Winter Wheat Yield Estimation Coupling Weight Optimization Combination Method with Remote Sensing Data from Landsat5 TM

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Xingang Xu[1,2,3,*], Jihua Wang[1,2,3], Wenjiang Huang[1,2,3], Cunjun Li[1,2,3], Xiaoyu Song[1,2,3], Xiaodong Yang[1,2,3], Hao Yang[1,2,3]

[1]National Engineering Research Center for Information Technology in Agriculture, Beijing 100097, China
[2]Department of Precision Farming Applications, National Remote Sensing Center of China Beijing 100097, China
[3]Beijing Research Center for Information Technology in Agriculture, Beijing 100097, China

xxg2007@yahoo.com.cn

Abstract. Crop yield models using different VIs (vegetation index) from remote sensing data show the various precision, but each of them can provide useful information related with yield. So it is very significant how to integrate the useful information of these models. In this study, a few of typical VIs, such as *NDVI* (Normalized Difference Vegetation Index), *SR* (Simple Ratio index), *TCARI/OSAVI* (Trans-formed Chlorophyll Absorption Ratio Index (*TCARI)*, and Optimized Soil-Adjusted Vegetation Index (*OSAVI*)), *NDWI* (Normalized Difference Water Index) extracted from Landsat5 TM image covering Beijing region, are used to build yield modes of winter wheat, respectively. And then the Weight Optimization Combination (WOC) method is utilized to integrate the models by calculating optimized weights to form the combining model. It is proved that the combining model with WOC exhibits better performance with the slightly higher determination coefficient R^2 in comparison with each single yield models with four different VIs, respectively. The analysis of comparing the weights in the combining model with WOC indicates that the two VIs, *SR* and *NDWI* are more sensitive to winter wheat yield than the other two during the winter wheat jointing stage. The preliminary results of coupling the WOC method with remote sensing imply that WOC can be used to improve the accuracy of yield estimation based on remote sensing.

Keywords: Weight optimization combination, remote sensing, yield estimation, winter wheat, Landsat5 TM

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* Corresponding author; Email: xxg2007@yahoo.com.cn
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1 Introduction

Crop yield are impacted by a wide range of factors, not only natural environment conditions such as light, temperature, water, soil quality, terrain and so on, but also social factors, for instance, field management, agricultural machine, fertilizer, etc (Rieger et al., 2008; Xu et al., 2008). So it is difficult, and even impossible to establish the yield estimating models which can include all impact factors of crop yield. Although the factors influencing crop yield are many and complex, these factors are not independent and affect each other. In different stage, there are different dominant factors impacting crop growth, the estimating models of crop yield can be set up by using the dominating factors according to some principals and methods, Therefore, all kinds of models can all provide various useful-information more or less to some extent. If the scattered models are synthetically utilized to form the combining model and estimate crop yield, the precision of crop yield estimation will improve, Weight Optimization Combination (WOC) is just an algorithm for solving the type of problem. WOC aims at making best use of useful information from each of single models by giving the optimal weights to the single models to form the combining model with LSSE (Least sum of square error), and is often used in economic prediction and decision analysis fields (Tang, 1991, 1992; Tang et al., 1994), and seldom applied for yield estimation with remote sensing.

Remote sensing plays a unique role in estimating crop yield by its nondestructive, fast, and large-area-measurement characteristic. The typical vegetation indices (VIs) with different bands combination from remote sensing, such as *NDVI* (Rouse et al., 1974; Gitelson et al., 1994), *SR* (Jordan, 1969), *TCARI/OSAVI* (Daughtry et al., 2000; Rondeaux et al., 1996; Haboudane et al, 2002), *NDWI* (Gao, 1996) can monitor crop growth status in different stages, indirectly provide useful information on crop yield, and be used to estimate crop yield in this study. Since different VI can detect crop growth status from different views, crop yield models with different VIs can also provide some useful information from different ways, so if we integrate the scattered models together, and form the combining model in order to make full use of the useful information from each of the single scattered models, the precision of crop yield estimation can improve more or less.

The objective of the study is to compare the performance of the above VIs for estimating yield of winter wheat, and then the WOC principle is applied to integrate the single yield estimating models with the VIs to form the combining models, finally assess the performance of the WOC method with remote sensing for estimating yield of winter wheat.

2 Material and Method

2.1. Study area and data acquisition

The study area covers Shunyi & Tongzhou District in Beijing, China. The plant area of winter wheat in the two districts accounts for about 50% of the whole Beijing. Fgure 1 showed the location of the study area (116.45~117.01°E, 40.0~40.3°N), the triangles in Fig. 1 represent the 30 measured yield plots in winter wheat field. Among the plots, there are 15 plots in Shunyi, and the other 15 in Tongzhou District.

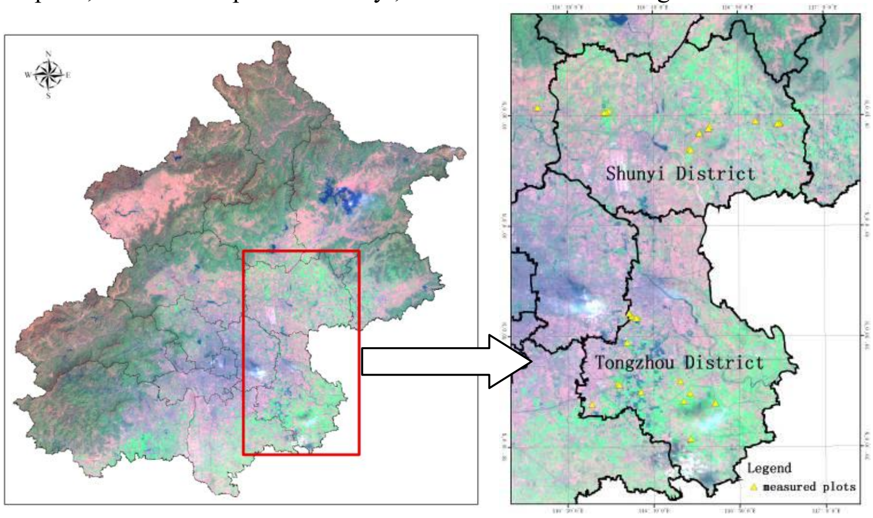


Fig. 1. Study area covering Shunyi & Tongzhou District(right), in Beijing(left), China.

2.2. Remote sensing data and preprocessing

In the study, a satellite image from Landsat5 TM which passed over the study area on April 15, 2009 is acquired to estimate yield of winter wheat for assessing the performance of WOC. Winter wheat is during the jointing stage. In order to eliminate some noises and improve data precision, the image is preprocessed by radiant calibration, atmospheric and geometrical corrections with ENVI software.

2.3. Vegetation Indices used in the study

In this analysis, the four vegetation indices, *NDVI*, *SR*, *TCARI/OSAVI* (the ratio of *TCARI* and *OSAVI* as a VI), and *NDWI* are utilized to estimate yield of .winter wheat in the study area in 2009. Table 1 showed the summary of the four vegetation indices, R is the land surface reflectance, and the subscripts *green, red, nir, and swir* were respectively band2, band3, band4 and band5 from the Landsat5 TM image.

NDVI (Normalized Difference Vegetation Index) should be the most extensively used VI which couples the reflection in the infrared with that in the red, and responds to changes in amount of biomass, chlorophyll and LAI. *SR* (Simple Ratio index) is directly formulated with the reflection in the infrared and that of the absorption in the red, and can enhance the contrast between soil and vegetation while minimizing the effect of the illumination conditions (Barnet and Guyot, 1991).

TCARI (Transformed Chlorophyll Absorption Ratio Index) is proposed to eliminate reflectance effect of background matters (soil and non-photosynthetic components) and to increase the sensitivity at chlorophyll content, and it is often formulated with 550,670, and 700nm in hyperspectral applications, the detailed description of the *TCARI* can be found in Daughtry et al. (2000). In the study, in order to use the multispectral wide-band image, the calculation of *TCARI* is modified with bands from Landsat5 TM as the formula in Table 1. *OSAVI* (Optimized Soil-Adjusted Vegetation Index) belongs to *SAVI* family (Huete, 1988), and is developed to further reduce background soils. The ratio of *TCARI* and *OSAVI* as a new index is proposed by Haboudane et al. (2002), which integrate advantages of indices minimizing soil background effects and indices that are sensitive to chlorophyll concentration. So the index of *TCARI/OSAVI* can monitor crop nutritional status, and further assess crop yield.

NDWI (Normalized Difference Water Index) is based on liquid water absorption band near 1240nm, and a relative non-absorption reference band near 860nm (Gao, 1996), so it can detect crop water stress. In the analysis, *NDWI* is modified by the combination of the reflectance in the Nir with that in the Swir (short infrared) from Landsat5 TM image bands.

In the present study, the four indices are relatively related with crop growth, nutrition and water, all of which interact with crop yield, so it is possible that integrating the single models with these indices establishes the combining model to estimates crop yield with higher precision.

Table 1 Summary of the four vegetation indices for this analysis

VI	Full name	Definition	Described by
NDVI	Normalized Difference Vegetation Index	$(R_{nir}-R_{red})/(R_{nir}+R_{red})$	Rouse et al., 1974; Gitelson et al., 1994
SR	Simple Ratio Index	$R_{nir}\ /\ R_{red}$	Jordan, 1969
TCARI/ OSAVI	Transformed Chlorophyll Absorption Ratio Index / Optimized Soil-Adjusted Vegetation Index	$\frac{3*((R_{nir}-R_{red})-0.2*(R_{nir}-R_{green})*(R_{nir}/R_{red}))}{(1+0.16)*(R_{nir}-R_{red})/(R_{nir}+R_{red}+0.16)}$	Daughtry et al., 2000; Rondeaux et al., 1996; Haboudane et al, 2002
NDWI	Normalized Difference Water Index	$(R_{nir}-R_{swir})/(R_{nir}+R_{swir})$	Gao, 1996

2.4. Weight optimization combination method

Weight optimization combination (WOC) is a method which computationally gives optimal weights of different models solving the same problem to form the combination model with the aim of the least errors (Xu et al., 2009). The principle of WOC is as the following:

There are different N models constructed with n samples for settling the same problem, where both N and n are the same as the following mentioned, respectively.

y_j : the measured value for j sample ($j = 1, 2, 3, \cdots, n$);

f_{ij} : the estimated result for j sample with i model($i = 1, 2, 3, \cdots, N$);

$e_{ij} = y_j - f_{ij}$: the error for j sample with i model;

The estimated value of the combination model formed by N models for j sample is defined as the following:

$$f_j = \sum_{i=1}^{N} k_i f_{ij} \qquad (1)$$

Here, k_i are weights of N single models, and k is constrained by the following conditions:

$$\begin{cases} k_i \geq 0 \\ \Sigma k_i = 1 \end{cases} \qquad (2)$$

The error of the combination model for j sample is formulated with the following:

$$e_j = y_j - f_j = \sum_{i=1}^{N} e_{ij} k_i \qquad (3)$$

For determining k_i, e_j is usually looked on as independent variable of the objective function, and the mathematic framework of WOC is commonly expressed as the following:

$$\begin{cases} E = \min E(k_1, k_2, \ldots, k_i) \\ \Sigma k_i = 1 \\ k_i \geq 0 \end{cases} \qquad (4)$$

Where, min$E$ is the objective function that can be the minimum error square sum, or minimum absolute error sum, or the other cost function.

The process solving the formula (4) for the acquisition of k_i is a little complicated, and there are various solving algorithms for the formula (4) with different effectiveness. In the study, the iterative optimization algorithm based on dual optimal combination is selected to calculate the optimal weights, whose detailed description can be found in Tang et al. (1994)

3. Result and Discussion

3.1. Yield estimation with single vegetation index

To set up the combining model of winter wheat yield estimation base on WOC, the above four VIs is firstly used to establish the yield models with the field measured yield data and the preprocessed remote image from Landsat5 TM, respectively. The LLST(Linear Least Squares Fit) is the main modeling method in the study; and the equations of the models with different index are as the following (5) – (8):

$$f_{NDVI} = 6879 * NDVI + 1970 \tag{5}$$

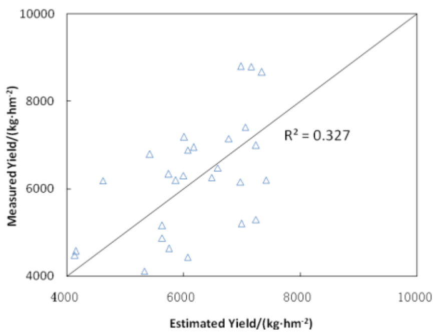
$$f_{SR} = 483.6 * SR + 3868 \tag{6}$$

$$f_{TCARI/OSAVI} = -1462 * TCARI / OSAVI + 6143 \tag{7}$$

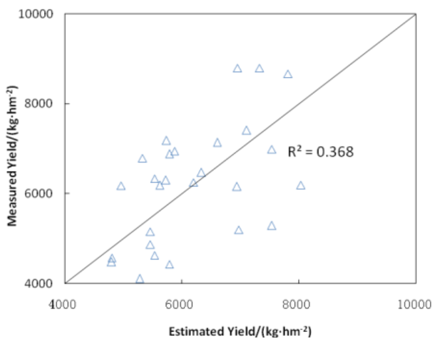
$$f_{NDWI} = 6801 * NDWI + 4764 \tag{8}$$

In the equation (5) ~ (8), f is yield calculated by the individual model from different vegetation index, and the unit is kg/hm.

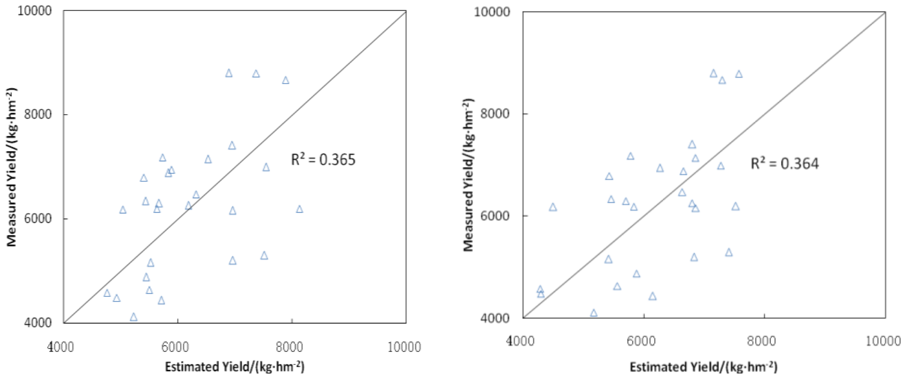
Figure 2 shows the correlation coefficients between the measured and estimated yield with four VIs models of winter wheat yield. From the figure, it is proved that the four models with different Vis have the approximate precisions, but the precisions of the models with three VIs, *SR*, *TCAI/OSAVI* and *NDWI* are more proximal, and the determinant coefficients R^2 are 0.368, 0.365 and 0.364, respectively.



(a) *NDVI*



(b) *SR*



(a) *TCARI/OSAVI* (d) *NDWI*

Fig. 2. Coefficients of correlation between the measured and estimated yield with different VI models of winter wheat

3.2. Estimating yield with the combining model

In order to use WOC to build the combining model for estimating yield of winter wheat, the above four models from the equations (5) ~ (8) are input into WOC, and then the iterative optimization algorithm above mentioned is applied to calculate the weights. The result is as Table 2 shows.

Table 2 Optimum weights of the estimating models with different VIs based on WOC

Model with different VIs	Weights	R^2 of yield estimation
SR	0.54	0.368
NDVI	0.00	0.327
TCARI/OSAVI	0.00	0.365
NDWI	0.46	0.364
Combining model	--	0.379

From Table 2, it can been seen that the combining model has better performance in comparison with the four individual models with different VIs, and its determinant coefficient R^2 arrives at 0.379 (also see Fig. 3) and are slightly higher than the four single models. In addition, Table 2 also shows that the two models with *NDVI* and *TCARI/OSAVI* obtain the zero weights, which indicates that the two models have no contribution to the combining model. In fact, in the process of using WOC with the iterative optimization algorithm, the more useful information the single model contributes to, the bigger weight it is given, and vice versa. That is to say, WOC has the function of judging the redundant information (Tang, 1992). As far as the single model providing little or useless information is concerned, WOC will give the model less or zero weight. Therefore, WOC can be employed to determine which of the VIs are more probably sensitive to winter wheat yield according to the weights when the four models as constructed separately by the above four VIs are input into WOC at the same time. In this study, the analysis demonstrates that the two yield models with the VIs *SR* and *NDWI* are enough, and the other two are redundant, which is significant for how to select the VIs sensitive to crop yield based on WOC. In the analysis, the two VIs SR and *NDWI* are probably more sensitive to winter wheat yield than the others two during the winter wheat jointing stage.

According to the result from table 2, the combining model can be described by the following equation (9):

$$Y = 0.54 f_{SR} + 0.46 f_{NDWI} \quad (9)$$

Here, Y is yield calculated by the combining model coupling the vegetation index *SR* with *NDWI* in terms of WOC, and the unit is kg/hm. both f_{SR} and f_{NDWI} are corresponding to dependent variables in the equations (6) and (8), respectively. Figure 3 displays the correlation between the measured and estimated yield with the combining model based on WOC by plotting scatter diagram.

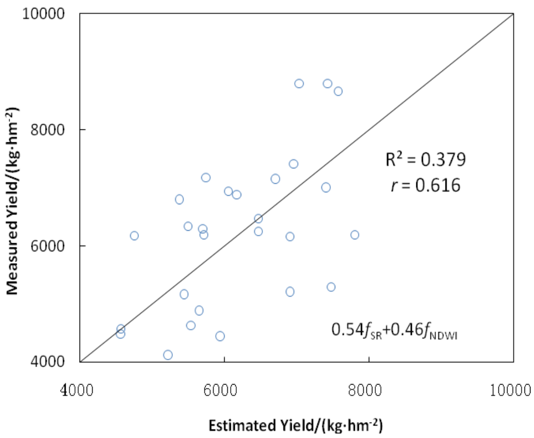


Fig. 3. Correlation between the measured and estimated yield with the combining model

4. Conclusion

In this study, the weight optimization combination method is introduced to the yield estimation of winter wheat with remote sensing data from Landsat5 TM. Firstly, the four typical vegetation indices, *NDVI, SR, TCARI/OSAVI* and *NDWI* are adopted to establish the yield estimating models, respectively, and then the four models with different VIs are input into WOC to calculate the optimum weights and form the combining model, and there are conclusions as the followings:

(1) In comparison with the single yield models of winter wheat with different vegetation indices from remote sensing data, the combining model based on WOC has slightly higher precision for estimating winter wheat yield.

(2) In the combining model using WOC with the four VIs yield models, the two models with *SR* and *NDWI* are given the non-zero weights, which indicate that the two VIs are probably more sensitive to winter wheat yield than the other two during the winter wheat jointing stage.

The study only discusses the ability of the WOC method for estimating winter wheat yield in one wheat growth period, and the following research work would focus on multi-periods with multi-temporal remote sensing data.

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