The Effects of Spatial Resolution on the Maize acreage estimation by Remote Sensing

Zhang Huanxue, Li Qiangzi*, Zhang Miao
Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences, West Beichen Road, Chaoyang District, Beijing, China, 100101
E-mail: zhanghx@irsa.ac.cn

Abstract. Crop acreage estimation is essential to forecast crop production using remote sensing. The different spatial resolution of remotely sensed data directly affects the accuracy of crop acreage estimation. It is necessary and valuable to study the effect of resolution on crop acreage estimation, from both qualitative and quantitative points of view. Therefore, this paper analysed the resolution effect on the accuracy of acreage estimation by using CBERS-02B imagery. Spatial statistics methods and manifold accuracy evaluation indices were used respectively to analyse the data with different spatial resolutions and crop proportion statistics. The study results indicate that decreased spatial resolution will lead to reduced regional accuracy in addition to increased standard deviation, RMSE and bias due to the augmentation of mixed pixels. A replacement of higher resolution data by lower resolution data will have an important impact on the derived crop proportions. The regional accuracy of crop statistics can remain higher than 88%, when the crop proportion is higher than 40%. In summary, the higher resolution of the imagery can lead to increased average regional accuracy. The results of this paper also provide academic and experimental reference to resolve the problem of data selection in crop acreage estimation by remote sensing.

Key words: spatial resolution; scale; acreage estimation; remote sensing

1. Introduction

Crop acreage estimation is a key aspect to forecast crop production, which is critical for national food security as it is a requirement for decision making on economic policies and price optimization[1,2]. Maize acreage estimation becomes more and more important because the fast production changes following the market dynamism[3]. Remote sensing represents a powerful tool to derive quantitative and qualitative information on crop identification and acreage estimation[4].

One of the fundamental characteristics of a remotely-sensed image is spatial resolution, or the size of the area on the ground from which the measurements that comprise the image are derived[5]. Thanks to second- and third-generation sensor systems as Thematic Mapper, SPOT, and AVHRR, a user of digital satellite imagery now has a choice of imagery with resolution ranging from 10m to 1km[6]. With the increasing availability and variety of remote sensing data, the question of choosing the appropriate spatial resolution for a given application has been widely addressed in the remote sensing community[5-8]. Many approaches have been developed to estimate the accuracy of crop recognition, using remotely sensed data with various spatial resolutions[6]. However, few studies have investigated the effects of spatial resolution on the regional accuracy of crop acreage estimation.

This paper addresses the question of the impact of the spatial resolution of remote sensed images on crop acreage estimation. In this paper, maize acreage generated from CBERS-02B satellite data
with 20m spatial resolution was considered as the “real value”, and then the maize acreage estimates at different administrative levels were generated by rescaling. Spatial statistic method and accuracy evaluation indices were used to analyze them with various spatial resolutions and crop statistics. The results of this paper also provide academic and experimental reference to resolve the problem of data selection in crop acreage estimation by remote sensing.

2. Materials

2.1 Study area
The study area is located in east of Xinxiang city (centered at 35°03′ N, 114°30′ E), Henan Province of China (Fig.1). This region belongs to the temperate climate zone and is a typical upland field agriculture area on the North China Plain. The annual precipitation is approximately 615.1 mm and the average temperature is about 13.9°C.

The study area is about 30 km*20 km. Although it is not a big region, it has the representative characteristics of crop pattern on the North China Plain. Within the area, maize, cotton, groundnut, soybean are planted, and maize is normally planted in June and harvested in September.

Figure 1. The location and data of study area

2.2 Data and pre-processing
One CBERS-02B CCD image was acquired on August 22, 2008 (Fig.1). The CCD sensor on CBERS-02B could provide high resolution (20 m), multi-spectral data with 5 spectral bands, including Blue, Green, Red, NIR1 and NIR2. The Spectral range is 0.45-0.52nm, 0.52-0.59nm, 0.63-0.69nm, 0.77-0.89nm, and 0.51-0.73nm. From its launch, CBERS-02B provides cost free products at 1B/2B level to users all over the world. The images have a swath of 113 km and revisit every 26 days.

Pre-processing of CBERS-02B CCD images mainly include geometric correction using 2-order polynomial model. More than 30 GCPs were selected to assure the accuracy. The spatial consistence errors were limited within 1 pixel.

3. Methodology
The methodology contains 3 steps (Fig.2): maize area extraction from CBERS-02B image; the establishment of rescaled series data; the accuracy analysis of crop acreage estimation under different scales (including spatial resolution and crop proportion).
In order to know the exact crop distribution characteristics of the study area, a field survey was carried out on 19 August 2008. Based on the field survey, 8029 pixels were selected as the training samples to identify maize in the study area. The maximum likelihood (MLC), support vector machines (SVM), artificial neural network (ANN) classifiers, which have been widely used for image classification\cite{9,10}, were selected in this study. Accuracy validation of the classified maps was based on the independent 6723 validation pixels, which were easily identified from the remote sensing images.

The result with the best overall classification accuracy and kappa statistics estimated from the confusion matrix (overall accuracy is 95.99\% and kappa coefficient is 0.94 by using SVM classifier) was selected as the final maize extraction result.

3.2 Rescaling
Downscaling refers to an increase in spatial resolution. Conversely, upscaling refers to a decrease or coarsening of spatial resolution\cite{11,12}. In the context of remote sensing, upscaling refers to an increase in the pixel size of remotely sensed images. Many researches now exist in which data are upscaled, such as, ground data are re-sampled to provide a more coherent match with image pixels\cite{7,11,13}. In this paper, the maize area extraction result derived from CBERS-02B image was successively rescaled through simple block averaging\cite{14} to the following spatial resolutions: 40m, 60m, 80m, 100m, 120m, 140m and 160m. Hereafter, we refer to these as the rescaled series.

3.3 Crop proportion estimation
In this research, we also study the effect of crop proportions under different spatial resolution. The crop proportions were obtained as following: (1) The 30km*20km study area was divided into 600 1km x 1km blocks. (2) Calculate the maize proportion of every block under 20m spatial resolution (“real value”) and rescaled series data. (3) Divide the blocks into ten child blocks according to the value of crop proportion. (4) Calculate the average area accuracy, standard deviation, root mean square error and bias of the ten child blocks compared to the “real value” by using Eq.(1)(2)(3)(4)(5).

3.4 Accuracy evaluation
In this paper, we adopt two index (average area accuracy, standard deviation) to compare the relative accuracy and two index (RMSE, bias) to measure absolute accuracy.

The regional accuracy $K(i)$ was defined by:

$$K(i) = \left(1 - \frac{|A_i - A_{\text{real}}|}{A_0}\right) \times 100\%$$

(1)
Where $A_0$ is the maize acreage extracted from CBERS 20m spatial resolution image, $A_i$ is the maize acreage extracted from rescaled series data.

The average regional accuracy $\bar{K}(i)$ and standard deviation $\delta(i)$ were defined by:

$$\bar{K}(i) = \frac{\sum_{i=1}^{n} K(i)}{n}$$

$$\delta(i) = \frac{\sum_{i=1}^{n} |K_i - \bar{K}|^2}{n}$$

The RMSE and bias were defined by:

$$\text{RESE}(i) = \left( \frac{\sum_{j=1}^{n} (\hat{a}_j - a_j)^2}{n} \right)^{\frac{1}{2}}$$

$$\text{bias}(i) = \frac{\sum_{j=1}^{n} (\hat{a}_j - a_j)}{n}$$

Where $a_j$ is the maize proportion obtained by CBERS 20m spatial resolution image, $\hat{a}_j$ is the maize proportion obtained by rescaled series data.

4. Results and discussion

4.1 Effect of spatial resolution on the accuracy

| spatial resolution/m | 40   | 60   | 80   | 100  | 120  | 140  | 160  |
|----------------------|------|------|------|------|------|------|------|
| average regional accuracy/% | 94.01| 91.34| 89.43| 88.08| 87.39| 86.32| 83.36|
| standard deviation/%   | 0.24 | 0.57 | 0.82 | 1.31 | 2.02 | 2.17 | 3.57 |
| RMSE/%                | 0.31 | 0.06 | 0.18 | 0.22 | 0.32 | 0.36 | 0.54 |
| bias/%                | 5.09 | 0.43 | 0.65 | 0.75 | 1.31 | 1.60 | 2.30 |

Spatial resolution has significant impact on the accuracy evaluation result (Table 1).

With the decrease of spatial resolution, the average regional accuracy will decrease. This is due to the increased errors in crop acreage estimation caused by mixed pixels. But even if the resolution drops to 160m, the accuracy can remain higher above 80%.

With the decrease of the spatial resolution, the standard deviation will increase. And the RMSE and bias (except for 40m spatial resolution) will also increase. When the resolution is 160m, the standard deviation is higher than 3%.

4.2 Effect of crop proportion on the accuracy

Crop proportion plays an important role in the effects of spatial resolution on crop acreage estimation by remote sensing (Fig.3).

Decreased spatial resolution will lead to reduced regional accuracy in addition to increased standard deviation, RMSE and bias due to the augmentation of mixed pixels.

With the increase of crop proportion, the average regional accuracy derived from series of images will increase. When the proportion is 0-10%, the average regional accuracy under all resolutions is lowest; with the increase of proportion, the accuracy increases rapidly. It gets maximum value above 88%, when the proportion is higher than 40%.

With the increase of crop proportion, the standard deviation will decrease, and the RMSE present a fluctuation trend. When the proportion is 0-10%, the standard deviation under all resolutions is highest. It gets lower than 5%, when the proportion is higher than 30%. When the proportion is between 40% and 60%, the RMSE gets the lowest, and both ends are higher. For the bias, it tends to 0 when the crop proportion is close to 50%, it is negative when the crop proportion is lower than 50%, and the other is positive.

It is noted that the bias is positive and the fluctuation trend is opposite when the spatial resolution is 50m. This may be related to the landscape spatial structure of the crop extraction results. For the study area, 50m resolution may be a sensitive response to the scale.
5. Conclusions
This paper addresses the effects of spatial resolution on crop acreage estimation. Results of accuracy analysis have shown that:
(1) With the decrease of spatial resolution, the average regional accuracy will decrease, and the standard deviation, RMSE, bias will increase due to the augmentation of mixed pixels.
(2) The crop proportion plays an important role on the accuracy. The regional accuracy of series data can all keep higher than 88%, when the proportion is higher than 40%. And the higher resolution of the imagery can lead to increased average regional accuracy.
(3) For a particular application, we can select the appropriate spatial resolution for the crop acreage estimation by remote sensing according to Fig.3. When the crop proportion is lower than 20%, we can use Landsat TM or IRS-P6 data to keep the regional accuracy higher than 90%; but when it is higher than 80%, MERIS or MODIS data can be selected instead.

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