has significantly performance in agricultural drought disaster in terms of food production.


Fig. 1 Map of study area

## 1.2 Data

Vegetation temperature condition index (VTCI) was proposed for monitoring drought based on the remotely sensed NDVI and LST, with the assumption that the scatter plot of NDVI versus LST falls into a triangular shape over a large area. The Aqua-MODIS surface reflectance products (MYD09GA) and land surface temperature products (MYD11A1) were used to calculated daily NDVI and LST in the Guanzhong Plain, the daily NDVI and LST were used to compose the maximum NDVI and LST at the ten-day intervals by using the maximum value composite technique, and the composited NDVI and LST were used to calculate VTCI[14,21]. About 12 typical sampling sites with wheat-growing were selected in the plain from 2008 to 2014, namely, north of Chencang District, north of Fufeng County, west of Fengxiang County, Wangcun of Heyang County, Shijia of Lantian County, Lindian of Linwei District, Changxing of Meixian County, Yaoshan of Pucheng County, Sunzhen of Pucheng County, Pucun of Qishan County, Shiniu of Qian County and Luqiao of Sanyuan County. The north of Fufeng County, Lindian of Linwei District, Changxing of Meixian County and Luqiao of Sanyuan County were irrigated sampling sites, and the others were rain-fed sampling sites. The pixel coordinates of the sampling sites on the remotely sensed VTCI images were calculated based on latitude and longitude of the sites, and the average VTCI values at the sampling sites were obtained from VTCIs of the central pixels with 3 pixels × 3 pixels around from major winter wheat growth period (March—May) in each year, and used as observation data at the regional scale. The data assimilation process used the CERES-Wheat model as the dynamic simulation model, which is one of modules of the decision support system for agro-technology transfer (DSSAT). Before the CERES-Wheat model was applied to the study area, the genetic parameters has to be calibrated, and the performance of the calibration has to be evaluated through field measurements, such as LAI, biomass, yields and harvest dates[22], the single point assimilation test and the regional scale assimilation test were conducted by using the 4D - VAR method after the calibration. Since the simulated VTCI cannot be obtained by the crop growth simulation model directly, but our previous studies found there were significant correlations between VTCI and soil surface water contents at 0 ~ 20 cm from March to May in the plain[23]. Therefore, the specific method for getting the simulated VTCIs of this study were as follows: getting the soil moisture contents (0 ~ 20 cm) by driving the model, building the regression model by using the ten-day average moisture data and the observed VTCIs during the main growth period of winter wheat, and calculating the ten-day simulated VTCIs by using the regression model.

## 1.3 4D - VAR algorithm

The four-dimensional variational assimilation algorithm (4D - VAR) defines a time window $T$ for the assimilation, all the observation data and the simulated status values of the assimilation window were used for the optimal estimation. The model initial field was adjusted constantly by an iterative method, and trajectory of the simulated parameters was fitted into all observations within the period in the assimilation window. The quantity of state at any time $t$ was obtained based on all observations on the optimization model predictions. Because of the errors of the model itself, the more the number of the observations which introduced once in the assimilation window, the higher assimilation accuracy in the variational algorithm, however, the computational cost was increased at the same time[24].

The selected cost function of the four-dimensional variational algorithm is

$$J(\boldsymbol{V}_0) = 0.5\,(\boldsymbol{V}_0 - \boldsymbol{V}_0^b)^{\mathrm{T}}\boldsymbol{B}^{-1}(\boldsymbol{V}_0 - \boldsymbol{V}_0^b) + 0.5\sum_{i=0}^{n_1}(\boldsymbol{H}_i(\boldsymbol{V}_i) - \boldsymbol{V}_i^{obs})^{\mathrm{T}}\boldsymbol{O}_i^{-1}(\boldsymbol{H}_i(\boldsymbol{V}_i) - \boldsymbol{V}_i^{obs}) \tag{1}$$

Where $\boldsymbol{V}_0$ is state vector of the assimilation window at the initial time; $\boldsymbol{V}_0^b$ is background VTCI values at the initial time, that is the simulated VTCI values at the initial time; $\boldsymbol{V}_i$ is background values at the moment $t$ which are the calculated by imputing $\boldsymbol{V}_0$ into the model operator $M$; $\boldsymbol{V}_i^{obs}$ is observed VTCI values at the moment $t$; $\boldsymbol{B}$, $\boldsymbol{O}_i$ are simulated error covariance matrix and observed error covariance matrix; $\boldsymbol{H}_i$ is observation operator; $n$ is ten-day VTCI number of the iterative assimilation window.

The specific operation process of the assimilation system can be briefly described as: firstly, defining the ten-day number $n$ of the iterative assimilated window for calculating the simulated error covariance matrix $\boldsymbol{B}$, observed error covariance matrix $\boldsymbol{O}_i$ and $\boldsymbol{V}_i$ ($i=1,2,\cdots,n$), and then substituting into cost function Eq. (1). Based on the past experience, about 3% of the observed values were set as the observed coarse errors. The gradient method was used to minimize the cost function, and $\boldsymbol{V}_0$ became the initial time optimal when the function $J(\boldsymbol{V}_0)$ was in its minimum value, that was the assimilation value of the initial time $\boldsymbol{V}_0$. Then the assimilation window entered into the next moment, the above process was repeated, and the assimilation was ended until all the observations were introduced.

## 1.4 Winter wheat yield estimation method and accuracy assessment

### 1.4.1 Improved analytic hierarchy process

The main growth stages for winter wheat include the green-up stage (from early March to mid-March), the jointing stage (from late March to mid-April), the heading-filling stage (from late April to early May) and the milk stage (from mid-May to late May)[25]. According to the degree of drought impact on wheat grain yield at different growth stages, the comparison matrix $\boldsymbol{B}(b_{mn})$ was established as follow

$$\boldsymbol{B}(b_{mn}) = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 2 & 1 & 2 & 2 \\ 2 & 0 & 1 & 2 \\ 2 & 0 & 0 & 1 \end{pmatrix} \tag{2}$$

Where, 0 represents the growth stage $m$ is less important than the growth stage $n$, 1 represents the growth stage $m$ is equally important with the growth stage $n$, and 2 represents the growth stage $m$ is more important than the growth stage $n$.

$$r_n = \sum_{m=1}^{4} b_{mn} \tag{3}$$

The judgment matrix $c_{mn}$ and Quasi optimal consistent judgment matrix $\boldsymbol{C}(c_{mn})$ were calculated by considering the important coefficients at the four stages in the Guanzhong Plain.

$$c_{mn} = \begin{cases} (k-1)\dfrac{r_m - r_n}{r_{\max} - r_{\min}} + 1 & (r_m \geqslant r_n) \\ \left[(k-1)\dfrac{|r_m - r_n|}{r_{\max} - r_{\min}} + 1\right]^{-1} & (r_m < r_n) \end{cases} \tag{4}$$

$$\boldsymbol{C}(c_{mn}) = \begin{bmatrix} 1 & 1/7 & 1/5 & 1/3 \\ 7 & 1 & 3 & 5 \\ 5 & 1/3 & 1 & 3 \\ 3 & 1/5 & 1/3 & 1 \end{bmatrix} \tag{5}$$

Where, $r_{\max} = \max\{r_n\}$, $r_{\min} = \min\{r_n\}$, and $k = \dfrac{r_{\max}}{r_{\min}}$.

Normalized the Quasi optimal consistent judgment matrix, and then got the weights at different growth stages of winter wheat.

### 1.4.2 The entropy method

Construction of data matrix $\boldsymbol{A}(a_{mn})_{N\times 4}$ by using the VTCI data of the four growth stages ($n$) in the study area from 2008 to 2014, Calculated the entropy of each growth stage $h_n$[26], as follow

$$h_n = -\frac{1}{\ln N}\sum_{m=1}^{N}\left(\frac{a_{mn}}{\sum_{m=1}^{N} a_{mn}} \ln \frac{a_{mn}}{\sum_{m=1}^{N} a_{mn}}\right) \quad (n=1,2,3,4) \tag{6}$$

Where $N$ is total number of the selected years in the study.

Calculated the difference coefficient $g_n$ of the stage $n$, and normalized them for getting the weight $w_n$ of stage $n$, as follows

$$g_n = \frac{1-h_n}{4-\sum_{n=1}^{4} h_n} \quad (n=1,2,3,4) \tag{7}$$

$$w_n = \frac{g_n}{\sum_{n=1}^{4} g_n} \quad \left(0 < w_n < 1,\ \sum_{n=1}^{4} w_n = 1\right) \tag{8}$$

### 1.4.3 Combination weighting method

The combination weighting method integrates the improved analytic hierarchy process and the entropy method effectively, and the basic principle is to find a weight that can obtain largest distance between the subjective weight determined by the improved analytic hierarchy process and the objective weight determined by the entropy method effectively. Assuming that the weight determined by the subjective weighting method is $\boldsymbol{W}^1 = [w_1^1 \quad w_2^1 \quad w_3^1 \quad w_4^1]$, the weight determined by the objective weighting method is $\boldsymbol{W}^2 = [w_1^2 \quad w_2^2 \quad w_3^2 \quad w_4^2]$, and the weight determined by the combination weighting method is $\boldsymbol{W} =$

$[w_1 \quad w_2 \quad w_3 \quad w_4]$, in order to make the combined weight close to the subjective and objective weights, the constructed optimization model should meet condition as follow[25]

$$y = \max \sum_{k=1}^{2} \left(1 - \sqrt{\frac{1}{n}\sum_{n=1}^{4} (w_n - w_n^k)^2}\right) \quad (9)$$

$$\sum_{n=1}^{4} w_n = 1 \quad (10)$$

The model was used to calculate the combined weight $\boldsymbol{W}$.

**1.4.4 Calculation of the weighted VTCI and development of the yield estimation model**

The county boundary map of Shaanxi was overlapped with and the remotely sensed VTCI images, and the VTCI values of the counties (districts) in the Guanzhong Plain were calculated. According to the method for calculating VTCI, VTCI time series data at ten-day intervals were obtained during major winter wheat growth period (March—May) from 2008 to 2014. The average VTCI of a county was calculated by averaging the VTCIs of all pixels in the county (district) at the ten-day intervals, respectively. The VTCI of each growth stage of wheat was the average value of VTCIs at the ten-day intervals belonging to the stage at the county level. The weighted VTCIs and the assimilated ones during the main growth stage for all counties in the plain were calculated by using the improved analytic hierarchy process, the entropy method and the combination weighting method, respectively. The linear regression analysis was applied to study the correlations between the weighted VTCIs and the wheat yields, and the correlation with the highest correlation coefficients was selected as the yield estimation model (because of the measured wheat yields of the year 2011 were used to validate the accuracy of the estimation model, the data of each county in 2011 were not employed to establish the model).

## 2 Results and analyses

### 2.1 Assimilation results and analyses

To obtain the remotely sensed VTCI values at the ten-day intervals from March to May in the years from 2008 to 2014 in the 12 sampling sites, the VTCI values of 3 pixels × 3 pixels adjoining to the coordinates of a sampling site were averaged as the VTCI values of the site which was regarded as the observed VTCI. An empirical regression model was established by employing the linear regression analysis between the observed VTCIs and the measured soil surface water contents at the sampling sites, and then was used to calculate the simulated VTCIs at the sites. The assimilated VTCIs were obtained by using the 4D-VAR assimilation algorithm and the simulated VTCIs. In order to verify whether the assimilation results at the sampling sites better responded to the external observation data, a linear regression analysis was conducted between the assimilated VTCIs and observed VTCIs in the years from 2008 to 2014 in the 12 sampling sites (Fig. 2). The results showed that the assimilated VTCIs and the observed ones were more consistent in overall, the correlation coefficient was 0.660 ($P < 0.001$), and the root mean square error (RMSE) between assimilated VTCIs and the observed VTCIs was 0.016.

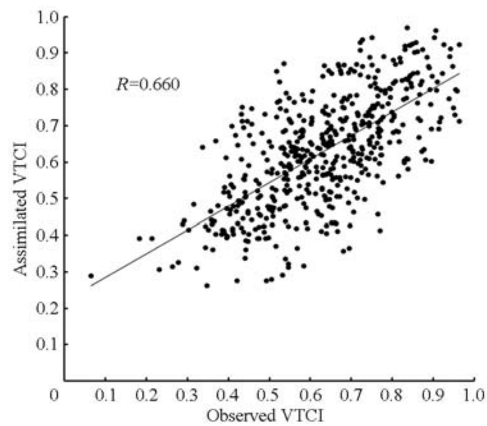


Fig. 2 Correlation between the observed VTCIs and the assimilated VTCIs using the 4D-VAR

It is testified that the VTCI can be used to effectively monitor the drought over a large area in the real time, and has a significant correlation with precipitation. To further validate whether the assimilated VTCIs at the sampling sites were better correlated with precipitation, the sampling site of Shiniu of Qian County was taken as an example. The scatterplots between the observed VTCIs and assimilated VTCIs and precipitation at the ten-day interval were shown in Fig. 3. In general, the temporal change trends of the observed VTCIs and the assimilated ones were similar to those of the precipitation, and the changes of the assimilated VTCIs were improved compared to those of the observed ones. The precipitation amounts of the early March in 2009, early May in 2010, and early April in 2012 are all zero, the original observed VTCIs were 0.97, 0.60 and 0.93, while the assimilated VTCIs were adjusted to 0.31, 0.42 and 0.27, and the assimilation made more substantial adjustment on the basis of the original observation which were too larger, so that it could be better integrated with the precipitation data. The precipitation of the late May in 2013 is more than 60mm, and the assimilated VTCI value was about 0.9 which did not belong to the scope of drought. Compared with the unassimilated (observed) VTCIs, the assimilated ones of the late April in 2009, mid-May in 2009, late March in 2011 and early May in 2013 were all had different degrees of the adjustment that made the results reflected the actual situation better.

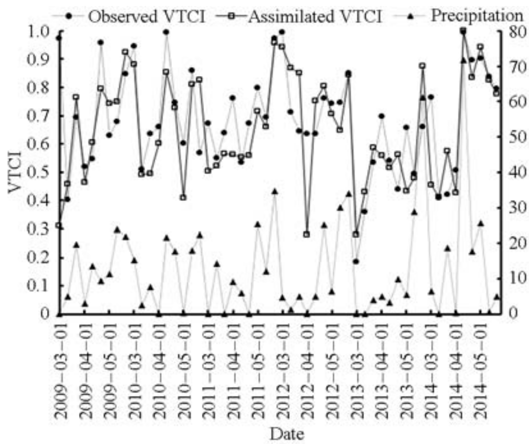


Fig. 3 Observed VTCIs and assimilated VTCIs by using the 4D – VAR and precipitation

Assuming that the 12 sampling sites can represent of the Guanzhong Plain, this was because that the selected sites are more evenly distributed throughout the study area, the linear regression equation between the assimilated VTCIs and the observed VTCIs was established, and by this way, regional scale assimilated VTCI products were achieved for the ten-day intervals in the years from 2008 to 2014. The regional assimilated VTCIs and observed VTCIs at the last ten-day interval in the years of 2012, 2013 and 2014 were selected and compared (Fig. 4), and were also compared with the precipitation data provided by the Shaanxi Provincial Meteorological Bureau. In general, the palin has rare rainfall in late March of 2012 (Figs. 4a and 4b), and the droughts obviously occurred in the plain. As shown in the assimilated VTCI image (Fig. 4b), the VTCI values were generally around 0.5 which belongs to the mild drought category. There is almost no precipitation in late March of 2013 in central of the plain, such as Xianyang City and Xi'an City, we could see from the images (Figs. 4c and 4d) that the regional observed VTCI values were about 0.7 which belongs to the no-drought category, while the assimilated ones were adjusted to the scope of the moderate category (about 0.45). Therefore, the assimilation results could make the actual situation

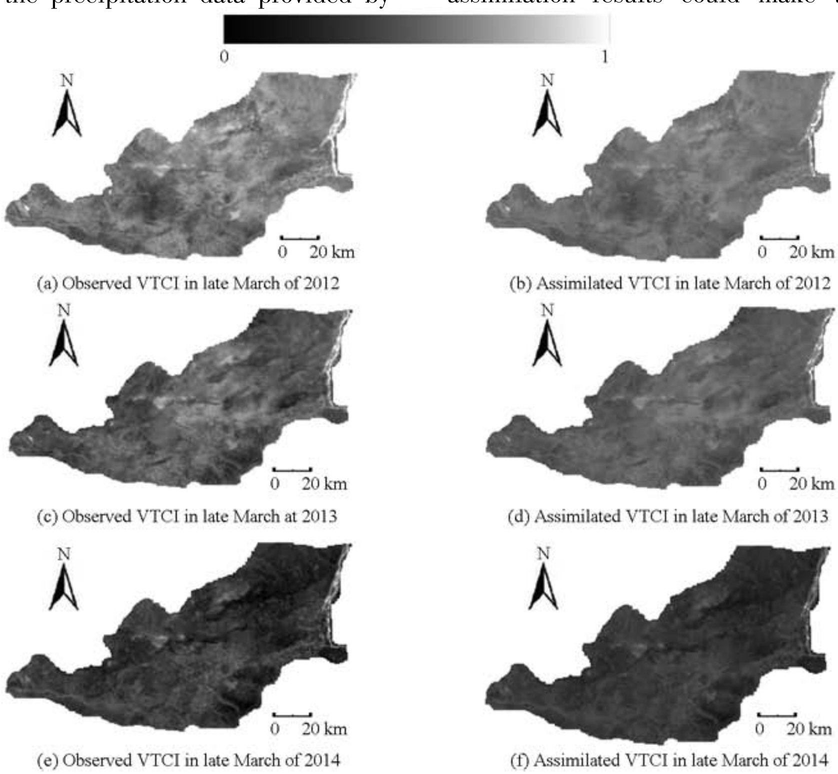


Fig. 4 Observed VTCIs and assimilated VTCIs using the 4D – VAR at regional scale

adjustments no matter in the whole or in the local. In addition, compared with the observed VTCIs, the assimilated VTCI values around neighboring pixels are more smoother, and the whole images had better texture because the assimilated VTCIs integrated the simulated VTCIs and the observed ones (Figs. 4d and 4f). Compared with the observed ones, the sharp changes in the assimilated VTCIs decreased (Figs. 4c and 4e), and the texture of the assimilated VTCI images was better.

## 2.2 Regional yield estimation and validation

Tongchuan City locates in the transition zone between the Guanzhong Plain and the Loess Plateau, and the winter wheat area is relatively small and mainly grown in Weibei tableland which is in the city's southern part[25], therefore, this study chose the 29 counties (districts) in the plain (except counties in the Tongchuan City) as the study area for the winter wheat yield estimation. The weights of droughts at different growth stages of winter wheat on wheat grain yields were obtained using the improved analytic hierarchy process, the entropy method and the combination weighting method (Tab. 1). Based on agronomic knowledge, the weights determined by the improved analytic hierarchy process and the combination weighting method were more reasonable, this was because that the jointing and the heading-filling stages are the transition stages of winter wheat from the vegetative stages to reproductive stages, which is the critical period of winter wheat yield formation, and in these stages winter wheat requires a lot of water and nutrients. If droughts occur at the jointing and the heading-filling stages, the final yields will be affected directly. Little weights were assigned to the reviving stage and the dough stage, this was because that the water stress of these two stages had limit effect on the wheat growth and yield, and were not particularly obvious. Roots, leaves and tillers of winter wheat grow mainly at the reviving stage, so water should not need too much. The grain structure often forms at the dough stage, and winter wheat shows a strong tolerance to a certain water deficit at this stage. In summary, the degree of water stress at the reviving and dough stages had less effect on yield relatively.

Based on the weights listed in Tab. 1 and the observed and assimilated VTCIs in the main growth stages of winter wheat (Year 2008 – 2014, except 2011), the weighted VTCIs of each county (district) were calculated respectively, the linear regression analysis between the weighted VTCIs and wheat yields was applied to establish the yield estimation models, and the models were also validated (the last three columns of Tab. 1).

**Tab. 1 Weights of monitored VTCIs and assimilated ones at the key growth stages of winter wheat and yield estimation models**

| Weighting method | VTCI | Reviving stage | Jointing stage | Heading-filling stage | Dough stage | Yield estimation model | Correlation coefficient $R$ | Significant test |
|---|---|---|---|---|---|---|---|---|
| Improved analytic hierarchy process | Observed | 0.055 | 0.564 | 0.263 | 0.118 | $y = 8\,619x - 1\,138.2$ | 0.561 | $P = 0.017$ |
| | Assimilated | 0.055 | 0.564 | 0.263 | 0.118 | $y = 13\,896x - 4\,491.3$ | 0.630 | $P = 0.011$ |
| Entropy method | Observed | 0.247 | 0.252 | 0.251 | 0.250 | $y = 7\,979x - 722.4$ | 0.521 | $P = 0.137$ |
| | Assimilated | 0.206 | 0.295 | 0.255 | 0.244 | $y = 12\,632x - 3\,680.0$ | 0.565 | $P = 0.025$ |
| Combination weighting method | Observed | 0.051 | 0.450 | 0.356 | 0.143 | $y = 10\,695x - 2\,536.3$ | 0.669 | $P < 0.001$ |
| | Assimilated | 0.043 | 0.487 | 0.362 | 0.108 | $y = 14\,490x - 5\,009.8$ | 0.784 | $P < 0.001$ |

Note: $y$ and $x$ mean the estimated yield and weighted VTCI.

From Tab. 1, the correlation coefficients of the yield estimation models based on the assimilated VTCIs were all higher than those based on the observed ones, indicated that the estimated yields had better accuracy based on the assimilated VTCIs. No matter the observed VTCIs or the assimilated ones, the estimation models constructed from the combination weighting method were better than those constructed from the improved analytic hierarchy process and the entropy method, and the correlation coefficients were up to 0.669 and 0.784 respectively, which were at a significance level of 0.01 ($P < 0.001$). Compared the yield estimation model with the observed VTCIs, the accuracy of the yield estimation model with the assimilated VTCIs was improved, so we chose this model as the optimal yield estimation model for wheat yield estimation. In order to verify the accuracy of the estimation model, the wheat yields were estimated in 2011 in the 29 counties (districts) of the Guanzhong Plain application, and the relative errors and the root mean square errors (RMSE) between the estimated yields and the field measured yields were used to validate the accuracy. Results showed that the relative errors were less than 10% in 16 counties of the plain, such as Changan District, Lantian County and Liquan County. The actual yield of Chang'an District was 4 254 kg/hm$^2$, the estimated yield was 4 399 kg/hm$^2$, and the relative error was 3.4%; the actual yield of Hu County was 5 001 kg/hm$^2$, the estimated yield was 5 074 kg/hm$^2$, and the relative error was 1.5%; the actual yield of Qian County was 4 356 kg/hm$^2$, the estimated yield was 4 430 kg/hm$^2$, and the relative error was 1.7%; the actual yield of Xingping City was 4 664 kg/hm$^2$, the estimated yield was 4 826 kg/hm$^2$, and the relative error was 3.5%; the actual yield of Fuping County was 3 693 kg/hm$^2$, the estimated yield was 3 838 kg/hm$^2$, and the relative error was 3.9%. The relative errors were from 10% to 15% in 12 counties (districts) of the plain, such as Lintong District, Tongguan County and Mei County. On the whole, except for the Pucheng County (relative error was 17.8%), the estimated yields' relative errors of other 28 counties in the plain were all less than 15%. In general, the average relative error of the estimated yields was 8.68%, and the RMSE was 421.9 kg/hm$^2$, indicated that the optimal yield estimation model based on the assimilated VTCIs had a better performance.

Application of the optimal estimation model to estimate the winter wheat yields in the whole plain from 2008 to 2014, as shown in Fig. 5, results indicated that the yearly estimated yields from 2008 to 2014 were in an increased trend with fluctuation. The precipitation in the main growth period of winter wheat was relatively small in 2013, showing there were drought occurrences, and the yield estimates are lowest among the seven years. For the spatial distribution of the yields, the yields were the highest in the central of the plain, and the yields in the west were higher than those in the east.

## 3 Discussion

This study combined the remotely sensed VTCIs and simulated soil surface moisture by the CERES-Wheat model by using the four-dimensional variational (4D – VAR) data assimilation approach, the assimilated VTCIs can better respond to external observation no matter in a sampling site or in the regional scale, and the assimilation results are more in agreement with prior knowledge of droughts in the study area. This is mainly because that the data assimilation is a proper method for combining the two kinds of information (model and observation) which comes from different sources but complementary, and then generates a set of the states that not only close to the real state (observed) but also considers the physical process (model). Data assimilation can solve model forecasting errors that come from the model stand alone, inaccuracy of the internal parameters and the errors of predictability in a certain extent, and the process of data assimilation can guarantee the model system close to the true value in a certain extent. The past studies on data assimilation algorithms often only used a given year remotely sensed data to estimate crop yields[17], this study chose the years from 2008 to 2014 as the study periods, analyzed of the problem for estimating the yields using both the annual yield variation and inter-annual yield difference in the data assimilation process. For the previous VTCI assimilation by using the 4D – VAR assimilation algorithm, only the effect of assimilation was described[23], this paper did a further study that integrated the assimilated VTCIs into regional winter wheat yield estimation, The results showed that the assimilated VTCIs were more applicable to the regional drought monitoring and impact assessment. However, because of the VTCI characteristics itself, only the ten-day steps were chosen for the data assimilation. For the purposes of the 4D – VAR assimilation method, the future ten-day change trends should be considered when assimilating the current ten-day data, which made the computational cost increases, therefore, combining the VTCI with other variables for a multivariate assimilation yield estimation will be the focus of future research.

The weights of the main growth stages of winter wheat after wintering determined by the improved analytic hierarchy process and the combination weighting method were more reasonable, this was due to that the combination weighting method could combine the subjective weights and objective weights, which also not only reflect subjective views but avoid excessive arbitrariness effectively of subjective factors. By this way, we can obtain the weighted results that were in better agreement with prior knowledge of agronomy. The optimal estimation model for the yield estimates was selected, and the spatial and temporal yield variation characteristics of the plain were analyzed. Compared with the actual yields, the estimated yields had high precision based on the assimilated VTCIs, and the model was more suitable for winter wheat yield estimation in the study area.

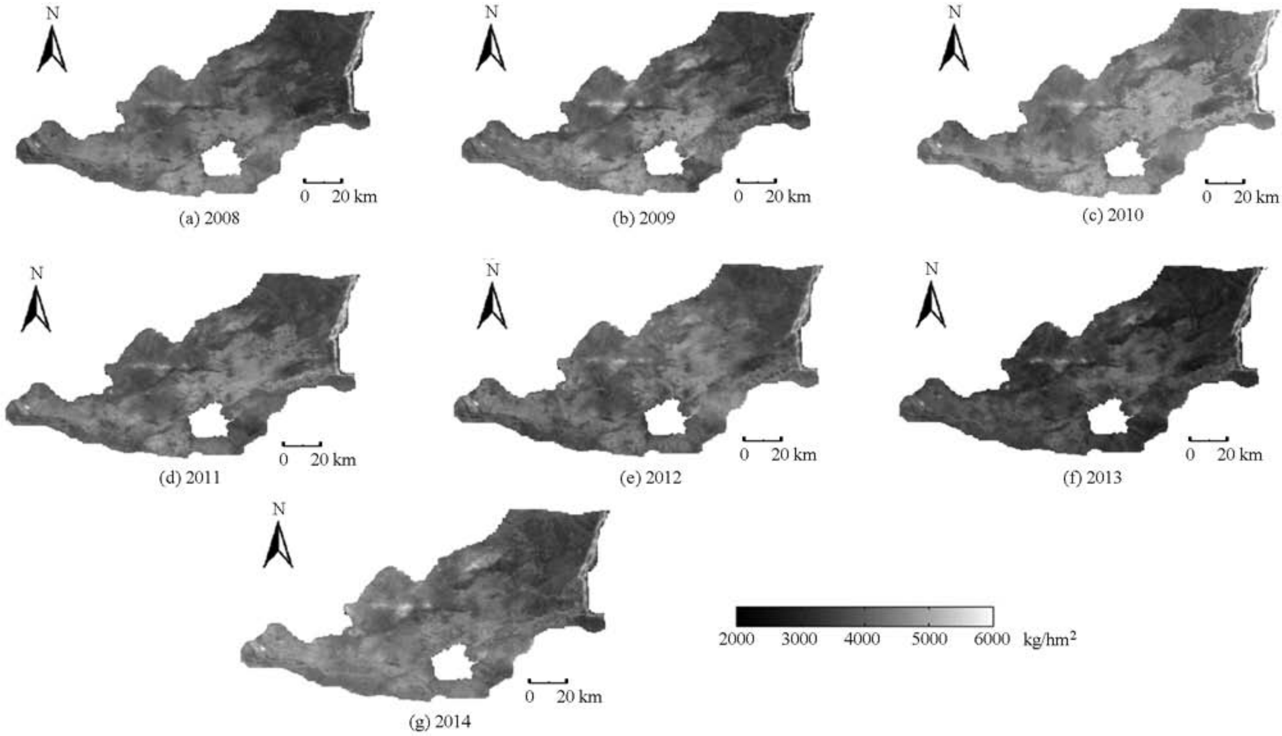


Fig. 5 Estimated yields of winter wheat in different counties of the Guanzhong plain from 2008 to 2014

## 4 Conclusions

(1) Taken the 12 sampling sites for the single point assimilation experiment by usingthe 4D - VAR assimilation algorithm, the assimilated VTCIs had comprehensive advantages of the model simulation and the remotely sensed observation. We compared the assimilated VTCIs at the eight rainfed sampling sites with the ten-day cumulative precipitation, and the results showed that the assimilated VTCIs improved the observation significantly on the basis of compliance with the original change trends of the ten-day precipitation data. The assimilated of VTCIs at the sampling sites (a single point scale) were extended to a regional scale, and the results showed that the assimilated VTCI images had better texture, reduced the sharp changes of the VTCIs in adjacent pixels of the observed VTCI images. Therefore, the assimilated VTCIs were better than the observed VTCIs for more suitable regional drought monitoring and impact assessment.

(2) The optimal winter wheat yield estimation model determined by the combination weighting method based on the assimilated VTCI had a higher estimation precision, and the correlation coefficient of the developed model reached to 0.784. Using the optimal model to estimate the yields in the counties (districts) of the Guanzhong Plain in 2011, the results showed that the estimated yields had less deviation from the actual results in most areas of the plain, the average relative error of the estimated yields was 8.68%, and the root mean square error was 421.9 $kg/hm^2$. Analysis the temporal and spatial variations of the yield estimates in the study area from 2008 to 2014, the results showed that the yields in recent years had an increased trend with fluctuation in the plain, and for the spatial distribution of the yields, the yields were the highest in the central of the plain, followed in the west and in the east. The regional yield estimates were consistent with the actual situation of winter wheat

production both in temporal distribution and spatial distribution, indicating that the higher estimation accuracy was obtained by using the assimilated VTCIs and the optimal winter wheat yield estimation model was more suitable for the regional winter wheat yield estimation.

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# 基于4D-VAR和条件植被温度指数的冬小麦单产估测

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**摘要**：条件植被温度指数（VTCI）综合了地表主要参数——归一化植被指数（NDVI）和地表温度（LST），能够较为准确地对干旱进行监测，可为抗旱救灾、作物估产等提供科学依据。为了提高VTCI的区域估产精度，以陕西省关中平原为研究区域，将遥感反演的VTCI与CERES-Wheat小麦生长模型模拟的土壤浅层含水率相结合，通过四维变分（4D-VAR）同化算法实现2008—2014年冬小麦主要生育期旬尺度VTCI的同化。将同化和未同化的VTCI分别运用改进的层次分析法、熵值法及两者组合赋权法建立冬小麦单产估测模型，选择最优估测模型对2011年关中平原各县（区）进行单产估测和精度评价，并分析2008—2014年关中平原冬小麦单产的时空分布特征，结果表明：无论是在单点尺度还是区域尺度，同化的VTCI均能更好地响应外部观测数据，区域VTCI纹理性更好，更符合VTCI的先验知识。与未同化VTCI构建的估测模型相比，应用同化的VTCI所建的估测模型的估测精度明显提高，相关系数达到0.784（$P < 0.001$）。应用最优估测模型对2011年关中平原29个县（区）估产结果中，有16个县（区）的估测单产相对误差小于10%，28个县（区）的估测单产相对误差小于15%，总体平均相对误差为8.68%，均方根误差为421.9 kg/hm$^2$。近年来关中平原的冬小麦单产呈现个别年份波动、总体增长的年际变化规律，且呈现出中部单产最高、西部次之、东部最低的空间分布特征，与实际情况符合。

**关键词**：冬小麦；条件植被温度指数；四维变分；同化；作物生长模型；产量估测

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# Winter Wheat Yield Estimation Based on 4D Variational Assimilation Method and Remotely Sensed Vegetation Temperature Condition Index

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**Abstract**: Vegetation temperature condition index (VTCI) combines the main parameters of normalized difference vegetation index (NDVI) and land surface temperature (LST), and is applicable to a more accurate monitoring of droughts in the Guanzhong Plain, Shaanxi, China. VTCI also provides a scientific basis for drought relief and crop yield estimation by using remotely sensed data. This study chose Guanzhong Plain as the study area, and was to combine the remote sensed VTCI and simulated soil surface moisture by the CERES-Wheat (Crop environment resource synthesis for wheat) model to get a high regional yield estimation accuracy by using the four-dimensional variational (4D-VAR) data assimilation approach. The improved analytic hierarchy process, the entropy method and the joint the two weighting methods were used to establish winter wheat yield estimation models by using the monitored VTCI and the assimilated ones respectively. The optimal model for estimating winter wheat yields in the study area from 2008 to 2014 was selected, and the measured wheat yield of the year 2011 was used to validate the accuracies of the optimal model. The results showed that no matter at the sampling sites or at the regional scale, the assimilated VTCIs were all better able to respond the monitored VTCIs and the

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surface moisture data, and the texture of assimilated VTCI images was better and more consistent with the regional drought distribution. Compared the yield estimation models with the monitored VTCIs, the accuracies of the yield estimation models with the assimilated VTCIs were improved, and the correlation coefficients of the optimal yield estimation model with the weighted VTCIs of 0.784 ($P<0.001$). The optimal yield estimation model was applied to estimate wheat yields in 29 counties of the Guanzhong Plain, and the results showed that except for the Pucheng County, the estimated yields' relative errors of other 28 counties in Guanzhong Plain were less than 15%, and the errors were less than 10% in 16 counties of Guanzhong Plain. In general, the average relative error of the estimated yields was 8.68%, and the root mean square error was 421.9 kg/hm$^2$, indicating the optimal yield estimation model had a better performance. The yearly estimated yields from 2008 to 2014 were in an increasing trend with fluctuation in Guanzhong Plain. For the spatial distribution of the yields, the yields were the highest in the central of Guanzhong Plain, and the yields in the west were higher than those in the east.

**Key words**: winter wheat; vegetation temperature condition index; 4D－VAR; assimilation; crop growth model; yield estimation

## 引言

冬小麦是我国最主要的粮食作物之一。及时、准确地对作物产量进行估测和预测,对有效掌握粮食生产状况、指导农业生产及辅助政府有关部门制定科学合理的粮食政策具有重要意义[1-2]。目前,将遥感数据与作物生长模型结合是当前作物产量估算研究的重要内容和发展趋势之一。遥感数据能够宏观监测作物长势,作物生长模型通过计算机模拟可动态反映作物生长发育过程,而数据同化方法能够将遥感信息与作物生长模型结合,较好地解决作物生长模型从单点研究发展到区域应用时遇到的问题[3-7]。常用的数据同化方法有变分同化算法和顺序同化算法[8]。与三维变分(3D－VAR)算法相比,四维变分(4D－VAR)算法考虑了背景场信息随时间的变化,因此4D－VAR算法更能体现复杂的非线性约束关系[9-11]。解毅等[12]采用4D－VAR和集合卡尔曼滤波(EnKF)算法同化CERES－Wheat (Crop environment resource synthesis for wheat)模型模拟的叶面积指数(LAI)和遥感数据反演的LAI,并将同化值由单点尺度扩展到区域尺度,认为2种同化算法均能综合反演LAI和模拟LAI的优势,同化后的LAI更符合冬小麦LAI的实际变化。NGODOCK等[13]将4D－VAR数据同化系统与海洋模型相结合进行了一系列双数据试验,结果表明所有的同化试验都能较好地选择性吸收观测数据,提高观测精度,减小预测误差。

在归一化植被指数(NDVI)和地表温度(LST)的散点图呈三角形区域分布的基础上,王鹏新等[14]提出条件植被温度指数(VTCI)的干旱监测方法,并成功应用于干旱预测及其影响评估、产量预测等研究[15-16]。以往大多数的同化估产研究往往只针对某一年的遥感数据估算农作物的单产,缺乏对遥感数据和同化算法在年内作物产量及年际间产量差估测中作用的分析[17]。组合预测是根据各个模型的信息贡献程度,赋予不同的权系数,进而组合一个单一的预测,从而减少预测误差和提高预测精度[18],但以往农业方面组合估产模型的构建大多只采用主观赋权法或者客观赋权法的单一赋权方法[19],不能同时反映主观意愿和客观公度。本文以陕西省关中平原2008—2014年为研究时段,选择VTCI为同化系统状态变量,运用4D－VAR算法对遥感反演的VTCI和CERES－Wheat模型模拟的土壤浅层水分进行同化,应用主观赋权法中改进的层次分析法、客观赋权法中的熵值法和基于两者的组合赋权方法分别计算同化和未同化的加权VTCI,进而结合小麦实际单产数据构建估产模型,并应用2011年的单产数据对模型进行验证。

## 1 材料与方法

### 1.1 研究区域概况

研究区关中平原位于陕西省中部,西起宝鸡,东至潼关,南接秦岭,北到陕北高原,其行政区域包括西安市、宝鸡市、咸阳市、渭南市、铜川市5市及杨凌示范区(图1)。地理位置为106°22′~110°24′E、33°57′~35°39′N。该地区地势平坦,西高东低,土质肥沃,盛产小麦,是陕西省的粮仓,种植模式主要为冬小麦与夏玉米轮作。关中平原属大陆性季风气候,处于暖温带半湿润与半干旱气候的过渡地带,年降水量多在500~700 mm之间。20世纪90年代以来,关中平原整体上气候暖干化特征显著,同时暖春、暖冬化、春旱、伏旱等也愈加显著[20],农业旱灾


图 1　研究区域概况

Fig. 1　Map of study area

在粮食减产方面表现明显。

### 1.2　试验数据的准备

条件植被温度指数是基于遥感反演的归一化植被指数和地表温度特征空间呈三角形区域分布的特点提出的，主要用于监测旱情。基于 Aqua－MODIS 日地表反射率产品（MYD09GA）和日地表温度产品（MYD11A1）获取的日 NDVI 和 LST，应用最大值合成技术分别生成旬 NDVI 和 LST 最大值合成产品，并以此计算条件植被温度指数 VTCI[14, 21]，得到旬尺度 VTCI。选取 2008—2014 年位于关中平原小麦种植区的 12 个典型样点作为研究样点，依次为：陈仓区北、凤翔县城西、扶风县城北、合阳县王村镇、蓝田县史家寨乡、临渭区蔺店镇、眉县常兴镇、蒲城县城北尧山、蒲城县孙镇、岐山县蒲村镇、乾县石牛乡和三原县鲁桥镇，其中扶风县城北、临渭区蔺店镇、眉县常兴镇和三原县鲁桥镇为灌溉样点，其余为旱作（雨养）样点。根据田间实测获取的样点经纬度坐标计算其在遥感影像上的像素坐标，提取每年冬小麦主要生育期（3—5 月份）每旬 VTCI 影像中以样点为中心，3 像素 ×3 像素区域内所含像素的 VTCI 均值作为单点同化试验的外部观测数据，以涵盖以上样点的关中平原遥感反演的 VTCI 作为区域尺度的观测数据。同化过程的动态模型采用农业技术转移决策支持系统（Decision support system for agro-technology transfer, DSSAT）支持下的 CERES－Wheat 模型，结合当地实际测量的叶面积指数、生物量、单产、收获日期等对作物品种遗传特性参数进行本地化标定[22]，在此基础上进行 4D－VAR 的单点与区域尺度的同化试验。由于研究所需的样点模拟 VTCI 不能由作物生长模型直接模拟得到，根据以往的研究结果表明，该地区多年旬尺度的 VTCI 与土壤浅层水分具有显著相关性[23]，因此本文获取模拟 VTCI 的具体方法为：驱动模型运行得到以天为步长的土壤浅层（0～20 cm）含水率，取冬小麦主要生育期内每旬水分数据均值与观测的 VTCI 建立线性回归模型，并通过回归模型计算得到同化所需的旬尺度模拟 VTCI。

### 1.3　四维变分同化算法

四维变分算法是定义一个同化的时间窗口 $T$，利用该同化窗口内的所有观测数据和模型状态值进行最优估计，通过迭代而不断调整模型初始场，最终将模型轨迹拟合到在同化窗口周期内获取的所有观测数据上。任意 $t$ 时刻的状态量是根据 $[T, t+T]$ 时间内所有观测值对模型预测值进行优化得到的。因此由于模型本身存在误差，同化窗口内一次引入的观测值数量越多，变分方法的同化精度就会越高，同时计算代价也随之增加[24]。

选取的四维变分代价函数为

$$J(\boldsymbol{V}_0)=0.5\,(\boldsymbol{V}_0-\boldsymbol{V}_0^b)^{\mathrm{T}}\boldsymbol{B}^{-1}(\boldsymbol{V}_0-\boldsymbol{V}_0^b)+0.5\sum_{i=0}^{n_1}(\boldsymbol{H}_i(\boldsymbol{V}_i)-\boldsymbol{V}_i^{obs})^{\mathrm{T}}\boldsymbol{O}_i^{-1}(\boldsymbol{H}_i(\boldsymbol{V}_i)-\boldsymbol{V}_i^{obs}) \tag{1}$$

式中　$\boldsymbol{V}_0$——同化窗口初始时刻 VTCI 的状态向量

$\boldsymbol{V}_0^b$——初始时刻 VTCI 的背景值，即初始时刻 VTCI 的模拟值

$\boldsymbol{V}_i$——$\boldsymbol{V}_0$ 代入模型算子 $M$ 运行到 $i$ 时刻的背景值

$\boldsymbol{V}_i^{obs}$——$i$ 时刻的 VTCI 观测值

$\boldsymbol{B}$、$\boldsymbol{O}_i$——模拟误差协方差矩阵和观测误差协方差矩阵

$\boldsymbol{H}_i$——观测算子

$n_1$——迭代同化窗口内 VTCI 旬数

同化系统的具体运行过程可简要描述为：首先定义迭代同化窗口旬数 $n$，求得同化窗口内模拟误差协方差矩阵 $\boldsymbol{B}$ 和观测误差协方差矩阵 $\boldsymbol{O}_i$ 以及 $\boldsymbol{V}_i$（$i=1,2,\cdots,n_1$），然后代入代价函数式（1），根据以往经验，设置观测值的 3% 作为同化系统的观测项粗略误差。运用梯度法最小化代价函数，$J(\boldsymbol{V}_0)$ 取最小值时的 $\boldsymbol{V}_0$ 值即为初始时刻的最优解，也就是初始时刻 $\boldsymbol{V}_0$ 的同化值。进入下一时刻同化窗口，重复以上过程，直到所有时刻观测值均被引入，同化系统结束运行。

### 1.4　冬小麦单产的估测方法与精度评价

#### 1.4.1　改进的层次分析法

将冬小麦越冬后划分为返青期（3 月上旬—中旬）、拔节期（3 月下旬—4 月中旬）、抽穗-灌浆期（4 月下旬—5 月上旬）和乳熟期（5 月中旬—下旬）4 个主要生育时期[25]，根据各生育时期发生干旱对其生长的影响程度建立比较矩阵 $\boldsymbol{B}(b_{mn})$，即

$$\boldsymbol{B}(b_{mn})=\begin{bmatrix}1 & 0 & 0 & 0\\ 2 & 1 & 2 & 2\\ 2 & 0 & 1 & 2\\ 2 & 0 & 0 & 1\end{bmatrix} \tag{2}$$

式中,0 表示第 $m$ 个生育时期没有第 $n$ 个生育时期重要,1 表示第 $m$ 个生育时期与第 $n$ 个生育时期同样重要,2 表示第 $m$ 个生育时期比第 $n$ 个生育时期重要。

计算 4 个生育时期的重要性系数

$$r_n = \sum_{m=1}^{4} b_{mn} \tag{3}$$

获得关中平原主要生育时期的判断因子 $c_{mn}$ 和拟优一致判断矩阵 $\boldsymbol{C}(c_{mn})$ 分别为

$$c_{mn} = \begin{cases} (k-1)\dfrac{r_m - r_n}{r_{\max} - r_{\min}} + 1 & (r_m \geqslant r_n) \\ \left[(k-1)\dfrac{|r_m - r_n|}{r_{\max} - r_{\min}} + 1\right]^{-1} & (r_m < r_n) \end{cases} \tag{4}$$

$$\boldsymbol{C}(c_{mn}) = \begin{bmatrix} 1 & 1/7 & 1/5 & 1/3 \\ 7 & 1 & 3 & 5 \\ 5 & 1/3 & 1 & 3 \\ 3 & 1/5 & 1/3 & 1 \end{bmatrix} \tag{5}$$

其中 $r_{\max} = \max\{r_n\}$ $r_{\min} = \min\{r_n\}$ $k = \dfrac{r_{\max}}{r_{\min}}$

对拟优一致判断矩阵进行归一化处理得到冬小麦各生育时期的权重。

#### 1.4.2 熵值法

应用研究区域 2008—2014 年冬小麦 4 个生育时期($n$)的 VTCI 数据构建数据矩阵 $\boldsymbol{A}(a_{mn})_{N\times 4}$,计算各个生育时期的熵值 $h_n$[26],即

$$h_n = -\frac{1}{\ln N}\sum_{m=1}^{N}\left(\frac{a_{mn}}{\sum_{m=1}^{N} a_{mn}} \ln \frac{a_{mn}}{\sum_{m=1}^{N} a_{mn}}\right)$$
$$(n=1,2,3,4) \tag{6}$$

式中 $N$——研究选取的总年份数

计算第 $n$ 个生育时期的差异性系数 $g_n$,并对其进行归一化处理得到第 $n$ 个生育时期的权重 $w_n$,即

$$g_n = \frac{1-h_n}{4-\sum_{n=1}^{4} h_n} \tag{7}$$

$$w_n = \frac{g_n}{\sum_{n=1}^{4} g_n} \quad \left(0 < w_n < 1,\ \sum_{n=1}^{4} w_n = 1\right) \tag{8}$$

#### 1.4.3 组合赋权法

基于改进的层次分析法与熵值法的组合赋权法的基本原理是寻找一组与主观权重和客观权重之间的总距离最大的权重。设主观赋权法确定的权重为 $\boldsymbol{W}^1 = [w_1^1 \quad w_2^1 \quad w_3^1 \quad w_4^1]$,客观赋权法确定的权重为 $\boldsymbol{W}^2 = [w_1^2 \quad w_2^2 \quad w_3^2 \quad w_4^2]$,应用组合赋权法确定的组合权重为 $\boldsymbol{W} = [w_1 \quad w_2 \quad w_3 \quad w_4]$,为使其与主、客观权重尽可能贴近,构造的优化模型需满足条件[25]

$$y = \max \sum_{k=1}^{2}\left(1 - \sqrt{\frac{1}{n}\sum_{n=1}^{4}(w_n - w_n^k)^2}\right) \tag{9}$$

$$\sum_{n=1}^{4} w_n = 1 \tag{10}$$

利用该模型求解出组合权重 $\boldsymbol{W}$。

#### 1.4.4 加权 VTCI 的计算与单产估测模型的构建

将陕西省行政区县边界的矢量图分别与研究区域 VTCI 遥感影像图叠加,获取关中平原各县(区)VTCI。根据 VTCI 的计算方法,生成 2008—2014 年冬小麦主要生育期 3—5 月份以旬为单位的 VTCI 时间序列数据,取各县(区)内所包含像素的 VTCI 平均值作为该县(区)的旬 VTCI。取各生育时期内所包含的多旬 VTCI 平均值作为该生育时期的 VTCI。如此,计算关中平原每年各县(区)冬小麦各生育时期的 VTCI。分别应用改进的层次分析法、熵值法和组合赋权法计算冬小麦各生育时期同化和未同化 VTCI 的权重,进而计算各县(区)每年的加权 VTCI,将 3 种不同方法得到的加权 VTCI 分别与小麦实际单产进行线性回归分析,建立单产估测模型(研究选用 2011 年用于单产估测精度的验证,故 2011 年各县(区)的相关数据未参与模型的构建)。

## 2 结果与分析

### 2.1 VTCI 同化结果与分析

分别对 12 个样点 2008—2014 每年 3—5 月份遥感反演的旬尺度 VTCI 进行取值,以该样点坐标相邻的共 3 像素 ×3 像素的平均值作为该样点 VTCI 的观测值,应用反演(观测)VTCI 值与模型模拟的土壤浅层含水率建立经验回归模型,并以此模型计算得到该样点模拟 VTCI 值,进而代入 4D - VAR 同化算法获得单点同化结果。为了验证单点同化结果能否较好地响应外部观测数据,将 7 a 12 个样点的单点 VTCI 的 4D - VAR 同化结果与原观测结果进行线性回归分析(图 2),可以看出,总体上 VTCI 的同化结果和观测数据较为吻合,相关系数为 0.660($P<0.001$),所有样点同化 VTCI 与观测 VTCI 间的均方根误差为 0.016。

研究证明 VTCI 是一种近实时的干旱监测方法,其与降水量数据有显著的相关性。为了进一步验证同化之后的单点 VTCI 是否较之前更好地与降水量数据结合,以乾县石牛乡样点为例,将观测 VTCI 和同化 VTCI 分别与旬累积降水量数据进行对比(图 3)。可以看出,无论是观测 VTCI 还是同化 VTCI 均大体上符合旬累积降水量的变化趋势,但同化 VTCI 在遵循原有变化趋势的基础上对观测值有较大改善。2009 年 3 月上旬、2010 年 5 月上旬和

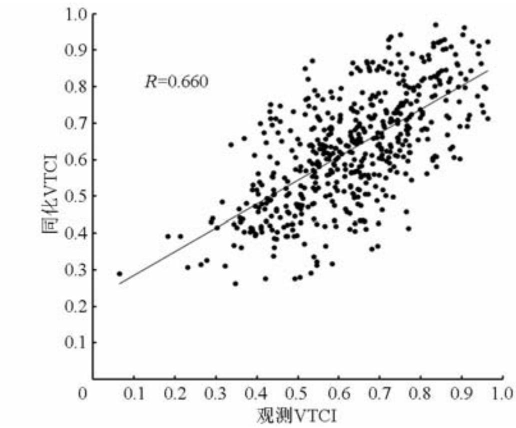


图 2　4D－VAR 同化值与观测值相关性分析结果

Fig. 2　Correlation between observed VTCIs and assimilated VTCIs using 4D－VAR

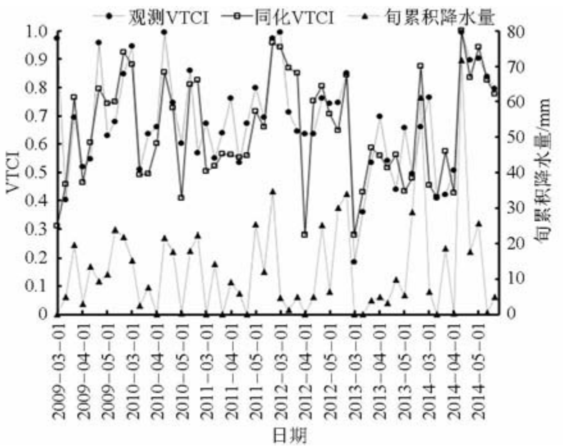


图 3　观测 VTCI、同化 VTCI 与旬累积降水量

Fig. 3　Observed VTCIs, assimilated VTCIs using 4D－VAR and cumulative rainfall

2012 年 4 月上旬乾县的累积降水量均为零，同化 VTCI 值由原观测值 0.97、0.60、0.93 分别调整为 0.31、0.42、0.27，在原观测偏大的基础上做出了较大幅度调整，使其能更好地与降水数据结合。对于 2013 年 5 月下旬累积降水量在 60 mm 以上，同化 VTCI 值达到了 0.9 左右，属不旱范围。另外，2009 年 4 月下旬、5 月中旬，2011 年 3 月下旬和 2013 年 5 月上旬等相对未同化 VTCI 均有不同程度的调整，使结果更能反映实际情况。

由于所选取的 12 个试验样点较为均匀地分布在整个关中平原，故假设该 12 个试验样点特性可以代表整个关中平原区域，以同化试验中点上同化结果与原观测 VTCI 建立线性回归方程，实现区域尺度的 VTCI 遥感产品的同化。由此可以得到每年 3、4、5 月以旬为单位的区域 VTCI 同化结果，这里选取 2012、2013、2014 年每年 3 月下旬的区域 VTCI 同化结果与原观测结果（图 4），并结合陕西省气象局提供的有关降水资料进行对比，2012 年 3 月下旬（图 4a、4b）整个关中平原降雨稀少，干旱现象明显，从同化 VTCI 图像（图 4b）可以看出，VTCI 值普遍在 0.5 左右，属轻旱范围；2013 年 3 月下旬（图 4c、4d）咸阳市、西安市等关中平原中部区域几乎无明显降雨现象，同化 VTCI 值从原观测图像的不旱范围（0.7 左右）调整为中旱范围（0.45 左右），因此同化试验结果对原观测图像整体和局部均能做出较符合实际情况的调整。另外，对比同化和观测的 VTCI 的图像，发现区域尺度的同化试验中，由于同时结合了模型模拟值和原观测值，同化 VTCI 邻近像素间 VTCI 数值过渡较平稳，图像纹理更好（图 4d、4f），减少了原观测图像中数值陡升陡落的情况（图 4c、4e），效果优于遥感反演结果。

## 2.2　区域单产的估测与验证分析

铜川市是关中平原向陕西黄土高原的过渡地带，冬小麦面积相对较小，且主要分布在其南部的渭北旱塬[25]，因此本研究选择除铜川市以外的关中平原 4 市的 29 个县（区）作为冬小麦估产研究区。根据不同赋权方法获取冬小麦各主要生育时期的权重（表 1），依据农学知识，改进的层次分析法和组合赋权法确定的权重较为合理，这是由于冬小麦的拔节期和抽穗－灌浆期处在冬小麦从营养生长阶段向生殖生长阶段的过渡时期，是冬小麦产量形成的关键时期，需要大量的水分和营养物质，因此如果这些时期发生干旱，将会直接影响最终产量。返青期和乳熟期被给予的权重不大，可能是因为这 2 个时期水分因素尽管对小麦生长发育和产量形成起限制作用，但不是特别明显，返青期主要是生根、长叶和分蘖，水量不宜过大。乳熟期穗粒结构已经形成，对一定的水分亏缺表现出较强的忍耐力，因此返青期和乳熟期水分亏缺程度对产量的影响相对较小。

基于表 1 中的权重，结合冬小麦主要生育期的观测 VTCI 和同化 VTCI（2008—2014 年，除 2011 年）分别计算各县（区）的加权 VTCI，构建 3 种赋权方法计算的加权 VTCI 与实际单产间的线性回归方程作为冬小麦单产的估测模型（表 1）。可以看出，基于同化 VTCI 的估测模型的相关系数均大于基于观测 VTCI 的估测模型的相关系数，表明应用同化 VTCI 的单产估测精度更高。无论是观测 VTCI 还是同化 VTCI，组合赋权方法构建的估测模型均优于改进的层次分析法和熵值法确定的估测模型，相关系数 $R$ 分别达到 0.669 和 0.784，加权 VTCI 与单产间的相关性均达到极显著水平（$P < 0.001$），基于同化 VTCI 的估测模型的精度明显提高，为最优的单产估测模型。为了验证估测模型的精度，应用最优估测模型对关中平原 2011 年各县（区）的冬小麦单产进行估测，分析 29 个县（区）估测单产与实际单产的

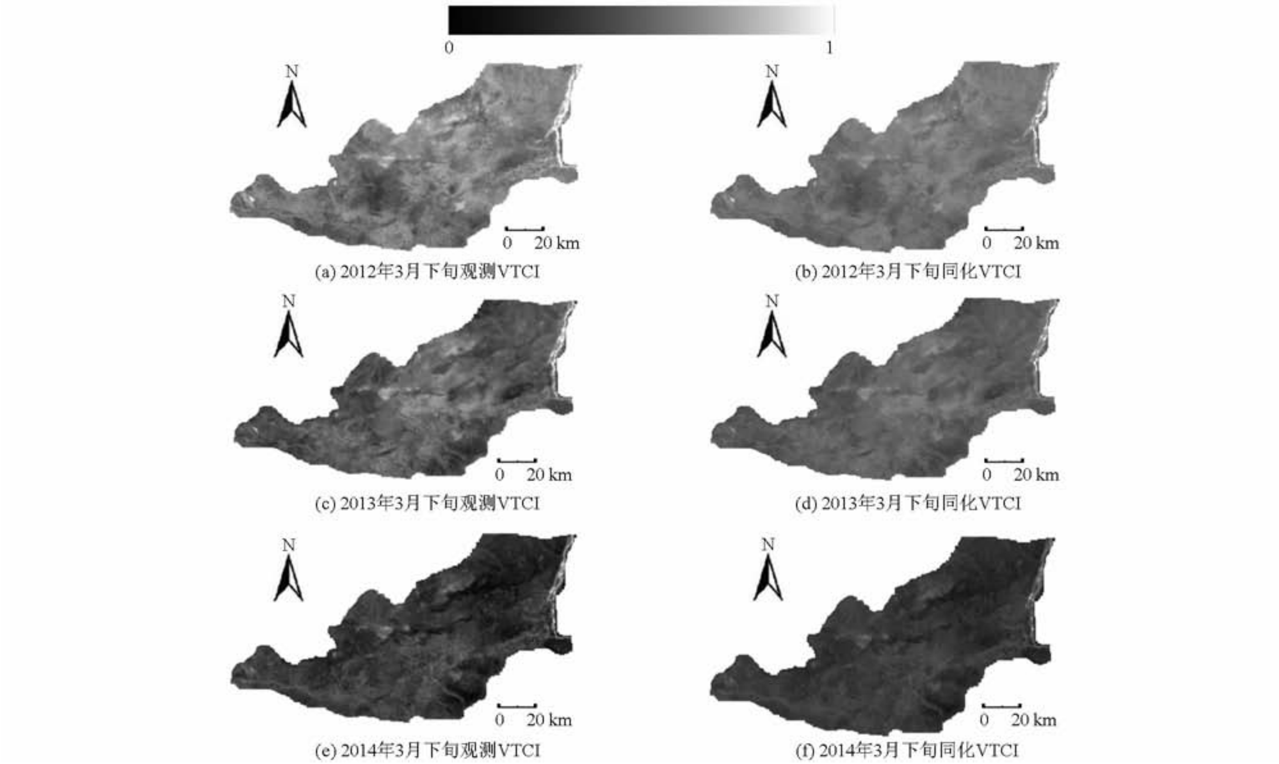


图 4 四维变分区域同化结果与观测结果

Fig. 4 Observed VTCIs and assimilated VTCIs using 4D - VAR at regional scale

**表 1 3 种方法确定的冬小麦主要生育期的观测和同化 VTCI 的权重和单产估测模型**

**Tab. 1 Weights of monitored VTCI and assimilated ones at key growth stages of winter wheat and yield estimation models**

| 赋权方法 | VTCI | 返青期 | 拔节期 | 抽穗-灌浆期 | 乳熟期 | 单产估测模型 | 相关系数 $R$ | 显著性检验 |
|---|---|---|---|---|---|---|---|---|
| 改进的层次分析法 | 观测值 | 0.055 | 0.564 | 0.263 | 0.118 | $y = 8\,619x - 1\,138.2$ | 0.561 | $P = 0.017$ |
| | 同化值 | 0.055 | 0.564 | 0.263 | 0.118 | $y = 13\,896x - 4\,491.3$ | 0.630 | $P = 0.011$ |
| 熵值法 | 观测值 | 0.247 | 0.252 | 0.251 | 0.250 | $y = 7\,979x - 722.4$ | 0.521 | $P = 0.137$ |
| | 同化值 | 0.206 | 0.295 | 0.255 | 0.244 | $y = 12\,632x - 3\,680.0$ | 0.565 | $P = 0.025$ |
| 组合赋权法 | 观测值 | 0.051 | 0.450 | 0.356 | 0.143 | $y = 10\,695x - 2\,536.3$ | 0.669 | $P < 0.001$ |
| | 同化值 | 0.043 | 0.487 | 0.362 | 0.108 | $y = 14\,490x - 5\,009.8$ | 0.784 | $P < 0.001$ |

注：$y$ 和 $x$ 分别表示估测单产和加权 VTCI。

相对误差和均方根误差。结果表明，长安区、蓝田县、礼泉县等 16 个县(区)的相对误差均低于 10%，其中长安区实际单产为 4 254 kg/hm$^2$，估测单产为 4 399 kg/hm$^2$，相对误差为 3.4%；户县实际单产为 5 001 kg/hm$^2$，估测单产为 5 074 kg/hm$^2$，相对误差为 1.5%；乾县实际单产为 4 356 kg/hm$^2$，估测单产为 4 430 kg/hm$^2$，相对误差为 1.7%；兴平市实际单产为 4 664 kg/hm$^2$，估测单产为 4 826 kg/hm$^2$，相对误差为 3.5%；富平县实际单产为 3 693 kg/hm$^2$，估测单产为 3 838 kg/hm$^2$，相对误差为 3.9%；临潼区、潼关县、眉县等 12 个县(区)的相对误差均低于 15%；仅蒲城县的相对误差大于 15%，为 17.8%。从关中平原整体看，所有县(区)估测单产的平均相对误差为 8.68%，均方根误差为 421.9 kg/hm$^2$，表明基于同化 VTCI 的冬小麦单产估测模型的估产精度较高。

基于同化的 VTCI，应用最优估测模型对 2008—2014 年各县(区)的冬小麦单产进行估测(图 5)，可以看出，从年际变化看，关中平原 2008—2014 年各县(区)的单产个别年份有波动，但总体呈平稳增长的趋势，其中 2013 年关中平原冬小麦生育期降水相对较少，干旱偏重，有一定程度的减产。从单产的空间分布看，整体呈现中部小麦单产高于东部和西部，西部小麦单产高于东部的分布特征。

## 3 讨论

运用 4D - VAR 同化算法对 CERES - Wheat 模型模拟的土壤浅层含水率与遥感反演的 VTCI 进行同化，同化 VTCI 从单点尺度和区域尺度均能较好地响应外部观测，同化结果更符合研究区 VTCI 的先验知识。这主要是由于数据同化本身是一种将来源不同而又互补的 2 种信息(模型与观测)融合在一起，并生成一组既逼近真实状态(观测)又考虑物理过程(模型)的状态分析值的方法，它在一定程度上解决了模型独立运行时，由于内部参数的不准确

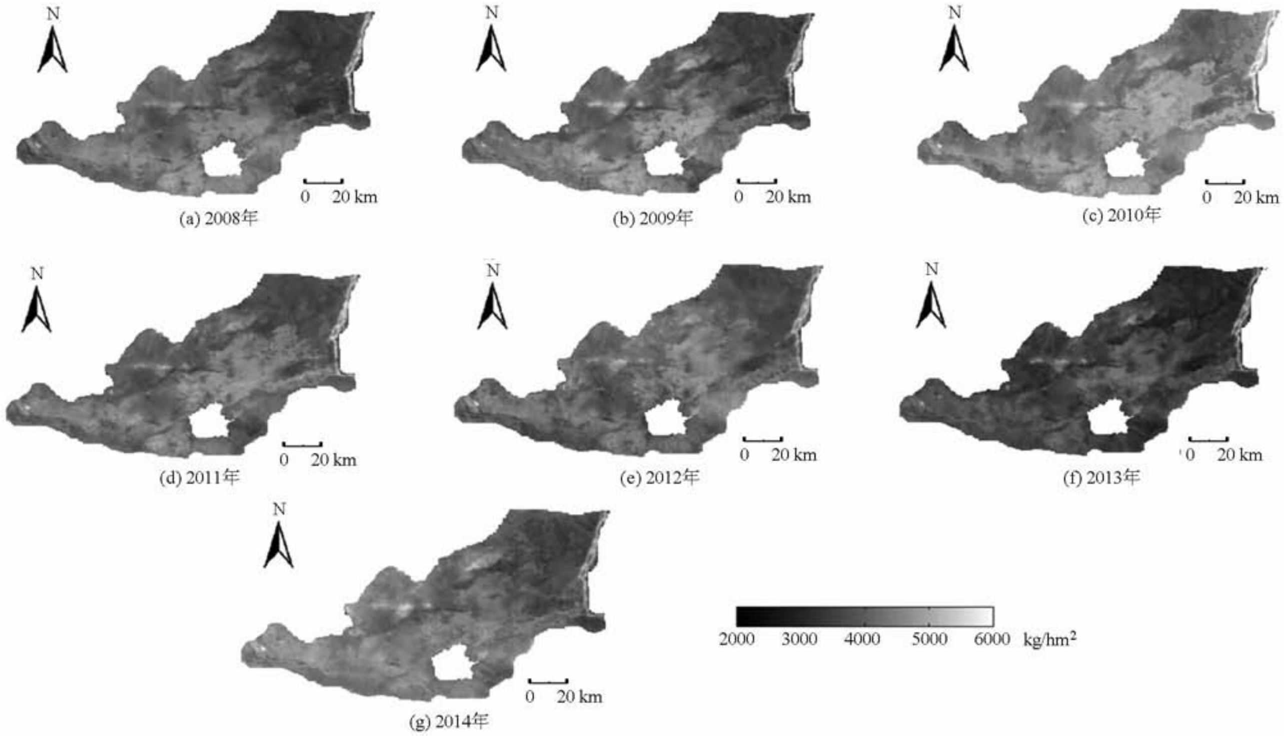


图 5　2008—2014 年关中平原各县(区)冬小麦单产估测结果

Fig. 5　Estimated yields of winter wheat in different counties of Guanzhong Plain from 2008 to 2014

性以及预见性误差而产生的模型预报误差，利用同化的数据处理过程能够最大程度保证模型系统一定程度靠近真值。

以往同化算法在估产研究方面往往只针对某一年的遥感数据估算农作物的单产[17]，本文选择关中平原 2008—2014 年为研究时段，分析了遥感数据和同化算法在年内作物单产及年际间单产差估测中的作用问题。针对以往 4D－VAR 同化算法应用于 VTCI 同化研究时，只对同化效果进行描述[23]，本文进一步将 VTCI 同化结果用于区域冬小麦单产的估测研究，结果表明，同化 VTCI 对区域旱情监测与影响评估更适用。但由于 VTCI 本身的特性，只能选择以旬为步长进行数据同化试验，且对于 4D－VAR 的同化方法而言，在对当前一旬进行同化时需考虑未来一旬的变化趋势，使计算代价增加，因此，将 VTCI 与其他变量结合进行多变量同化估产研究是未来研究工作的重点。

基于改进的层次分析法和熵值法的组合赋权方法确定的越冬后冬小麦各主要生育时期的权重较合理，这是由于综合主、客观权重的组合赋权方法能将主观权重与客观权重相结合，既能反映参与者的主观意愿又能有效避免主观因素过多的随意性，可获得更符合农学先验知识的赋权结果。选取最优估测模型进行单产估测研究时，从时空分布上分析了研究区各县(区)单产变化规律特征，将估测单产与实际单产进行比较分析表明，基于同化 VTCI 的估测模型的精度较高，更加适用于研究区域冬小麦单产的估测研究。

## 4　结论

(1)采用 4D－VAR 同化算法对 12 个研究样点进行单点同化试验，同化 VTCI 能较好地综合模型模拟值与遥感观测值的优点，选择 8 个旱作样点分别与旬累积降水量数据对比分析结果表明，同化 VTCI 在符合旬尺度降水量数据原有变化趋势的基础上明显改善。将样点 VTCI 同化值从单点尺度扩展到区域尺度，同化 VTCI 图像的纹理更好，减少了相邻像素间 VTCI 陡升陡落的现象，效果要优于遥感反演 VTCI，更适合区域旱情监测及影响评估研究。

(2)基于同化 VTCI，采用不同赋权方法确定的最优冬小麦单产估测模型的估产精度较高，相关系数达到 0.614。2011 年各县(区)估产结果中，大多数区域单产的估测结果与实际结果偏差较小，估测单产的平均相对误差为 8.68%，均方根误差为 421.9 $kg/hm^2$。对 2008—2014 年研究区域估产结果的时间演变规律和空间变化特征进行分析的结果表明，近年来关中平原冬小麦单产呈现个别年份波动，总体平稳增长的年际变化特点，并呈现中部单产最高、西部次之、东部最低的空间分布特征。区域估产结果的时空分布与关中平原冬小麦生产的实际情况相符，表明应用同化 VTCI 的单产估测精度更高，更适用于区域冬小麦单产的估算。

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