A new methodology to map double-cropping croplands based on continuous wavelet transform

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\textbf{A R T I C L E    I N F O}

\textbf{Article history:}
Received 8 February 2013
Accepted 31 May 2013

\textbf{Keywords:}
Cropping intensity
Continuous wavelet transform
MODIS
EVI
Double-cropping croplands

\textbf{A B S T R A C T}

Cropping intensity is one of the major factors in crop production and agricultural intensification. A new double-cropping croplands mapping methodology using Moderate Resolution Imaging Spectroradiometer (MODIS) time series datasets through continuous wavelet transform was proposed in this study. This methodology involved four steps. First, daily continuous MODIS Enhanced Vegetation Index (EVI) time series datasets were developed for the study year. Next, the EVI time series datasets were transformed into a two dimensional (time–frequency) wavelet scalogram based on continuous wavelet transform. Third, a feature extraction process was conducted on the wavelet scalogram, where the characteristic spectra were calculated from the wavelet scalogram and the feature peak within two skeleton lines was obtained. Finally, a threshold was determined for feature peak values to discriminate double-cropping croplands within each pixel. The application of the proposed procedure to China’s Henan Province in 2010 produced an objective and accurate spatial distribution map, which correlated well with in situ observation data (over 90% agreement). The proposed new methodology efficiently handled complex variability that might be caused by regional variation in climate, management practices, growth peaks by winter weed or winter wheat, and data noise. Therefore, the methodology shows promise for future studies at regional and global scales.

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1. Introduction

Agricultural activities have played an essential role in providing food for China since 7500 BC. With the largest population in the world, China has less than 10% of the total global cropland area, ranked third after the US and India. As indicated by sown area from the statistical datasets, the cropping intensity (number of crops per year in a unit area) increased dramatically during the late 1980s and 1990s (\textit{National Bureau of Statistics of China}, 2011). However, cropping intensity decreased slightly during the early 2000s, partially due to the large migration of the agricultural workforce to urban areas (\textit{National Bureau of Statistics of China}, 2011). While triple rice crops were common in the 1970s, double paddy rice crops are currently more prevalent and there is an increasing trends toward single paddy rice in southern China (Peng et al., 2011). Stable agricultural intensity is crucial to guarantee future food security in China (Fan and Wu, 2004). In addition, understanding cropping intensity by using remote sensing technology provides insight into the direction and magnitude of impacts on the natural and agricultural environments (Galford et al., 2008). Accurate, updated, and spatially explicit information on cropping intensity is urgently needed but is not included in large-area land cover datasets.

Different crop types have distinct phenomenology that can be observed in Vegetation Index (VI) time series datasets (Lunetta et al., 2010). Over the past few decades, numerous methods were developed and successfully applied in the field of crop mapping (Xiao et al., 2005; Arvor et al., 2011; Howard et al., 2012; Singh et al., 2012; Vintrou et al., 2012). Only a few studies, however, aimed to provide information on cropping intensity (Galford et al., 2008; Zhang et al., 2008; Lunetta et al., 2010; Biradar and Xiao, 2011). In these studies, cropping intensity was generally evaluated through identifying the frequency of VI peaks and troughs from the intra-annual VI temporal profiles (Sakamoto et al., 2006; Galford et al., 2008; Biradar and Xiao, 2011). For example, two or three pairs of peaks and troughs were identified as double- and triple-cropping croplands respectively (Biradar and Xiao, 2011). Although these methods were easy to understand and implement, they might introduce error (Galford et al., 2008). There were at least two issues that needed to be further explored. The first issue

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http://dx.doi.org/10.1016/j.jag.2013.05.016
was noise disturbances, especially cloud cover, which were commonly observed in the remote sensing datasets. The original VI time series datasets with cloud cover and abnormally low values, which could be identified as troughs, were examined using these methods. The second issue was that the growth cycle of one specific crop did not exactly correspond to one peak observed in the VI time series dataset. Two peaks could be observed within one growth cycle of a crop, which could have resulted from precipitation, management decisions, or other factors. For example, two peaks were observed in the annual VI time series in the winter wheat cultivated land, one in the winter and another in the spring. Although several studies have been conducted to diminish these problems, most of them focused on noise reduction or setting constraint conditions (Sakamoto et al., 2009; Lv and Liu, 2010; Peng et al., 2011; Chen et al., 2012; Liu et al., 2012). The existing Cropping Index (CI) mapping approaches largely rely on the de-noising filtering algorithms to obtain a smoothed VI profile before detecting peaks (Liu et al., 2012). Moreover, they are susceptible to noise and need a priori knowledge and extra constraints that could not be directly derived from the VI time-series data to identify the true peaks, which hinder them from mapping CI accurately (Zhu et al., 2008). A more robust and generalized methodology was urgently needed to overcome these issues (Liu et al., 2012).

One major challenge associated with the NDVI-based categorization approach was the within-class variability of crop phenology across a large geographic study area (Lunetta et al., 2010). The time-series MODIS VI data for a given crop exhibited considerable intra-class variability due to regional variations in climate and management practices (Wardlow et al., 2007). For example, the phenology of a specific crop type (e.g., corn) in the northern part of a region may be different from that in the southern part. The crop VI profiles also vary from year to year due to specific weather conditions throughout the growing season (Siebert and Ewert, 2011). These within-class and inter-annual variations have not been accounted in existing approaches (Foerster et al., 2012; Liu et al., 2012).

This paper proposes an efficient methodology to map double-cropping croplands that accounts for regional variation in climate, management practices, growth peaks by winter wheat or wheat, and data noise through continuous wavelet transform (CWT). CWT is emerging as a promising tool in the geographic, biochemistry and hydrology research fields (Gauchere, 2002; Cheng et al., 2010; Ullah et al., 2012). CWT proved to be efficient in decomposing the original signal into a number of scale components, where each component was directly comparable to the original one (Gauchere, 2002). In this study, we aim to extract wavelet features sensitive to changes in crop shifting but insensitive to variations in the temporal EVI profiles which are not corresponded to any specific crop growth cycles. It was hoped that the wavelet spectra, through continuous wavelet transform based on EVI time series, could provide adequate and non-redundant information on crop shifting. The proposed methodology was applied to Henan Province, the food base of China, and the validation of the algorithm was also provided.

2. Methodology

2.1. Remotely sensed input and data preprocessing

Moderate Resolution Imaging Spectroradiometer (MODIS) images have been utilized in recent years because they offer a distinctive capability in maintaining both spatial and temporal density for crop mapping from regional to global scales (Arvor et al., 2011; Biradar and Xiao, 2011). In this study, the 8-day, 250 m composite datasets (MOD09) were used. In order to calculate the EVI, the 8-day blue band at 500 m resolution was interpolated to 250 m resolution. The 8-day, 250 m EVI products were derived using the standard formula (Huete et al., 2002). EVI was chosen because it had a greater dynamic range than the more commonly used NDVI, and thus was more capable of discriminating dynamic crop phenology without reaching saturation (Huete et al., 2002).

In order to obtain a daily continuous EVI time series, the following data preparation processes were conducted. First, the non-vegetated areas were excluded from further processing. The mask of non-vegetated areas could be derived from existing land cover datasets or the MODIS EVI time series. For example, a pixel was assumed to be a non-vegetated area if its EVI values were less than a threshold (i.e., 0.14) in most observations (i.e., 42) in a year. Second, each observation (46 observations over the calendar year) with cloud contamination was discarded. If a value of “1” was obtained for an observation in its corresponding pixel reliability image, which indicated that the target was not visible and covered with clouds, the observation was considered unreliable and excluded for further analysis. Third, the daily continuous EVI time series datasets were produced through linear interpolation during the study period of one year. In order to eliminate the edge effects induced by wavelet transform, a total of 3 full-year daily continuous EVI time series datasets were developed through duplication.

2.2. Temporal EVI profiles of forest, single- and double-cropping croplands

The different temporal behaviors of forests, single- and double-cropping croplands are shown in insert Fig. 1 for 2010. The EVI value of a forest increased dramatically when spring came, reaching a peak, then leveled off for almost 4 months, and then descended quickly in late autumn or early winter (Insert Fig. 1a). For a single cropping site, the EVI value started to increase in April, which meant that crops were planted in spring. The EVI values then reached a peak in July, and then declined gradually until harvest in late September (Insert Fig. 1b). For a double-cropping site, the intra-annual EVI profile presented tri-modal dynamics: the first and third modes represented the crop cycle of winter wheat from October to next May, and the second mode represented the crop cycle from June to September (Insert Fig. 1c).

The forests, single- and double-cropping croplands exhibited clearly distinct temporal EVI profiles. It was possible to distinguish them by monitoring their seasonal behavior. Nevertheless, one peak did not necessarily correspond to one vegetation growth cycle (Insert Fig. 1). Many small local peaks and troughs were observed among their intra-annual EVI profiles, which might be might correspond to local climate conditions, management decisions, data noise problems, or other related factors. Therefore, a more robust method than peak detection was developed to deal with this problem, which is described in detail in the following sections.

2.3. Algorithm for double-cropping croplands mapping

A new methodology for quantifying double-cropping croplands based on continuous wavelet transform was developed (Insert Fig. 2). First, a continuous wavelet transform was performed on daily continuous MODIS EVI time series datasets of each pixel over the entire study area. A wavelet scalogram was obtained for each pixel, representing the similarity of the intra-annual EVI profile to the mother wavelet at each specific time and scale. Second, a feature selection process was performed to determine the intra-annual characteristic spectrum, from which two skeleton lines and characteristic points within those two skeleton lines at each scale were
derived. Finally, criteria that discriminated double-cropping croplands were established and classification results were obtained. In the following sections, these steps are described in great detail. Both the continuous wavelet analysis and the entire procedure were executed using the Matlab software package (The MathWorks, Natick, Massachusetts, USA).

2.4. Continuous wavelet transform and feature selection procedure

2.4.1. Continuous wavelet transform

A wavelet transform is particularly adapted for investigating non-stationary processes such as vegetation indices (Rouyer et al. 2008). A wavelet transform allows for the time-localization of the variability of a given signal, and thus provides an efficient tool for extracting relevant information from VI time series datasets (Sakamoto et al. 2006; Galford et al., 2008; Singh et al., 2012). Wavelet analysis is capable of handing the range of agricultural patterns that occur over time, as well as the spatial heterogeneity that results from precipitation and management decisions, because the transform is localized in both time and frequency (Galford et al., 2008). In agricultural applications, a wavelet-smoothed time series was generally applied through discrete wavelet transform (DWT) (Sakamoto et al., 2006; Galford et al., 2008). Unlike DWT, continuous wavelet does not need inverse transformation to construct the original signal (Cheng et al., 2010). The coefficients of continuous wavelet transformation (CWT) are easily interpretable and can be directly compared with the original MODIS EVI time series datasets. Several types of mother wavelets are available for CWT. The Mexican hat wavelet is a real symmetric function that detects peaks and valleys. It allows for an accurate description of temporal resolution (Gaucherel, 2002) and also has a similar shape to the EVI time profile. The main characteristics of crop phenology and crop shifting can be precisely localized during an entire study year. Therefore, the simple and commonly used ‘Mexican hat’ mother wavelet was utilized as the mother wavelet.

CWT converts the EVI time series into sets of coefficients by scaling (scale parameters a) and shifting (time-localized parameter b) the mother wavelet function.

\[ \psi_{a,b}(t) = |a|^{1/2} \psi\left(\frac{t-b}{a}\right) \]  

(1)

The continuous wavelet transform (CWT) of a signal f(t) is given as:

\[ W_{\psi}(a,b) = |a|^{1/2} \int_{R} f(t) \psi\left(\frac{t-b}{a}\right) dt \]  

(2)

For all scales of decomposition, the CWT coefficients \( W_{\psi}(a_i, b_j), i = 1, 2, \ldots, m, j = 1, 2, \ldots, n \) constitute a two-dimensional matrix (i.e., a \( m \times n \) matrix) called a scalogram (Insert Fig. 3). One dimension is the scale \( (1, 2, \ldots, m) \) and the other is time \( (1, 2, \ldots, n) \). The wavelet power, which refers to the magnitude of each wavelet coefficient, measures the correlation between the scaled and shifted mother wavelet and intra-annual EVI profile and thus indicates the similarity of the intra-annual daily EVI profile to the mother wavelet. The wavelet power can be utilized to identify the variation of MODIS EVI values across the whole year, which is probably caused by crop shifting.

2.4.2. Feature selection from wavelet scalogram

As demonstrated in Insert Fig. 3, distinct wavelet scalograms were obtained from forests, single- and double-cropping croplands through continuous wavelet transform. A feature selection procedure was required to identify the key features used to quantify double-cropping croplands. The method to extract meaningful
wavelet features comprised three main steps. For step 1, an intra-annual characteristic spectrum was derived from the wavelet scalogram through the following procedure (Insert Fig. 3): in the wavelet scalogram, a value of “1” was assigned to a cell with positive wavelet coefficients on one neighboring side and negative wavelet coefficients on another neighboring side in the same line. Otherwise, a value of “0” was assigned to other cells with two negative or positive wavelet coefficients on both neighboring sides in the same line. The cells with a value of “1” were termed the characteristic cells. Many characteristic cells, observed from low to high scales, generally formed different shapes of lines in the characteristic spectra, which were called characteristic lines. In the wavelet scalogram, the positive value in a unit (particular time and scale) indicated that the original daily EVI profile at that particular time and scale was similar to the mother wavelet, while the negative value in a unit revealed the amount of dissimilarity between them. Therefore, the characteristic lines identify the shift between similarity and dissimilarity of the original daily EVI profile to the mother wavelet.

For step 2, two skeleton lines were derived from the intra-annual characteristic spectrum. In the wavelet scalogram, high-frequency components could characterize the small and detailed features and low-frequency components were well suited to define the overall shape of an intra-annual EVI profile. These characteristic lines, at lower scale (Insert Fig. 3), corresponded to small local peaks or troughs with relatively high frequency in its corresponding intra-annual EVI profile (Insert Fig. 1). The characteristic lines generally decreased with scale, and only two characteristic lines were observed at relatively larger scales. These two characteristic lines, which extended from high to low scales, were termed the skeleton lines. These two characteristic lines could be utilized as an indicator separating dense/sparse vegetated periods with relatively high/low EVI values.

When crops were planted in croplands, land cover varied from bare land or sparse weed to mixed land between vegetation and soil or water (rice) in the first month, almost full vegetation in the following months, and bare land again after harvesting time. If another crop was planted immediately, the entire crop growth cycle would be present until no other crop was planted and there was bare area again. There were primary two phases for croplands: one phase comprised the growing season from a single crop (single-cropping croplands) or multiple crops (multiple-cropping croplands), which was characterized with considerably dense vegetation, while the other phase consisted of the slack season, which had bare land or very sparse vegetation. It is similar for forests: one phase with better vegetation conditions in the summer, and another phase with relatively poor vegetation in the winter. The two skeleton lines generally separated the two different vegetation phases.

The process extracting two skeleton lines was as follows. First, the two separate characteristic cells at the highest scale (128 in this study) were localized and assigned as “bone1” and “bone2” each. Then, a neighboring searching process was conducted from the highest scale to the lowest scale with its window centered at the cells with values of bone1 and bone2 respectively. The characteristic cells within the neighboring window 3 × 3 of bone1 (bone2) were assigned as “bone1(bone2)”. When there was no characteristic cell within its neighboring window of bone1 (bone2), the searching process ended and the two skeleton lines were obtained.

For step 3, the number of characteristic points within those two skeleton lines was calculated at each scale. A vector, termed a “feature_point” variable, recorded its values in sequence from a daily scale to a scale of 120 days or more on a regular daily basis. In general, large values were observed from low scales and very small values were obtained from relatively higher scales. With an increase in scale, the values of the feature_point variable decreased to two, leveled off for certain scale ranges and finally reached zero at one specific higher scale. This specific scale was termed the feature peak. The characteristic points within the two skeleton lines acted as an indicator of the shift between peaks and valleys of the original
daily EVI profile. The feature peak variable recorded the frequency of shifting between peaks and valleys at each scale. The feature peak recorded the frequency threshold of shifting and non-shifting within the growing periods. The feature peak highlighted the magnitude of variation during the relatively dense-vegetated period. As illustrated in Insert Fig. 3, double-cropping croplands were observed with fairly high feature peak values, and single-cropping croplands had considerably low feature peak values. Therefore, the feature peak could be utilized to identify the change in shape and depth of EVI values induced by changes in crop shifting. This indicated that pixels with relatively large feature peak values could be classified as double-cropping croplands.

2.5. Criteria quantification

The goal of this study was to separate double-cropping croplands from other vegetated areas. The continuous wavelet transforms and feature selection process suggested that the values of the feature peak of double-cropping croplands would be larger than those of single-cropping croplands and other vegetated areas. A simple threshold of the feature peak could be applied to carry out the classification process. However, the threshold was difficult to determine for at least two reasons. One reason was the existence of mixed pixels in the coarse images. If the threshold was too large, the result might be accurate but pixels with a large proportion of double-cropping croplands might be omitted. However, if the threshold value was too small, pixels with very low proportion of double-cropping croplands, or even pixels totally belonging to single-cropping croplands, might be included in the classified results. Another reason was the possible difference of feature peaks among various double-cropping croplands, e.g., winter wheat-maize, winter wheat-rice.

The values of feature peaks from double-cropping croplands were assumed to be normally distributed. Therefore, its mean value ($\mu$) and standard deviation ($\sigma$) could be derived by examining relatively pure double-cropping pixels. In addition, the distribution of feature peaks from double-cropping croplands could also be confirmed by examining the histogram across the whole study area.

3. Results: implementation of the proposed method in Henan province

3.1. Study area

The proposed methodology was applied in Henan Province (Insert Fig. 4). Henan Province is located between latitudes 31°23′–36°22′N and longitudes 110°21′–116°39′E in central China. It is approximately 520 km long and 572 km wide. It is characterized by a warm temperate climate with a small portion of mild subtropical climate in the south. The annual mean temperature fluctuates between 12 and 16 °C and the yearly precipitation varies between 500 and 900 mm, decreasing from south to north. The mean elevation is 252 m above sea level. The province has a very diverse relief, with elevations ranging from zero in the east to 2319 m in the west. Cultivated land comprises 47.5% of the total area (Henan, 2010). Henan Province has ranked first in food production in China over the past decade. The crop intensity of Henan Province is 1.971 (Henan, 2010), which indicates an overall double-cropping cropland. A related study revealed that relatively little cloud cover noise was observed in the MODIS EVI time series during 2001–2011 in the Henan province (Qiu et al., 2013).

3.2. Spatial distribution of double-cropping cropland

In the Henan province, training samples from 59 sites with relatively pure double-cropping croplands were selected and processed with the above procedure. The feature peak of double-cropping croplands ranged from 36 to 61 with a mean value ($\mu$) of 48 and standard deviation ($\sigma$) of 6 in the study area. The threshold was determined through the mean value of those training samples with two times the standard deviation, which would be within the range of 36–60 ($\mu - 2\sigma, \mu + 2\sigma$). Additionally, a tri-modal distribution was observed in the histogram of the feature peaks for all pixels in the study area (Insert Fig. 5). Those three distributions of feature peaks could be separated through the histogram minimums. Consequently, all pixels with a feature peak higher than or equal to the second minimum (36) were classified as double-cropping croplands.

The spatial distribution of double-cropping croplands in 2010 in Henan Province is given in Insert Fig. 6 and shows some expected patterns. Cropping intensity has a strong east–west divide. The MODIS-derived map indicates that large areas in the east of Henan Province are double-cropping croplands. The western part of Henan Province supports fewer double-cropping croplands, and is primarily forest land.

![Fig. 4. The study area and survey sites.](image-url)
3.3. Accuracy assessment

Assessing the accuracy of moderate resolution land cover products is a challenging task, as these maps cover large areas and can over- and under-estimate areas of land cover types due to fragmentation and sub-pixel proportion of individual types (Wulder et al., 2006). We evaluated the MODIS-derived cropping intensity map based on ground truth data collected at individual sites as well as agricultural census data at the county level. In early August 2012, a field survey was carried out to collect in situ data in the study area. These fields were selected from 45 counties of total 98 counties in plain, which had a relatively long and stable planting history of at least 5 years and were distributed throughout the Henan province. A minimum field size of 500 m × 500 m was established to ensure that the selected fields were sufficiently large to collect a spectral-temporal signal. The crop calendar data provided by the National Meteorological Bureau of China were also applied (see locations in Insert Fig. 4). These ground truth data were important for identification of double-cropping croplands. Among the 85 ground truth observation data points denoting double-cropping croplands, 77 were identified as double-cropping croplands in the classification (77 out of 85, 90.6% agreement).

To better understand how well the MODIS-based double-cropping croplands compared to the estimates reported by the National Statistical Bureau of China (NSBC), the 250 m MODIS product was aggregated to the county level (http://www.ha.stats.gov.cn/hntj/index.htm). There were no statistical datasets of double-cropping croplands at the county level. The sown area of cereals, which was calculated as the sum of twice the area of double-cropping croplands and the area of single-cropping croplands, were utilized instead. The area of double-cropping croplands and its proportion of the entire province were calculated for each county. These values were compared to the proportions of sown area of cereals obtained from the agricultural statistical database. The MODIS-estimated and NSBC datasets agreed reasonably well, with an r-squared value of 0.7492 (Insert Fig. 7, N = 107). However, there were relatively large discrepancies between these two datasets in several counties with considerably small proportions of double-cropping croplands.

4. Discussion

The results of the new cropping intensity methodology presented here suggested that it is capable of mapping double-cropping croplands across large regions. This method provides an easy and automatic way to estimate cropping intensity. This method utilizes three novel ideas: (1) employing the continuous wavelet transform method to convert intra-annual EVI profile to a time-frequency two-dimensional wavelet spectra; (2) extracting two skeleton lines to separate dense/sparse vegetated periods, thus eliminating the disturbance from small peaks observed in winter originating from winter wheat or weed; and (3) computing the characteristic points within the two skeleton lines at each scale to evaluate crop shifting, as well as excluding the disturbance of small peaks and troughs within one specific growing season through frequency. Current related approaches generally derive cropping intensity from the occurrences of peaks (maximums) calculated from the yearly VI profile (Galford et al., 2008; Biradar and Xiao, 2011). Obviously, these methods might introduce errors (Galford et al., 2008). As described in the introduction section, the occurrences of peaks and troughs might be introduced by a great number of circumstances that do not correspond to any specific growing cycles. These kinds of local peaks and troughs can generally be classified in two groups: (1) local variability with high frequency, generally originating from the local peaks and troughs within one crop growth cycle or data noise; or (2) relatively lower magnitude of variability

![Fig. 6. The spatial distribution of (a) feature peak and (b) double-cropping croplands derived from this study.](image)

![Fig. 7. Correlation between the proportions of NSBC reported sown land of cereals and MODIS-estimated double-cropping croplands at county level.](image)
with lower frequency, i.e. winter growth cycles originating from winter wheat or weed.

Instead of directly applying the original EVI profile, the methodology proposed in this study overcomes these challenges through transforming the original EVI profile into a time-frequency dimension wavelet power spectra. It efficiently tackles the aforementioned problems in the following four ways: (1) by using continuous wavelet transform, local peaks and troughs with high frequency will not lead to feature points of the characteristic spectra at relatively low frequency (large scales); (2) those points with a relatively lower magnitude of variability with lower frequency are also excluded from the two skeleton lines and thus eliminated for further analysis; (3) the characteristic spectra derived from wavelet scalogram are generally more comparable to the original EVI profile, since it reveals the magnitude of variability at time-frequency representation relative to total annual variability; and (4) crop shifting from one crop to another crop could easily be identified at relatively lower frequency from the variable of feature point, which is robust to the intra-class variability due to regional variations in climate and management practices.

The MODIS-derived results were consistent with in situ observation data (over 90% agreement). The very few mismatched sites were generally located in or near the mountainous and hilly regions in the southern and western areas of the Henan province, which posed more challenges in identification due to fragmentation and sub-pixel proportion of both croplands and forests. The spatial distribution of double-cropping croplands derived from the MODIS images generally agreed with that of the national agricultural census data at the county level. The relatively large discrepancies in several counties between these two datasets could be due to the differences in the methodology used and the aggregation of census data. The sown land of cereals obtained from the agricultural statistical database included the total areas, including both double-cropping and single-cropping croplands. This kind of comparison was more easily influenced by the single-cropping croplands in the case of counties with very low proportion of double-cropping croplands (Insert Fig. 8). Counties with relatively large single-cropping croplands tended to have a lower estimated sown area from MODIS images, e.g., Gushi County. The counties with a considerably large proportion of croplands generally had the tendency to be overestimated compared with NSBC-reported areas. Another reason might be the limitation of the 250 m resolution MODIS-based algorithm in identifying small patches of agricultural field sizes (Biradar and Xiao, 2011).

The methodology proposed in this study could be applied to other regions. However, further investigation should be carried out to evaluate and determine the proper threshold for separating double- and non-double cropping lands. The threshold might be different in other regions due to the difference in the length of fallow periods as well as crop cultivation. Field surveys and other reference data could be applied to identify the proper threshold.

The methodology proposed in this study could also be applied in identifying triple-cropping croplands. Since there were no triple-cropping croplands in the Henan province, the daily continuous EVI time series was simulated and processed using the described methodology in this study. Similar to double-cropping croplands, considerably large feature peaks were observed from triple-cropping croplands as shown in Insert Fig. 9. In contrast to double-cropping croplands, as the scale increased, the values of the feature point variable for triple cropping croplands would decrease.

**Fig. 8.** The spatial distribution of proportion of (a) double-cropping cropland derived from MODIS data and (b) sown area of cereals at county level in the Henan province in 2010.

**Fig. 9.** The simulated EVI profile (a) and its corresponding characteristic spectra (b) of triple-cropping croplands.
to four, level off for certain scale ranges, decrease to two (the second feature peak), and finally reach zero within a short period (the first feature peak). Therefore, within the framework of this methodology, pixels observed with two relatively high feature peaks could be considered triple-cropping croplands.

There are some limitations of the 8-day composite 250-m resolution MODIS imagery when applied to identify agricultural fields. Without the date of observation flags, the 8-day composite product flags assumed evenly spaced observations. However, in fact, the observations could be up to 16 days apart or as few as 2 days apart. Additional research could be done to use the date of observation flag, included in the data product as the day of the year for each observation, to first create an unevenly-spaced time series for a given pixel and then create a daily continuous E VI profile.

5. Conclusions

A novel procedure for mapping and monitoring double-cropping croplands based on MODIS time series data was proposed in this study. The procedure was built on five parts: (1) creation of daily continuous MODIS E VI datasets during the study year and its two neighboring years; (2) characterizing the intensity and frequency of variability at each specific time interval through a two-dimensional (time-frequency) wavelet scalogram based on continuous wavelet transforms; (3) obtaining the feature peak through calculation of characteristic points within the two skeleton lines at each scale; (4) establishing criteria separating single- and double-cropping croplands; and 5) estimating the areas of double-cropping croplands. As an objective and semiautomatic methodology, it is robust enough to handle the complex variability that might be caused by vegetation phenology, small growth peaks caused by winter weed and winter wheat, and data noise. Its successful application in Henan province, China, warrants a promising application in other regions. The resulting geospatial dataset of double-cropping croplands could be utilized to address many important questions relevant to science and society, including food security and global climate change.

Acknowledgements

The authors gratefully acknowledge the financial support received for this work from the National Natural Science Foundation of China (NSFC) (grant no. 41071267), Scientific Research Foundation for Returned Scholars, Ministry of Education of China ([2012]940) and the Science & Technology Department of Fujian Province, China (grant nos. 2012I0005, 2012J01167).

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