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# Winter Wheat Yield Forecasting Based on Time Series of MODIS NDVI

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**Abstract:** The large regional-scale crop yield forecasting is of great significance to ensure national food security and agricultural sustainable development. To predict regional-scale winter wheat yield, the winter wheat forecasting method proposed by Becker-Reshef was implemented in major winter wheat planting areas in China. Firstly, the winter wheat planting areas were extracted through time series of MODIS NDVI with 250 m spatial resolution in Hebei, Henan and Shandong Provinces. Winter wheat adjusted NDVI peak at the heading stage was used to analyze the correlation with winter wheat yield on the purest wheat pixels from 2000 to 2010. Winter wheat yield prediction models were established through the regression statistical relationship between NDVI peak at heading stage and winter wheat yield at the prefecture-city unit from 2000 to 2009. The results showed that the dense wheat planted cities had good model accuracy. Finally, the accuracy of prediction models was evaluated by using the statistical winter wheat yield in 2010. The results showed that winter wheat yields could be forecasted two months in advance with average forecasting error of 7.49%, and the yield forecasting method using adjusted NDVI peak at heading stage had considerable potential applications at the prefecture-city scale in China. The study provides basis and a method for other crops yield forecasting in agricultural regions.

Key words: winter wheat; yield forecasting; time series; MODIS NDVI

# 0 Introduction

Winter wheat is one of the major food crops in China. Large-scale winter wheat growth monitoring and yield forecast is of great significance to the timely and accurate understanding of national grain production status for grain regulations and international agricultural trade. Currently, the yield forecast models include crop growth models and empirical regression models. Assimilating remote sensing observations into crop growth model is also an important method for crop yield forecast. The crop growth model requires a large number of input parameters and the calibration of large scale crop modeling is especially difficult, which thus has some limitations for developing an operational yield estimation system at a large scale<sup>[1]</sup>. Empirical regression models are often used to estimate crop yield through establishing the regression relationships between remote sensing derived indicators (e.g., vegetation index (VI)) and crop yield. This method requires fewer input parameters and is easily to be implemented, but it is lack of universality. In such studies, the normalized difference vegetation index (NDVI) is commonly used for crop growth monitoring and yield prediction<sup>[2]</sup>. Huang et al. utilized NOAA NDVI and MODIS NDVI to establish a provincial rice yield estimation model in Sichuan, Hunan, Guangxi, Jiangxi and Heilongjiang Provinces<sup>[3]</sup>, and winter wheat yield estimation model in Henan Province<sup>[4]</sup>, which reached preferable vield estimation accuracy. Becker-Reshef et al. proposed a generalized winter wheat yield regression forecast model, which was originally established in Kansas and subsequently, directly applied to Ukraine in Europe<sup>[5]</sup>. This model forecasted the yield in Ukraine six weeks ahead of winter wheat maturity, with a forecast error of about 15% for the yield and about 10% for the total production, and the total winter wheat yield prediction error is about 6.3% when running the data in May 2009. Compared with the United States, the cropping

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system of main winter wheat producing areas is more fragmented and complicated in China. Therefore, it is of practical significance to verify the applicability of Becker-Reshef et al. 's<sup>[5-6]</sup> crop yield model in China. Based on the MODIS NDVI noise adjusted method proposed by Becker-Reshef et al. <sup>[5-6]</sup>, the adjusted NDVI peak at the heading stage of winter wheat was used to build the yield forecast model at the prefecturelevel city scale in Hebei, Henan and Shandong provinces, and the accuracy and applicability of this yield estimation model at the prefecture-level city scale was evaluated in the main winter wheat producing region in China.

# 1 Data and methods

# 1.1 The study area

Winter wheat producing areas in Shandong, Henan and Hebei of China's Huanghuaihai region were selected as the study area (Fig. 1). The dominant soil type is alluvial soil, with partial yellow soil and brown soil. These areas have good soil quality and are the high producing regions of winter wheat in China. The winter wheat production in the three provinces makes up about 67% of the total in  $China^{[7-8]}$ . Winter wheat and summer corn were the typical crops in this area. Generally, late February to early March is the green-up stage, early April is the jointing stage, early to middle May is the heading and milking stage and the maturity and harvest are around early June. Overall, the phenology of winter wheat in Henan province is about 10 to 20 days earlier compared with Hebei province. In addition, central and southern Hebei province, northwest and southwest Shandong province, northern, central and eastern Henan province have higher winter wheat planting density.



Fig. 1 Study area

#### 1.2 Data

1.2.1 Remote sensing and statistical data

The MODIS NDVI data with a spatial resolution of 1 km and a temporal resolution of 8-day from 2000 to 2010 were downloaded from the UMD global agriculture monitoring (GLAM) system with website of "http:// pekko. geog. umd. edu/usda/beta/". The winter wheat yields and planting areas for the prefecture-level city were obtained from the national statistical yearbook.

# **1.2.2** Winter wheat planting area extraction from time series MODIS NDVI

The classification method based on the feature matching of phenological curve was adopted to derive the winter wheat planting areas from the 250 m resolution MOD09A1 reflectance data during critical winter wheat growth stages in 2010<sup>[9]</sup>. Based on the validation from field sample plots (main land cover types include winter wheat, cotton, other crops,

building, bare soil, forests and water), the overall classification accuracy of the winter wheat is about 89.3% and the Kappa coefficient is about 0.85. Then, a 1 km grid was overlaid on the 250 m land cover mask to obtain a pixel purity map based on the percentage of winter wheat in each cell of the grid.

# 1.3 Data processing method

#### 1.3.1 Time-series analysis of NDVI

Based on winter wheat purity (the winter wheat percentage in each pixel) distribution in 2010, the pixels of top 5% purity (1 km resolution) were selected as the mask for winter wheat of each prefecture-level city. This data can be used for extracting and analyzing NDVI profile<sup>[10]</sup>, and the winter wheat NDVI peak at the tillering and heading stages can be obtained from the masked 8-day NDVI data from 2000 to 2009<sup>[5]</sup>.

# 1.3.2 NDVI peak algorithm

Considering the noise representing winter wheat growth conditions, the NDVI noise suppression method proposed by Becker-Reshef et al. was used, i. e. the maximum NDVI (MA\_NDVI) is equal to the NDVI peak value at winter wheat's heading stage minus the lowest average NDVI value of background noise. NDVI peak is the main input parameters for yield estimation model. The heading stage determines the grain number per spike to some extent and is a good indicator of final wheat yield.

The maximum adjusted NDVI (MA\_NDVI) for each prefecture-level city was extracted from time-series NDVI data from 2000 to 2010, which equals the maximal 95th percentile of NDVI minus multi-year average of the minimal 5th percentile of the average<sup>[5]</sup>.

$$MA\_NDVI_{y} = I_{\max 95, y} - \frac{1}{N} \left( \sum_{y=1}^{N} I_{\min 5, y} \right)$$
(1)

where, N is the number of years from 2000 to 2010;  $I_{\max 95, y}$  is the maximal 95th percentile of NDVI during winter wheat growing period for year y;  $I_{\min 5, y}$  is the minimal 5th percentile of NDVI during winter wheat growing period for year y.

# 1.3.3 Winter wheat yield forecast method

NDVI peak reflects the photosynthesis and growth of winter wheat. Least squares method was used to forecast winter wheat yield from NDVI peak. The relationship between NDVI peak during winter wheat's heading stage and yield was analyzed using the 10-year data from 2000 to 2009, the correlation was used to represent the relationship between NDVI peak and yield, and the relative error and root mean square error were used to indicate the model accuracy and predictive ability.

# 2 Results

#### 2.1 The winter wheat purity analysis

According to the 250 m winter wheat planting distribution in 2010, the Zonal Statistics function in ArcGIS software was used to derive the 1 km  $\times$  1 km winter wheat purity (i. e. the percentage of winter wheat planting area in each pixel). Fig. 2 shows the distribution of winter wheat purity.



Fig. 2 Purity map of winter wheat

In general, the winter wheat planting is relatively stable in our study area, thus the purity of winter wheat planting area in 2010 was used to reflect the entire time series from 2000 to 2010. It can be seen that the pixels of high winter wheat purity are mainly located in southern Hebei, western Shandong and most of Henan, and the rest of the planting area has relatively low purity. Since there is no winter wheat planting in Chengde and Zhangjiakou, these two cities were not included in the subsequent analysis. Luohe, Zhoukou, Xuchang, Shangqiu, Heze, and Puyang have high winter wheat purity and are the major producing areas of the three provinces. Due to the influence of topography, climate and other factors<sup>[11]</sup>, Sanmenxia, Luoyang, Rizhao and Langfang have a relatively low percentage of winter wheat.

# 2.2 Time series of NDVI

The winter wheat NDVI value for each prefecturelevel city was extracted using the pixels of top 5% purity from the 8-day data to derive the NDVI time series from 2000 to 2010. The NDVI peaks of top 5%



Fig. 3 NDVI time series for four cities (Numbers represents winter wheat yield per unit for each year)

From the 8-day MODIS NDVI curves of four cities, there are three peaks each year, which correspond with the winter wheat heading stage, the summer maize maturity stage and the winter wheat's tillering stage for the next season. However, the winter wheat's heading stage of Tangshan city does not appear to be obvious characteristics partly due to its relatively low winter wheat purity (44.60%). For the entire time series, the NDVI value of heading stage remains relatively stable. However, the yield shows an increasing trend, which is related with the crop varieties improvement, technical progress and field management.

From Fig. 3, it can be seen that the NDVI values of winter wheat's heading stage in Tangshan, Yantai and Cangzhou reach 0.5 to 0.6, and the corresponding winter wheat yield are about 3 000 to 5 500 kg/hm<sup>2</sup>. In Puyang city, the value is about 0.6 to 0.8, and the wheat yield is relatively high, ranging from 5 800 to 7 000 kg/hm<sup>2</sup>.

In general, winter wheat yield and NDVI peak at heading stage show positive correlation at the prefecture city scale. It should also be noted that there are also exceptions. In the regions without sufficient irrigation, the favorable weather conditions during winter wheat's jointing stage to heading stage will cause a higher NDVI peak at heading stage. However, if the winter wheat suffers from adverse weather conditions in the post-heading growing stage, it will lead to the difficulty in grouting and thus low yield. On the contrary, the unfavorable weather conditions during winter wheat's jointing and heading stage would lead to a low NDVI peak during heading stage; however, the favorable conditions in the post-heading growing stage can result in a high yield. Additionally, in the regions with complicated topography, the micro-climate and terrain factors have great impacts on the wheat yield.

winter wheat purity for all prefecture-level cities show

high consistency with the trend of yield. Four cities

with different purities Tangshan with purity 44.60%, Yantai with purity 78.03%, Cangzhou with purity

89. 10% and Puyang city with purity 100%, were used

to show the NDVI time series (Fig. 3).

From the Fig. 3b, it can be seen that the NDVI peak at winter wheat was higher in Yantai in 2002, but its yield presented a decreasing trend as compared with the previous year due to the prolonged rainfalls in early May 2002. On the contrary, in Fig. 3c, NDVI peak in Cangzhou City in 2003 was low, but the winter wheat yield was relatively high, which is possible because the drought happened at the green-up stage, but the rainfalls and irrigations in the later growing season were favorable for the recovery of winter wheat, resulting in

no obvious crop yield loss.

# 2.3 Yield prediction model based on NDVI peak at winter wheat heading stage

Regression forecast model at each prefecture-level city was built between NDVI peak and wheat yield from 2000 to 2009 using least square method. The feasibility and reliability of yield estimation model were analyzed by the correlation coefficient (R), the significance test F value, the relative error  $(\Phi)$  and the root mean square error (RMSE). For simplicity, the estimation models for 12 typical cities in 43 cities were selected to be shown in Tab. 1.

Tab. 1	Models for forecasting	winter wheat	vield in Shandong.	Hebei and Henan Provinces
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Provinces	Cities	Yield prediction models	Purity/%	R	F	$\Phi/\%$	$RMSE/(t \cdot hm^{-2})$
	Jining	$y = 6\ 005.\ 45x + 1\ 601.\ 52$	86. 87	0.88	15.53	4.13	0.31
Cl 1	Taian	$y = 2\ 049.\ 95x + 4\ 985.\ 75$	98.68	0.87	5.35	2.95	0.23
Shandong	Weifang	y = 2508.13x + 4100.49	92.39	0.32	0.25	7.24	0.55
	Zibo	$y = 9\ 479.\ 54x - 585.\ 16$	99. 78	0.20	0.47	7.16	0.51
	Xuchang	$y = 2\ 639.\ 50x + 3\ 247.\ 10$	95.47	0.67	7.01	2.97	0.24
Henan	Nanyang	$y = 10\ 012.\ 53x - 2\ 076.\ 36$	94.21	0.69	3.63	6.32	0.41
Henan	Jiaozuo	$y = 10\ 048.\ 69x - 2\ 827.\ 62$	95.29	0.03	0	5.46	0.46
	Sanmenxia	$y = 7\ 509.\ 96x - 103.\ 95$	7.24	0.34	3.37	15.42	0.56
	Cangzhou	$y = 615.\ 80x + 5\ 130.\ 74$	89.10	0.77	18.4	7.06	0.34
II 1 ·	Handan	$y = 3\ 293.\ 22x + 2\ 921.\ 84$	100.00	0.46	0.93	3.77	0.24
Hebei	Hengshui	y = 183.44x + 5541.40	96.02	0.05	0.46	3.36	0.23
	Shijiazhuang	$y = 9 \ 117. \ 49x - 867. \ 36$	100.00	-0.22	1.18	1.87	0.16

From Tab. 1, it can be seen that NDVI peaks of winter wheat heading stage show significantly positive correlation with winter wheat yield, with a varying model forecasting precision across the prefecture-level cities. Among them, most cities show a strongly positive correlation between NDVI peaks of the winter wheat heading stage and yields. Due to the impact of winter wheat purity, topography, landscape, cropping system, droughts at certain years, pests and other factors, some cities have low correlation for yield estimation model. The maximal error with 15. 42% was found in Sanmenxia, corresponding to the low winter wheat purity of 7. 24%; the minimal error of 1. 94% was found in Shijiazhuang, corresponding to the winter wheat purity of 100%.

Overall, most yield models have a estimation error below 9% with an average relative error of 6. 59% and a RMSE ranging from 0. 16 to 0. 80 t/hm<sup>2</sup>, showing the effectiveness of the yield estimation model.

In order to analyze the correlation between winter wheat NDVI peak of heading stage and the yield throughout the study region, the scatter diagram between NDVI peak at heading stage and yield from 2000 to 2010 was plotted for Henan Province and the entire study area, and the regression analysis was also conducted (Fig. 4).



The NDVI peaks at winter wheat heading stage range from 0. 25 to 0. 85 and the yields range from 2 000 to 8 000 kg/hm<sup>2</sup>. From Fig. 4a, it can be seen that the NDVI peak at heading stage in Henan province is highly correlated with winter wheat yield. According to Fig. 4b, the correlation coefficient is relatively low for the entire study area due to the complex spatial heterogeneity of land use and cropping pattern across different provinces.

Four prefecture-level cities (i. e., Dezhou, Anyang, Xinxiang and Puyang) with different correlations were explored using regression analysis, and the relationships between yield and NDVI peak at the heading stage were shown in Fig. 5.

In general, meteorological disasters, terrain factors and the purity of winter wheat are important factors for influencing the winter wheat yields, however, this model is difficult to detect these impacts on



Fig. 5 Regressions between winter wheat NDVI peak and yield

production. Fig. 5 shows the predicting ability of four typical yield regression models. Firstly, strongly positive correlation, such as Zaozhuang in Fig. 5a, these regions are the main winter wheat producing areas with high purity in the top 5% wheat pixels. The results showed that NDVI peak can effectively reflect its correlation with wheat yield. Secondly, moderately positive correlations, such as Hebi in Fig. 5b, these areas are also located in the main winter wheat productive areas with high purity in the top 5% wheat Because Hebi is located in the Taihang pixels. Mountains in western Henan, it is susceptible to drought due to the poor vegetation cover, thin soil layer and unfavorable weather condition<sup>[13]</sup>, which leads to the inconsistency but still strong correlation between NDVI peaking of heading stage and yield. Thirdly, weak positive correlation, such as Luoyang in Fig. 5c, the top 5% winter wheat pixels in such cities usually have low purity, and are also impacted by severe diseases and pests, it is reported that winter wheat yield decreased by  $20\% \sim 40\%$  due to the severe winter wheat powdery mildew of Luoyang in 2000<sup>[14]</sup> and extreme weather with the severe dry-hot wind weather of Luoyang in 2001, 60% ~ 70% of winter wheat was impacted at different levels<sup>[15]</sup>. Fourthly, weak correlation or no correlation. such as Puyang in Fig. 5d, although such regions are also the main winter wheat producing areas with high purity in the top 5%wheat pixels, severe natural disasters from 2000 to 2010 occurred in Puyang, such as a low temperature freezing weather occurred in April 2010, impacting 99% winter wheat<sup>[13]</sup>. In the same year, the prolonged drought had an impact on the city's 80% winter wheat at the grouting stage. As results, under these circumstances, the NDVI peak of heading stage shows weak correlation with yield, thus making it difficult to develop a perfect yield estimation model.

# 3 Model validation

To test and compare the accuracy and applicability of the yield prediction model for Shandong, Henan and Hebei provinces, the relative error (i. e., (yield forecast – yield statistics)/yield statistics) was calculated by comparing the forecasting winter wheat yield in 2010 with the statistical data. Results show that the precisions of prefecture level regression forecasting model for winter wheat vary across cities. Overall, the absolute value of the model testing error is between 0. 64% and 14. 91%, with a majority yield estimation error of less than 10% and an average error of 7. 49%, which shows that the model has potential applicability in winter wheat producing areas in China.

# 4 Conclusion

(1) The accuracy of winter wheat yield estimation model proposed by Becker-Reshef et al.<sup>[5]</sup> depends on the density of winter wheat. NDVI peaks have good correlation with the wheat yield in high winter-density regions, such as west of Shandong, south of Henan, middle and south of Hebei, and poor model results have been observed in low wheat-density areas.

(2) The winter wheat yield estimation model based on NDVI peak of heading stage can predict winter wheat yield 2 months in advance. The average wheat predicting error is about 7.49% at the prefecture level, which shows a satisfactory applicability in the winter wheat producing regions of Shandong, Henan and Hebei under some circumstances.

(3) As compared with the model applications in Kansas of USA and Ukraine of Europe, this model has great potential to be improved for application in China: the crop fields in Shandong, Henan and Hebei are relatively fragmented, leading to a low winter wheat purity; in North China, trees are often planted along the crop fields, which leads to the contribution of trees and other vegetation to NDVI. Thus, NDVI sometimes can not effectively describe the winter wheat growing conditions. Therefore, using medium spatial resolution remote sensing data (such as the Landsat8, HJ-1 A/B and GFI WVF data) can effectively reduce the effects

of mixed pixels and thus better reflect the growth of Additionally, this model uses the winter wheat. information of NDVI peak at the heading stage, without taking other relevant factors into account at postheading stages (e.g., drought, high temperature and pest). Thus, the model performance can be improved through incorporating the contribution of the impacts during multiple key growing stages. Furthermore, this study did not take the potential changes of winter wheat varieties into account. In fact, wheat variety also has impacts on the relationship between NDVI peak and wheat yield. For example, to avoid the wheat falling down and increase the efficiency of fertilizer, the modified short varieties were planted in some regions in recent years, which lead to a decreased NDVI peak value at the heading stage, despite similar or even increased production.

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# 基于时间序列 MODIS NDVI 的冬小麦产量预测方法

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摘要:选择我国河北、河南、山东3省作为研究区,在250m空间分辨率的冬小麦种植区和1km的冬小麦像元纯度 图的基础上,分析了2000—2009年 MODIS NDVI 抽穗期峰值与单产的时间序列变化关系。采用 Becker-Reshef 等 提出的去噪声修正后的冬小麦抽穗期 NDVI峰值与单产进行回归分析建立冬小麦产量预测模型,并分析冬小麦预 测精度的影响因素。最后,利用2010年地级市尺度的统计单产对所建立的预测模型进行精度验证,模型的平均估 产误差约为7.49%。结果表明,基于冬小麦抽穗期 NDVI峰值的产量预测方法在中国冬小麦主产区具有一定的应 用潜力。

关键词: 冬小麦; 产量预测; 时间序列; MODIS NDVI 中图分类号: S127 文献标识码: A 文章编号: 1000-1298(2016)02-0295-07

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Abstract: The large regional-scale crop yield forecasting is of great significance to ensure national food security and agricultural sustainable development. To predict regional-scale winter wheat yield, the winter wheat forecasting method proposed by Becker-Reshef was implemented in major winter wheat planting areas in China. Firstly, the winter wheat planting areas were extracted through time series of MODIS NDVI with 250 m spatial resolution in Hebei, Henan and Shandong Provinces. Winter wheat adjusted NDVI peak at the heading stage was used to analyze the correlation with winter wheat yield on the purest wheat pixels from 2000 to 2010. Winter wheat yield prediction models were established through the regression statistical relationship between NDVI peak at heading stage and winter wheat yield at the prefecture-city unit from 2000 to 2009. The results showed that the dense wheat planted cities had good model accuracy. Finally, the accuracy of prediction models was evaluated by using the statistical winter wheat yield in 2010. The results showed that winter wheat yields could be forecasted two months in advance with average forecasting error of 7.49%, and the yield forecasting method using adjusted NDVI peak at heading stage had considerable potential applications at the prefecture-city scale in China. The study provides basis and a method for other crops yield forecasting in agricultural regions.

Key words: winter wheat; yield forecasting; time series; MODIS NDVI

引言

冬小麦是中国的主要粮食作物之一,对冬小麦

进行大区域长势监测和产量预测,对于及时、准确地 掌握国家粮食生产状况并进行粮食宏观调控,以及 在国际农产品贸易中争取主动权都具有重要意义。

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目前,产量预测模型主要分为作物生长模型和经验 回归模型。作物生长模型结合遥感数据同化是当前 作物产量预测的一种重要方法。由于作物生长模型 需要大量输入参数,特别是大区域范围的作物生长 模型标定与校准困难,因此在大区域尺度运行产量 估测业务系统存在一定局限性<sup>[1]</sup>。经验回归模型 是通过选取与产量相关的指示参数,例如遥感反演 的植被指数和气象观测要素等实现估产。这种方法 要求较少的参数输入,方法容易实现,但是缺乏普适 性。在此类研究中,归一化植被指数 NDVI 普遍用 干进行作物长势监测和产量估测<sup>[2]</sup>。国内学者分 别利用 NOAA\_NDVI 与 MODIS NDVI 遥感数据,对 四川、湖南、广西、江西和黑龙江建立以省级为单位 的水稻估产模型<sup>[3]</sup>和冬小麦产量估算模型<sup>[4]</sup>,达到 了一定的估产精度。美国学者提出一种普适的冬小 麦产量回归预测模型,最初模型建立于美国堪萨斯 州<sup>[5]</sup>。随后,该模型在没有经过任何修改和标定的 情况下直接应用于欧洲乌克兰地区。在冬小麦成熟 期前6周预测单产,误差在15%左右,预测总产误 差在10%左右。而根据2009年5月数据运行模 拟,冬小麦总产预测误差约为6.3%。相对于美国 而言,中国冬小麦主产区农地破碎,种植制度复杂。 因此,在中国冬小麦主产区验证 Becker-Reshef 等[5-6]提出的冬小麦产量预测模型具有实际意义。 本文采用 Becker-Reshef 等提出的 MODIS NDVI 噪 声抑制方法,使用调整后的抽穗期 NDVI 峰值对河

北、河南、山东3个省地级市尺度的冬小麦单产进行 回归建模与预测,并评估 Becker-Reshef 的方法在中 国冬小麦主产区地级市尺度的精度和适用性。

# 1 资料和方法

# 1.1 研究区概况

选取我国黄淮冬麦区的山东、河南和河北3省 冬小麦主产区作为研究区(图1)。该区土壤类型 以石灰性冲积土为主,部分为黄壤与棕壤,质地良 好,是我国冬小麦高产区。3省的冬小麦产量约占 全国冬小麦产量的67%<sup>[7-8]</sup>。冬小麦和夏玉米的 轮作为本区典型的农业种植模式。全区气候温 和,雨量季节差异性较大。2月下旬—3月上旬为 冬小麦返青期,4月中上旬为拔节期,5月中上旬 为抽穗灌浆期,6月上旬前后成熟收割。总体来 说,河南省的冬小麦物候期较河北省提前10~ 20d左右。此外,河北省中南部、山东省的西北部 和西南部、河南省的北部以及中东部均具有较高 密度的冬小麦种植分布。

# 1.2 数据来源概述

# 1.2.1 遥感及统计数据源

所用 MODIS NDVI 数据来源于全球农业监测系统(GLAM)产品,1 km×1 km 空间分辨率,8 d 数据为一个时间步长,时间序列为 2000—2010 年;冬小麦单产和播种面积是以地级市为单位的统计数据,来源于《国家统计年鉴》。



1.2.2 基于时间序列 MODIS NDVI 数据的冬小麦 种植区提取

利用 2010 年 250 m 空间分辨率的冬小麦关键 生育期时间序列 MOD09A1 反射率数据,然后采用 物候曲线特征匹配的分类方法提取了研究区的冬小 麦种植区<sup>[9]</sup>。根据野外调查的样本点验证(主要地 物类型包括冬小麦、棉花、其他作物、建设用地、裸 土、森林和水体),冬小麦的分类总体精度为 89.3%,Kappa 系数为 0.85。

#### 1.3 数据处理方法

#### 1.3.1 时间序列变化分析

依据冬小麦像元纯度(每个像元冬小麦种植区 域面积占像元面积的百分比)分布,选取每个地级 市前5% 纯度像元(分辨率为1km×1km)作为冬小 麦分布的掩膜数据,利用此数据对 NDVI 时间序列 进行提取和分析<sup>[10]</sup>。通过分析 2000—2009 年时间 序列掩膜后 8 d 的 NDVI 数据,得出冬小麦冬前分蘖 期 NDVI 峰值、冬小麦抽穗期 NDVI 峰值等。

#### 1.3.2 NDVI 峰值算法

考虑到冬小麦产区 NDVI 数据表征冬小麦的生 长状况存在较大噪声,采用 Becker-Reshef 等提出的 NDVI 噪声抑制方法,即 NDVI 最大值(MA\_NDVI) 为冬小麦抽穗期的 NDVI 峰值减去背景噪音最低平 均 NDVI 值。在产量预测模型中,冬小麦抽穗期 NDVI 峰值为主要的模型输入参数,并且抽穗期一 定程度上决定了冬小麦的穗粒数,是冬小麦产量的 有效指示参数。

经过反复试验,从每个地级市冬小麦时间序列数据中(2000—2010年)提取每年冬小麦生长期调整后的 NDVI 峰值,即 NDVI 第 95 个最大百分位数减去多年冬小麦生长期 NDVI 第 5 个最小百分位数的平均值得到的效果最好<sup>[5]</sup>,即

$$MA\_NDVI_{y} = I_{\max95,y} - \frac{1}{N} \left( \sum_{y=1}^{N} I_{\min5,y} \right)$$
(1)

式中 N——年份数目,文中为2000—2010年

I<sub>min5,y</sub>——第 y 年冬小麦生长期 NDVI 最小值的第 5 个百分位

#### 1.3.3 冬小麦产量预测方法

NDVI峰值反映了冬小麦的光合作用和长势。 采用最小二乘法,使用 NDVI峰值算法预测冬小麦 产量,即通过 2000—2009 年共 10 年冬小麦抽穗期 NDVI峰值和冬小麦单产关系的研究,采用相关系 数 *R* 表征 NDVI峰值与单产之间的相关程度,用相 对误差和均方根误差来表示模型的精确度和稳 定性。

# 2 结果分析

# 2.1 冬小麦纯度分析

基于 2010 年 250 m × 250 m 的冬小麦种植空间 分布图,使用 ArcGIS 软件中的 Zonal Statistics 功能, 可以得到 1 km × 1 km 的冬小麦像元纯度图,即每个 像元冬小麦种植区域面积占像元面积的百分比,如 图 2 所示。



图 2 冬小麦像元纯度图 Fig. 2 Purity map of winter wheat

一般来说,像元的冬小麦种植相对稳定,故采用 2010年冬小麦种植的像元纯度来反映 2000—2010 年整个时间序列上冬小麦的种植情况。从图 2 可看 出,像元百分比最大的冬小麦分布区域分布于河北 南部、山东西部和河南大部,其余区域冬小麦种植范 围较小,纯度较低。河北北部的承德市、张家口市因 无冬小麦的分布,故在后续分析中不考虑这 2 个地 级市。另外,漯河市、周口市、许昌市、商丘市、菏泽 市、濮阳市等区域均分布有高纯度的冬小麦像元,此 类地级市为 3 省冬小麦的主产区。由于地形和气候 等因素的影响<sup>[11]</sup>,三门峡市、洛阳市、日照市、廊坊 市等地区的冬小麦像元百分比偏低。

# 2.2 NDVI 时间序列变化

利用 NDVI 的 8 d 数据表示冬小麦农情信息,提 取各地级市前 5% 纯度像元所对应的 NDVI,获得各 地级市 2000—2010 年 NDVI 时间序列变化图。结 合当年冬小麦单产对所有地级市时间序列的变化规 律进行分析,发现所有地级市中前 5% 纯度像元的 NDVI 变化趋势较为一致,均体现出与冬小麦农情 相吻合的变化规律。其中,以冬小麦种植纯度不同 的4个地级市河北省唐山市(纯度为44.60%)、山



东省烟台市(纯度为78.03%)、河北省沧州市(纯度 为89.10%)、河南省濮阳市(纯度为100%)为例, NDVI时间序列如图3所示。



图 3 4个地级市 NDVI 变化(图中曲线上的数字代表冬小麦单产,单位 kg/hm<sup>2</sup>) Fig. 3 NDVI time series for four cities (Numbers represents winter wheat yield for each year)

4 个地级市 8 d MODIS NDVI 变化曲线中,每年 按时间序列呈现 3 个峰值,与实际冬小麦抽穗期、夏 玉米成熟期和次年冬小麦分蘖期等作物物候期一 致。其中,河北省唐山市冬小麦抽穗期并不明显,这 与其冬小麦种植纯度(44.60%)较低有关。在整个 时间序列上,冬小麦抽穗期 NDVI 值保持相对稳定, 但是其产量却呈现增加的趋势,这与品种改良、技术 进步以及田间管理等措施有关。

从图 3 可以看出,唐山市、烟台市和沧州市的冬 小麦抽穗期 NDVI 值分布于 0.5~0.6之间,与之对 应的冬小麦产量为 3 000~5 500 kg/hm<sup>2</sup>;濮阳市冬 小麦抽穗期 NDVI 值分布于 0.6~0.8 之间,其产量 也相对较高,分布于 5 800~7 000 kg/hm<sup>2</sup>之间。

总体来说,在地级市尺度上,冬小麦单产与抽穗 期 NDVI 的峰值变化呈现正相关关系。但是也存在 如下异常的情况,在灌溉条件无法保证的区域,如果 冬小麦拔节期到抽穗期气候条件良好,造成抽穗期 NDVI 峰值偏大,若后期遭受不正常天气影响,则导 致冬小麦灌浆困难、单产较低。与此相反,如果冬小 麦拔节期到抽穗期遭遇不正常天气影响,会导致抽 穗期 NDVI 峰值偏低,而之后气候条件优越,冬小麦 却能达到高产。在地形较为复杂的地区,小气候与 地形因素会对冬小麦的产量产生一定的影响。

从图 3b 可看出,2002 年山东烟台市冬小麦抽 穗期 NDVI 峰值较大,但其产量相较于前一年呈现 出减少的趋势,这与 2002 年烟台 5 月上旬连续的阴 雨天气有关;而与此相反的情况如图 3c 所示,2003 年河北省沧州市冬小麦抽穗期 NDVI 峰值较低,与 之对应的却是当年较高的产量,原因是 2003 年河北 省沧州市冬小麦拔节到抽穗期发生干旱,而后期持 续的降雨和灌溉对冬小麦的生长恢复有补偿作用, 因此没有造成冬小麦减产。

# 2.3 基于冬小麦抽穗期 NDVI 峰值的产量预测模型构建

通过最小二乘法将各地级市 2000—2009 年冬 小麦抽穗期 NDVI 峰值与冬小麦单产建立回归预测 模型,并通过相关系数(*R*)、显著性检验 *F*值、相对 误差(Φ)、和均方根误差(RMSE)分析估产模型的 可信度和稳定性,从 43 个地级市中选取 12 个典型 地级市估产模型及参数如表 1 所示。

从表1可以看出,冬小麦抽穗期 NDVI 峰值与 冬小麦产量之间总体呈现显著正相关关系,且基于 地级市尺度上的回归预测模型的精度呈现出一定差 异。其中,大多数地级市冬小麦抽穗期 NDVI 峰值 与其产量呈现出较强的相关性;受到冬小麦像元纯 度、地形地貌以及当地种植制度、特殊年份出现的旱 灾、病虫害等对产量的影响,导致少数地级市相关性 较低。该估产模型的最大误差 15.42% 出现在三门 峡市,对应冬小麦像元纯度较低(7.24%);而最小 误差 1.94% 则为石家庄市,对应冬小麦像元纯度为 100%。

总体来看,大多数地级市估产误差在9%以下,

山东、河北、河南冬小麦产量预测模型

山东济宁市 $y = 6\ 005.\ 45x + 1\ 601.\ 52$ $86.\ 87$ $0.\ 88$ $15.\ 53$ $4.\ 13$ $0.\ 3$ 山东泰安市 $y = 2\ 049.\ 95x + 4\ 985.\ 75$ $98.\ 68$ $0.\ 87$ $5.\ 35$ $2.\ 95$ $0.\ 2$ 潍坊市 $y = 2\ 049.\ 95x + 4\ 985.\ 75$ $98.\ 68$ $0.\ 87$ $5.\ 35$ $2.\ 95$ $0.\ 2$ 淄博市 $y = 2\ 508.\ 13x + 4\ 100.\ 49$ $92.\ 39$ $0.\ 32$ $0.\ 25$ $7.\ 24$ $0.\ 5$ 淄博市 $y = 9\ 479.\ 54x - 585.\ 16$ $99.\ 78$ $0.\ 20$ $0.\ 47$ $7.\ 16$ $0.\ 5$ 小晶市市 $y = 2\ 639.\ 50x + 3\ 247.\ 10$ $95.\ 47$ $0.\ 67$ $7.\ 01$ $2.\ 97$ $0.\ 2$ 河南南阳市 $y = 10\ 012.\ 53x - 2\ 076.\ 36$ $94.\ 21$ $0.\ 69$ $3.\ 63$ $6.\ 32$ $0.\ 4$ 三门峡市 $y = 10\ 048.\ 69x - 2\ 827.\ 62$ $95.\ 29$ $0.\ 03$ $0$ $5.\ 46$ $0.\ 4$ 三门峡市 $y = 7\ 509.\ 96x - 103.\ 95$ $7.\ 24$ $0.\ 34$ $3.\ 37$ $15.\ 42$ $0.\ 5$ 河北邯郸市 $y = 3\ 293.\ 22x + 2\ 921.\ 84$ $100$ $0.\ 46$ $0.\ 93$ $3.\ 77$ $0.\ 2$			iouolo for forecasting white	i when yield in Sh		0.001 unu 110		
山东	省份	地级市	产量预测模型	平均像元纯度/%	R	F	$\Phi/\%$	$RMSE/(t \cdot hm^{-2})$
山东		济宁市	$y = 6\ 005.\ 45x + 1\ 601.\ 52$	86. 87	0.88	15.53	4.13	0.31
濰坊市 $y = 2508.13x + 4100.49$ 92.39    0.32    0.25    7.24    0.5      淄博市 $y = 9479.54x - 585.16$ 99.78    0.20    0.47    7.16    0.5      海南 $y = 2639.50x + 3247.10$ 95.47    0.67    7.01    2.97    0.2      南阳市 $y = 10012.53x - 2076.36$ 94.21    0.69    3.63    6.32    0.4      直门峡市 $y = 10048.69x - 2827.62$ 95.29    0.03    0    5.46    0.4      三门峡市 $y = 7509.96x - 103.95$ 7.24    0.34    3.37    15.42    0.5      沧州市 $y = 615.80x + 5130.74$ 89.10    0.77    18.40    7.06    0.3      河北    邯郸市 $y = 3293.22x + 2921.84$ 100    0.46    0.93    3.77    0.2	1. +	泰安市	$y = 2\ 049.\ 95x + 4\ 985.\ 75$	98.68	0.87	5.35	2.95	0.23
許昌市 $y = 2 639.50x + 3 247.10$ $95.47$ $0.67$ $7.01$ $2.97$ $0.2$ 南阳市 $y = 10 012.53x - 2 076.36$ $94.21$ $0.69$ $3.63$ $6.32$ $0.4$ 魚作市 $y = 10 048.69x - 2 827.62$ $95.29$ $0.03$ $0$ $5.46$ $0.4$ 三门峡市 $y = 7 509.96x - 103.95$ $7.24$ $0.34$ $3.37$ $15.42$ $0.5$ 沧州市 $y = 615.80x + 5 130.74$ $89.10$ $0.77$ $18.40$ $7.06$ $0.3$ 河北	田东	潍坊市	$y = 2 \ 508. \ 13x + 4 \ 100. \ 49$	92.39	0.32	0.25	7.24	0.55
南阳市 $y = 10\ 012.\ 53x - 2\ 076.\ 36$ 94. 21    0. 69    3. 63    6. 32    0. 4      河南    進作市 $y = 10\ 012.\ 53x - 2\ 076.\ 36$ 94. 21    0. 69    3. 63    6. 32    0. 4      進作市 $y = 10\ 048.\ 69x - 2\ 827.\ 62$ 95. 29    0. 03    0    5. 46    0. 4      三门峡市 $y = 7\ 509.\ 96x - 103.\ 95$ 7. 24    0. 34    3. 37    15. 42    0. 5      沧州市 $y = 615.\ 80x + 5\ 130.\ 74$ 89. 10    0. 77    18. 40    7. 06    0. 3      河北    邯郸市 $y = 3\ 293.\ 22x + 2\ 921.\ 84$ 100    0. 46    0. 93    3. 77    0. 2		淄博市	$y = 9 \ 479. \ 54x - 585. \ 16$	99.78	0.20	0.47	7.16	0.51
河南    無作市 $y = 10\ 048.\ 69x - 2\ 827.\ 62$ 95. 29    0. 03    0    5. 46    0. 4      三门峡市 $y = 7\ 509.\ 96x - 103.\ 95$ 7. 24    0. 34    3. 37    15. 42    0. 5      沧州市 $y = 615.\ 80x + 5\ 130.\ 74$ 89. 10    0. 77    18. 40    7. 06    0. 3      河北    邯郸市 $y = 3\ 293.\ 22x + 2\ 921.\ 84$ 100    0. 46    0. 93    3. 77    0. 2		许昌市	$y = 2\ 639.\ 50x + 3\ 247.\ 10$	95.47	0.67	7.01	2.97	0. 24
焦作市 $y = 10\ 048.\ 69x - 2\ 827.\ 62$ 95. 29    0.03    0    5. 46    0.4      三门峡市 $y = 7\ 509.\ 96x - 103.\ 95$ 7. 24    0. 34    3. 37    15. 42    0. 5      沧州市 $y = 615.\ 80x + 5\ 130.\ 74$ 89. 10    0. 77    18. 40    7. 06    0. 3      河北    邯郸市 $y = 3\ 293.\ 22x + 2\ 921.\ 84$ 100    0. 46    0. 93    3. 77    0. 2	्य म	南阳市	$y = 10\ 012.\ 53x - 2\ 076.\ 36$	94. 21	0.69	3.63	6.32	0.41
沧州市 $y = 615.80x + 5130.74$ 89.100.7718.407.060.3邯郸市 $y = 3293.22x + 2921.84$ 1000.460.933.770.2	- 71 円	焦作市	$y = 10\ 048.\ 69x - 2\ 827.\ 62$	95.29	0.03	0	5.46	0.46
第一部 第一 $y = 3 293.22x + 2 921.84$ 100 0.46 0.93 3.77 0.2 河北		三门峡市	y = 7 509. 96 $x - 103.$ 95	7.24	0.34	3.37	15.42	0.56
		沧州市	y = 615.80x + 5130.74	89.10	0.77	18.40	7.06	0.34
河北 衡水市 y = 183. 44x + 5 541. 40 96. 02 0. 05 0. 46 3. 36 0. 2	रेल्ट मह	邯郸市	$y = 3 \ 293. \ 22x + 2 \ 921. \ 84$	100	0.46	0.93	3.77	0.24
	7미 그는	衡水市	y = 183.44x + 5541.40	96.02	0.05	0.46	3.36	0.23
石家庄市 y = 9 117. 49x - 867. 36 100 - 0. 22 1. 18 1. 87 0. 1		石家庄市	$y = 9 \ 117. \ 49x - 867. \ 36$	100	-0.22	1.18	1.87	0.16

Tab. 1 Models for forecasting winter wheat yield in Shandong, Hebei and Henan Provinces

表 1

且平均相对误差为 6.59%,均方根误差分布于 0.16~0.80 t/hm<sup>2</sup>之间,说明此估产模型具有一定的精度和稳定性。

为了进一步分析冬小麦抽穗期 NDVI 峰值与其 产量在整个研究区和各省的相关关系,分别利用河 南省和整个研究区 2000—2010 年冬小麦抽穗期 NDVI 峰值与产量数据绘制散点图,并进行回归分 析,如图 4 所示。



图 4 整个研究区及河南省冬小麦抽穗期 NDVI 峰值与冬小麦单产的回归关系

Fig. 4 Regression between winter wheat NDVI peak at heading stage and yield in Henan Province

冬小麦抽穗期 NDVI 峰值分布于 0.25~0.85 之间,其产量分布于 2000~8000 kg/hm<sup>2</sup>之间。从 图 4a 可看出,河南省冬小麦抽穗期 NDVI 峰值与其 单产之间相关系数较高,回归效果较好;而图 4b 表 明,在整个研究区相关系数较低,原因是各省市由于 土壤、气候以及不同冬小麦品种导致植株茂盛程度 并不能完全决定其产量。

选取不同相关性的 4 个地级市(德州市、安阳 市、新乡市和濮阳市)进行回归分析,冬小麦抽穗期 NDVI 峰值与其单产之间的相关关系如图 5 所示。

总体来说,自然灾害、地形因素和冬小麦像元纯 度是影响冬小麦产量的重要因素,而此模型无法检 测其对产量的影响,图5显示4种典型产量回归模 型的预测效果。



Fig. 5 Regression between winter wheat NDVI peak and yield

①强正相关(图 5a 枣庄市),此类地级市一般 为冬小麦的主产区,且提取的前5%像元纯度较高, 极端天气影响较小,故冬小麦抽穗期 NDVI 峰值能 够较好地反映其与冬小麦产量的相关关系。②中等 强度正相关(图 5b 鹤壁市),此类地级市也为冬小 麦的主产区,且提取的前5%纯度的像元冬小麦百 分数高,由于鹤壁市地处河南西部太行山区,植被 差、土壤薄,极易发生干旱<sup>[13]</sup>,导致冬小麦抽穗期 NDVI 峰值反映冬小麦产量时并不能完全吻合,但 仍能体现出较强相关性。③弱正相关(图 5c 洛阳 市),此类地级市提取的前5%纯度的像元冬小麦百 分数较低,并且受到较为严重的病虫害(2000年洛 阳市冬小麦出现严重的白粉病,冬小麦减产20%~ 40%<sup>[14]</sup>)和极端天气(2001年洛阳市出现严重干热 风天气,60%~70%冬小麦受到不同程度影响<sup>[15]</sup>) 的影响。④极弱相关或无相关(图 5d 濮阳市),尽 管提取的前5%的纯度像元冬小麦百分数较高,但 濮阳市在 2000—2010 年间发生过多次严重的自然 灾害(2010年4月,出现低温霜冻天气,导致99%冬

小麦受到影响,不利于小麦苗情转化<sup>[13]</sup>;同年5月, 连续出现的干旱对全市 80% 冬小麦的灌浆产生影 响)使冬小麦抽穗期 NDVI 峰值与冬小麦产量之间 无法建立理想的模型,故表现出极弱的正相关。

### 3 模型验证

为了验证和比较上述产量预测模型的准确性和 适用性,针对山东、河南和河北3个省43个地级市, 利用冬小麦产量预测模型对2010年冬小麦产量进 行预测并与2010年统计数据对比,得出其相对误差 (单产预测值和单产统计值差值与单产统计值之 比)。结果显示:各地级市的冬小麦回归预测模型 精度各不相同。总体来看,该模型检验误差的绝对 值分布于0.64%~14.91%之间,并且大多数地级 市估产误差小于10%,平均误差(即各地级市相对 误差绝对值之和的平均)为7.49%,表明该模型在 中国冬小麦主产区具有一定的适用性。

#### 4 结论

(1)模型精度与大面积连片种植密度密切相关。山东西部、河南南部和河北中南部地区均是冬 小麦大片种植高纯度地区,抽穗期 NDVI 峰值与其 单产的相关性较好。

(2)基于抽穗期 NDVI 峰值的冬小麦产量预测

模型,能提前2个月左右预测冬小麦产量。在地级市的预测精度的平均误差为7.49%,表明在一定条件下,该方法在山东、河南、河北冬小麦区具有较好的适用性。

(3)相对于美国堪萨斯州和乌克兰来说,此方 法在中国的使用存在以下改进的空间:山东、河南和 河北省地块较为破碎,像元纯度不高;并目北方地区 有在田边种植树木的习惯,导致像元 NDVI 值有相 当的树木或其他植被贡献的成分,并不能完全反映 冬小麦的生长状况,因此使用分辨率较高的影像数 据(例如: Landsat8、HJ-1 A/B 和 GF1 WVF 数据), 能进一步减少混合像元效应,从而能够更好地反映 冬小麦的生长状况;再有,由于此预测模型仅仅利用 了抽穗期 NDVI 峰值的信息,没有考虑抽穗期后对 产量影响的因素(干旱、干热风、病虫害和洪涝等), 在特殊情况下,这些气候条件还起相当大的作用。 因此,今后的研究如果能结合多个关键生育期的影 响因子综合建模,有望能进一步提高冬小麦产量预 测模型的精度。此外,在研究的时间序列中,本文没 有考虑冬小麦品种的改变。事实上,作物品种对于 NDVI 峰值与作物产量的关系有较大影响,如近年 来不少地区为防止倒伏、提高施肥效率,改种改良的 低矮型品种,在同样产量、甚至产量提高情况下,抽 穗期 NDVI 峰值反而会有所下降。

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