International Journal of Applied Earth Observation and Geoinformation 16 (2012) 101–112

Contents lists available at SciVerse ScienceDirect

International Journal of Applied Earth Observation and Geoinformation

journal homepage: www.elsevier.com/locate/jag

Crop planting and type proportion method for crop acreage estimation of complex agricultural landscapes

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ARTICLE INFO

Article history:
Received 21 June 2011
Accepted 10 December 2011

Keywords:
Crop acreage estimation
Crop planting and type proportion
Remote sensing
Transact sampling
CropWatch

ABSTRACT

This study presents a crop planting and type proportion (CPTP) method for crop acreage estimation of complex and diverse agricultural landscapes. CPTP has three major components: (1) Crop planting proportion (CPP), estimated with wide-swath satellite remote sensing data to completely cover the monitoring area by segmenting cropped and non-cropped areas through unsupervised classification. (2) Crop type proportion (CTP), estimated by transect sampling and a special GPS-Video-GIS instrument (GVG) and a visual interpretation of crop type proportion in collected pictures for different strata. (3) Multiplication of CPP and CTP with arable land area at the strata level, summed to the province and national level. Validation has been done with *in situ* data for different agricultural landscapes over China. Both CPP estimation with remote sensing data and CTP estimation through ground survey have a high accuracy with average relative error (RE) and root mean square error (RMSE) equal to 1.42% and 1.67% for CPP and to 2.63% and 2.25% for CTP. The RE for crop acreage estimation equals to 4.09%. The CPTP method thus has a high accuracy, yields timely information at low costs, and is robust and provides objective results. The study concludes that the CPTP method can be used for large area crop acreage estimation of complex agriculture landscapes.

1. Introduction

Reliable and timely forecasting or estimation of crop production is critical for national food security as it is a requirement for decision making on economic policies and price optimization (Thornton et al., 1997; Wang et al., 2010a,b). Recently, arable land in China is decreasing, due to rapid urbanization and industrialization (Liu et al., 2005a,b; Chen, 2007; Liu and Liu, 2009), and enthusiasm of cereal production get lower due to the less income. Crop acreages are crucial for crop production forecasting or estimation besides crop yield. Thus it is essential to know the crop acreage timely. However, it is a challenge to offer timely, accurate crop acreage information in China due to the huge producing area, the complex agricultural landscapes with the variety of cropping systems, the diversification of crop types, the very small field sizes and the particular management practices (Wu and Li, 2004).

Various types of remote sensing data are available to estimate crop acreage at regional scales using digital classification methods, such as optical data with high spatial resolution (Castillejo-González et al., 2009; Oza et al., 2008), medium spatial resolution (Badhwar, 1984; Dutta et al., 1994; Yadav et al., 2002; Chang et al., 2007), and radar data (Bouman and Uenk, 1992; Chakraborty and Panigrahy, 2000; McNairn et al., 2009). However, Pixels in remote sensing data do not always correspond to a single crop type or field. Mixed pixels have a serious impact on crop classification accuracy in agriculture regions with small crop fields. Therefore, crop classification based on remote sensing data without a solid ground survey is not sufficient for estimating crop acreage.

Remote sensing based sampling methods have been shown good solutions for large area crop acreage monitoring systems (Macdonald and Hall, 1980; Cecil and Charles, 1984; Taylor et al., 1997; Tsiligirides, 1998; Sushil, 2001; Wu and Li, 2004; Gallego and Bamps, 2008; NASS of the USDA, 2009b). Methods integrating area sampling frames and remote sensing technique should also be considered to resolve the estimation of crop acreage in China. Yet, several obstacles must be removed. The small field size of cropland requires remote sensing data with spatial resolution finer than 10 m for accurate crop identification, especially in southern China. It is un-affordable and impossible to cover the major grain producing regions with such high resolution data. The policy of the household contracting responsibility system introduced in 1978 has given more freedom of crop planting to farmers. For food diversification purposes, a single family always plants more than 3 crops and in extreme cases even more than 10 crops, to obtain a sufficient variety of food. Yet this policy leads to extra complexity in the agricultural landscape, especially in the summer and autumn seasons

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doi:10.1016/j.jag.2011.12.006

Fig. 1. The complex Crop planting systems and representative agricultural landscapes in China. Left shows the big framing fields in Heilongjiang Province in Northeastern China; middle shows the interplant scene in Shanxi Province in Northern China, and the right shows small fields in mountain Chongqing in Southwestern China.

(Tan et al., 2006). The new method should be high efficiency that can deliver the results before the harvest time or within 3 months, high accuracy that can meet the complex agricultural system, economical that can afford the input of remote sensing data and ground inventory, and reliable that can provide satisfied and convincing tandem estimation.

Many countries still estimate crop acreage using traditional sampling techniques, sometimes in combination with remote sensing. The purpose of those studies, however, was to enhance, and not to replace a particular sampling method. A regression estimator and recent cropland mapping based on remote sensing data classification have been adopted by NASS of the USDA (2009a,b; Taylor et al., 1997), which needs intensive field data.

In this paper, a crop planting and type proportion (CPTP) method that integrates remote sensing data segmentation and transect sampling, is developed to operationally estimate large area crop acreage in China. The method has provided reliable crop acreage estimation since 2000. And the results have been adopted by State Grain Administration of China and other government bodies.

2. Study area

China has the third largest territory in the world and home to 1.3 billion people. The geomorphology of China is complex as approximately 67% of the land is occupied by mountains, plateaus and hills, whereas only approximately 15% of its total land area can be cultivated. The climate of China varies greatly from the Temperate Zone in the north, to a tropical zone in the south. Thus, the accumulated temperature above 10 °C varies from 1600 °C in northeast China to 7500 °C in south China (Sha et al., 2002), and precipitation varies from 203 mm in northwest China (Yinchuan, Ningxia Hui Autonomous Region) to 1900 mm in south China (Guilin, Guangxi Zhuang Autonomous Region).

The arable land area covers 121,716 kha, mainly occurring in the Northeast China plain, the North China plain, the Sichuan basin, and the middle and down-river plain of the Yangtse River. Due to the huge population, the average cultivated land per family was limited, leading to small field sizes, especially in Southern China. In addition, the complex geomorphologic and climatic characteristics lead to various crop rotations and diverse crop types with a long history of agricultural activities based on various agro-conditions. The crop planting pattern also varies from one-season cropping in the north to three-season cropping in the south.

Rice is the most important crop in China. It is planted in approximately 25% of the cultivated area, mainly to the south of the Huai River, in the Yangtze valley, the Pearl River delta, Sichuan Basin, and in the provinces Yunnan, Guizhou, and Guangxi autonomous region. Wheat is the second most important grain crop, planted throughout the country, but concentrated on the North China Plain, the Wei and Fen River valleys on the Loess plateau, and in the provinces Jiangsu, Anhui, Hubei, and Sichuan. Maize and millet are planted in north and northeast China, whereas soybean is mainly grown in Northeast China for the production of cooking oil.

Growing seasons of different crops overlap in different regions, Early rice, middle rice, and later rice in southern China; spring wheat, soybean, single rice, and maize in northeast China. The representative agricultural landscapes in China can be seen in Fig. 1. Recently, China strengthened the adjustment of its crop planting structure by stimulating a major transformation from grain crops to cash crops (Liu et al., 2009). In many regions several crops are planted simultaneously at present where only one crop was planted before. The complex and changing Chinese crop systems have thus lead to great challenges to estimate accurate crop acreage at the national scale.

3. Methodology

To address the large and complex crop systems and diverse crop types in China, a CPTP method that integrates remote sensing and transect sampling has been developed for crop acreage estimation (Fig. 2).

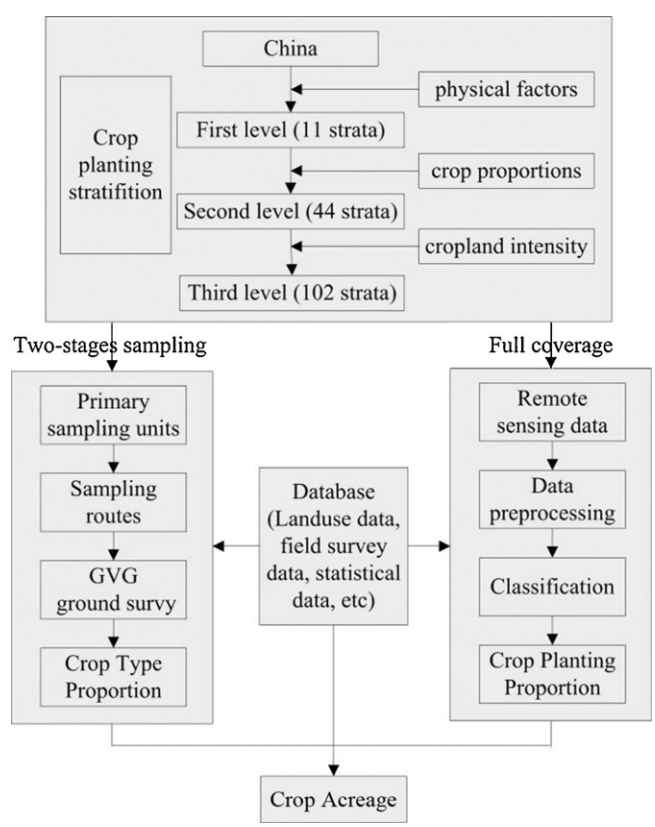


Fig. 2. Conceptual framework of the crop planting and type proportion method for crop acreage estimation of complex agricultural landscapes.

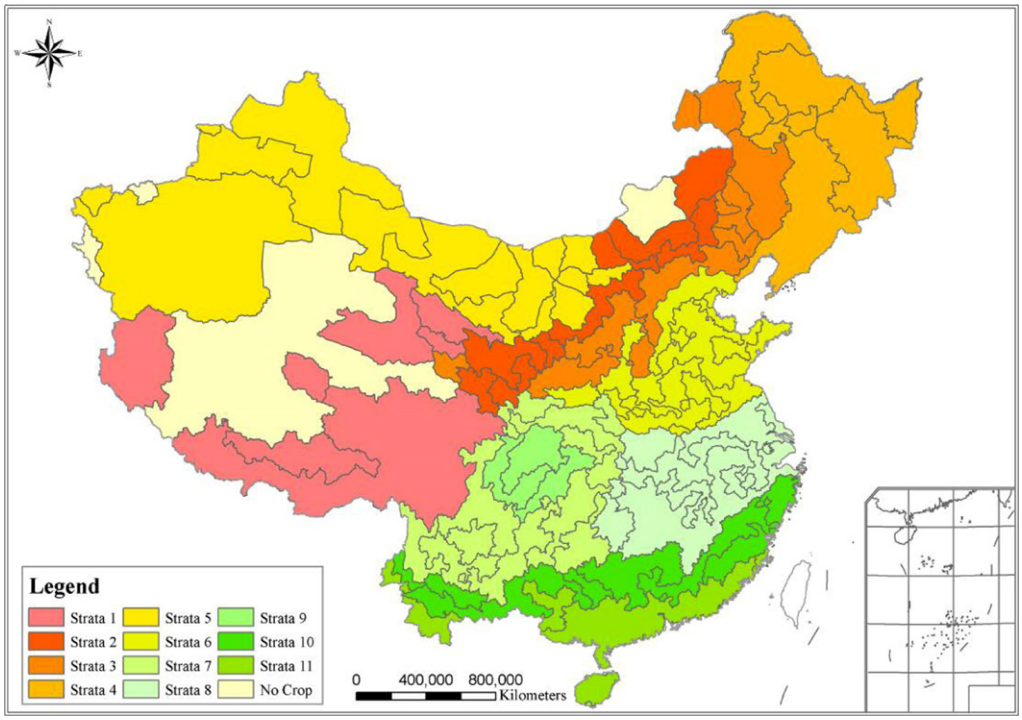


Fig. 3. Stratification used for crop acreage estimation in China. All the main crop regions of China are stratified into 102 strata at the 3rd level with similar cultivation characteristics. In the figure, strata 1: Chimonophilous crops domination region on Tibet plateau; strata 2: Chimonophilous crops domination region in southeast of inner-Mongolia autonomous region and the west part of loess plateau; strata 3: Thermophilic crops domination region in east part of inner-Mongolia autonomous region and loess plateau; strata 4: Chimonophilous crops domination region in the semi-wet or wet region in northeast China plain and hilly region; strata 5: Spring wheat, spring corn, and other cash crops domination region in Xinjiang autonomous region, Gansu corridor region; strata 6: Winter wheat-corn-soybean domination region in Yellow-Huaihe-Haihe Rivers Plain; strata 7: Paddy-upland farming crops concurrent domination region in the hilly region of Southwest China; strata 8: Rice planting region in the middle and lower reaches of Yangtze River; strata 9: Paddy-upland farming crops concurrent domination region in Sichuan Basin; strata 10: Double and single cropping rice domination region in the hilly region of southeast China; strata 11: Double cropping rice domination region in the plain region of south east China.

The CPTP method for crop acreage estimation consists of the crop planting proportion (CPP), *i.e.* the fraction of cropped arable land to total arable land and the crop type proportion (CTP), *i.e.* the percentage of a certain crop in the total cropped arable land estimated. For CPP estimation, the study area is fully covered by wide-swath remote sensing data, such as multi-spectral CCD data on board the HJ-1 A/B (Jia et al., 2010) and the BJ-1 satellite (Wang et al., 2010a), and AWIFS data on board the IRS P6 satellite (Kandrika and Roy, 2008). These sensors have short revisit periods because of the wide-swath properties (Kandrika and Roy, 2008; Sesha Sai and Narasimha Rao, 2008), enabling enough data acquisition for full coverage of the monitoring regions. To estimate CPP, the cropped areas and non-cropped areas are delineated by means of an unsupervised classification. Then, CTP is estimated through ground survey using the GVG (GPS-VIDEO-GIS) surveying system as a ground survey instrument under transect sampling (Wu et al., 2004a,b). Subsequently, crop acreage is computed by multiplying the arable land area, CPP and CTP at the strata level and then summed to provincial level and national level. The arable land area is obtained from an arable land database of China at a scale of 1:100,000 (Liu et al., 2005a,b), which is updated every 5 years.

3.1. Crop planting stratification

Cropland planting stratification is aimed at providing a uniform planting characteristic stratification to promote the estimation accuracy of crop acreage. Stratification is the division of a population into non-overlapping sub-populations. To obtain an efficient stratification for supporting crop acreage estimation, a physical stratification schema consisting of three levels has been adopted. The first level takes various physical factors into account, such as atmospheric temperature, precipitation, solar radiation, soil types and their physiognomic properties, crop rotation, crop calendar, etc. All the main crop regions in China are thus stratified into 11 strata at the first level. At the second level, crop regions with similar crop proportions are stratified using the crop acreage at the county level from agricultural statistics data for the dominant grain crops: rice, wheat, maize and soybean. This provides 44 strata at the second level. At the third level, the cropland intensity (*CI*) factors are taken into account. Four grades are used: >80%, 50–80%, 15–50%, and 0–15%, determined as:

$$CI = \frac{\text{crop land area}}{\text{territory area}} \quad (1)$$

Finally, to maintain consistency with the statistical data, each county is assigned to a single stratum and is not further subdivided. When a stratum has only one or two counties, it will be merged into the adjacent one. The regions with crops in China are thus stratified into 102 strata with similar cultivation characteristics (Fig. 3).

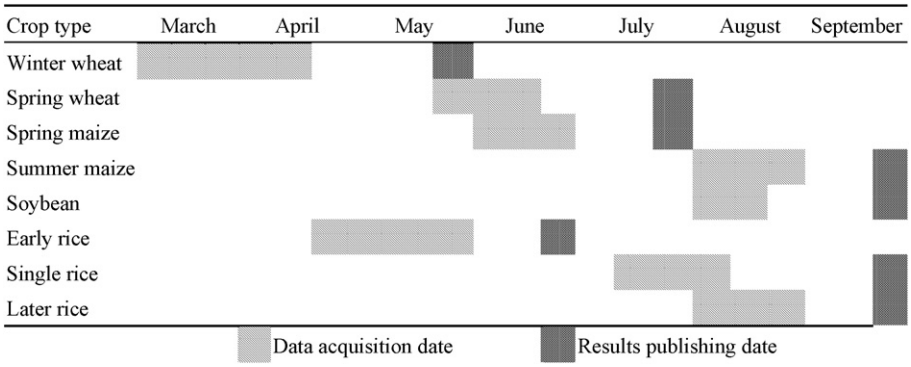
3.2. Crop plant proportion estimation

Crop planting proportion (CPP) is monitored to estimate how much of the arable land has been planted in the season. The key task here is to extract cropped area using remote sensing data.

3.2.1. Data sources and data acquisition schedule

Wide-swath high spatial resolution data, such as the HJ-1 A/B CCD, BJ-1 CCD, and IRS P6 AWIFS can provide a full coverage for large area CPP estimation. Those satellites have a swath width of over 700 km at every overpass, and have a potential data revisit time of every 4–5 days. The main winter wheat producing region

Table 1
Data acquisition and results publishing schedule for crop acreage estimation in China.



in China can be covered with 6 scenes of cloud free HJ-1 data, the spring wheat region with 5, the maize and soybean region with 11 scenes, the single rice region with 12 scenes and the early and late rice regions with 8 scenes. For regions that are difficult to completely cover with wide-swath remote sensing data, other high-resolution multi-spectral data have been used, like the Landsat TM/ETM, CBERS CCD, IRS P6 LISS-3, and SPOT HRV data.

Requirements of data acquisition depend on the spatial distribution of crops, crop calendar and crop rotation pattern. Therefore, the temporal window affects the estimation accuracy of crop acreage as well (Van Niel and McVicar, 2004). Data received 1 month after the sowing are considered suitable for the monitoring of the planting proportion. Data acquired earlier may result in a lower accuracy due to lower contribution of target crops in the spectral reflectance. A schedule of high-resolution remote sensing data acquisition for CPP estimation is shown in Table 1.

3.2.2. Data processing

For CPP estimation, the cropped and non-cropped areas needed to be delineated. An unsupervised classification method was used. Atmospheric corrections, geometric corrections and the soil adjusted vegetation index (SAVI) are processed before classification, as described below and shown in Fig. 4.

The MODTRAN algorithm removes the effects of atmospheric components, such as O_3, CO_2, water, and aerosols (Brazile et al., 2008). The meteorological observation data used in the atmospheric corrections, such as aerosol depth are obtained from the China Meteorological Administration.

For the geometric corrections, second-order polynomial models were applied to generate geo-referenced data. Reference data have been derived from topographic maps and reference data.

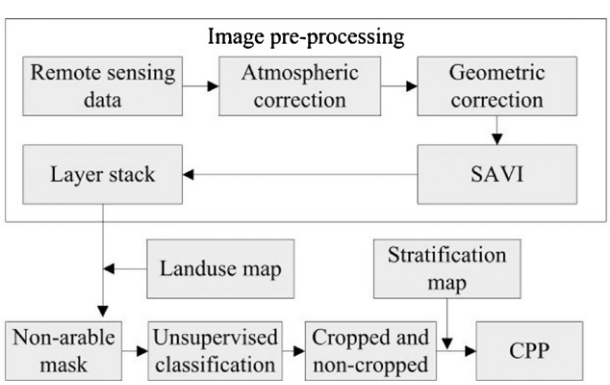


Fig. 4. Data processing flow for the monitoring of crop planting proportion (CPP). The stratification map is a map stratified at the 3rd level.

The soil adjusted vegetation index (SAVI) increases the spectral signals of crops compared to non-crop features. The SAVI is defined as

$$\mathrm{SAVI} = \frac{\mathrm{Ref_{NIR}} - \mathrm{Ref_{red}}}{\mathrm{Ref_{NIR}} + \mathrm{Ref_{red}} + L} \times M \tag{2}$$

where $\mathrm{Ref_{NIR}}$ and $\mathrm{Ref_{red}}$ are the band reflectance values at near infrared and red band respectively. Cropped pixels always have intermediate vegetation densities. There we set the adjustment factor L in SAVI in (2) equal to 0.5, whereupon SAVI effectively reduces soil noise (Huete, 1988). In this study, SAVI is used mainly as a band for classification of cropping and non-cropping areas. In order to obtain a larger data stretch, the multiplier M in (2) has been set equal to 100.

After stacking the SAVI layer with the geo-referenced data, land use maps have been used to mask non-arable land. The masked data is classified using the ISODATA algorithm. The class with SAVI >20 was extracted for further identifying cropped and non-cropped areas taking the spatial distribution and planting structure of crop phenology into account. Since the classification only delineates cropped from non-cropped areas, the classification accuracy can usually be above 98%.

3.2.3. CPP estimation

CPP is defined as the ratio of cropping arable land to total arable land, and can be described as in Eq. (3).

$$\mathrm{CPP} = \frac{A_1}{A_0} \tag{3}$$

where A_1 is the acreage of cropped arable land and A_0 is the acreage of arable land in each county, or strata, or province.

Cropped area and non-cropped area are calculated by summing the cropped and non-cropped pixels. Then the CPP is estimated at the county, strata, or provincial levels. For strata that are not fully covered by remote sensing data, the average CPP of neighboring strata or the administrative unit or upper stratification zone is adopted.

3.3. Crop type proportion inventory

To estimate crop type proportion (CTP), the GVG surveying system was designed and developed to carry out fast surveys of large areas, for which transect sampling has been applied.

3.3.1. Transect sampling

Sampling technique has been used in large area crop acreage estimation since LACIE program in 1970s. Tessellated plane sampling and continuous plane sampling had been used to guide the

Fig. 5. The GPS-VIDEO-GIS (GVG) surveying system.

ground survey before (Michael and Marian, 2002). Area frame sampling (Sushil, 2001; Gallego, 1995) is usually used for multi-purpose survey. Yet the efficiency cannot meet specific requirement on crop acreage estimation and in large area as entire cropping regions in China. So, transect sampling is applied for fast sampling along the road with the help of vehicles.

Transect sampling is a two-stage statistical sampling procedure. During the first stage, area frame sampling is applied. The frame is defined as a 4 km × 4 km area and there are about 200,000 frames over the main producing region of China. Then, primary sampling units (PSU) are systematically selected. The sampling size is calculated using the sampling size equation of the simple random sampling (Cochran, 1977). For strata with a sampling size above 5% of the population, the sampling size was set to 5%, whereas other strata adopted the calculated sampling size. Finally, 3579 frames were selected as the primary sampling units (PSU) for the 102 strata in China. The average sampling ratio is 1.79%.

At the second stage, roads within PSUs are selected randomly or systematically as sampling routes to survey CTP. Given the width of transect sampling routes, D, the sampling ratio n is as given by Eq. (4).

$$n = \frac{L \times D}{K^2} \times 100\% \tag{4}$$

where L is the length of transect sampling line, and K is the size of PSU. When K and D are fixed, L changes with the sampling ratio of n as described in Eq. (5).

$$L = \frac{K^2}{D} n \tag{5}$$

Here D, the sampling line width is set 0.1 km, and the sampling ratio is set 2%. Then the sampling route length L equals to 3.2 km in every PSU.

The inventory has been put on main producing regions, and at some remote PSUs with low productions, CTPs were set constant according to experience, and ground survey is not considered. As a result, the total transect sampling routes length was approximately 11,500 km, covering the entire grain producing region of China.

3.3.2. Fast ground survey for CTP

To improve the efficiency of ground survey, an instrument, the GVG surveying system has been invented and developed (Fig. 5).

The system integrates a GPS receiver, a video camera, and a GIS analysis system (Wu et al., 2004a,b). And the system is installed on a vehicle running along the transect routes when carrying out a ground survey. The camera snaps pictures continuously and the GPS receiver records the geo-location of each picture.

Considering the limitations of available survey time and the large survey area to be covered, the grain producing region of China is divided into eight sampling sub-regions, each being allocated to a local survey team with local experiences (Fig. 6). In this way, the CTP inventory efficiently meets the time limitation of crop acreage estimation.

A inventory schedule has been worked out to guide the CTP inventory that uses GVG instruments based on regional crop

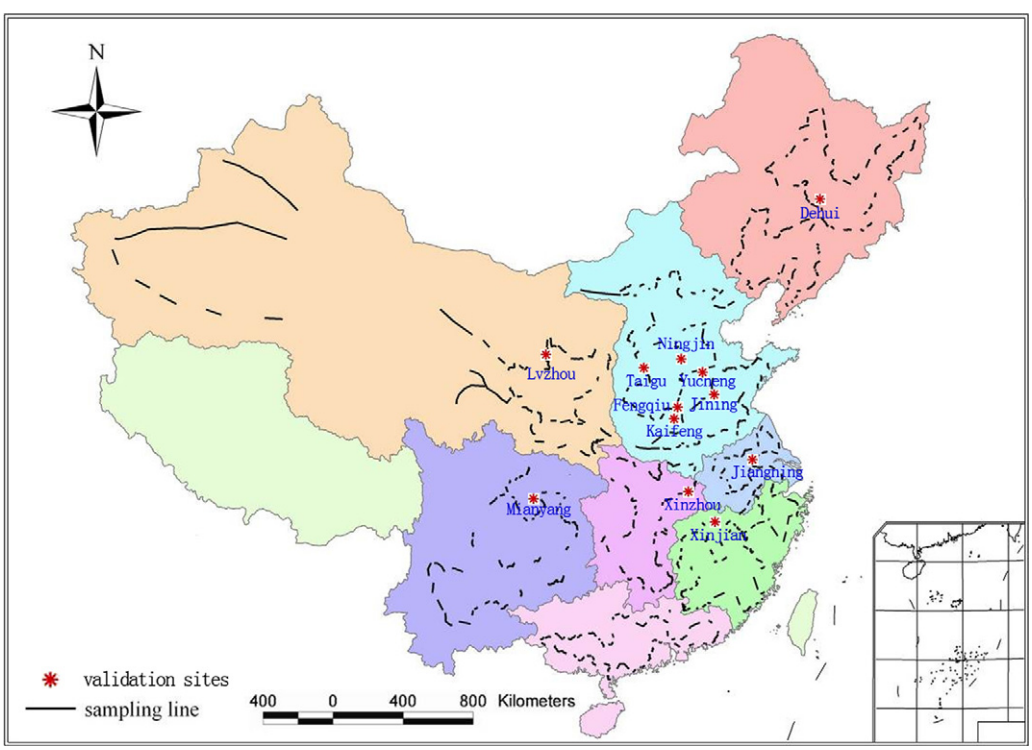


Fig. 6. Eight zones applicable for CTP surveying using the GVG sampling routes and location of thirteen validation sites, representing the major agricultural landscapes in China.

Table 2
Sampling schedule of different sampling sub-regions of China.

Zones	April	May	June	July	August
North east China			SW, SM, S, R		
North China		SW、SR	SW		MM, MR, S
East China	WW，SR		ER	MR, LR	
South east China		ER		MR, LR, MM	
Central China		WW，SR	ER		MR, LR
South China		ER，MM			LR, MM
South west China	WW，SR			MR	
North west China		WW，SR	SW		SM, MM, MR
	1st sampling		2nd sampling		3rd sampling

SR, seed rape; WW, winter wheat; SW, spring wheat; S, soybean; R, rice; ER, early rice; LR, later rice; MR, middle rice or single rice; SM, spring maize; MM, summer maize.

phenology (Table 2). The earliest survey begins at the beginning of March and the latest survey ends their work at the end of September. Meanwhile, the sampling and quality control handbook are send to every local survey team. Every year, all local survey teams get together to obtain training, to exchange their survey experiences, and to feedback the bugs, if any, on GVG surveying system.

3.3.3. CTP estimation

Each picture collected by GVG ground survey is visually interpreted to identify the proportion of each crop type by field surveyors immediately after the field survey. Normally, surveyors conduct survey in the daytime and interpretation in the evening with the help of GVG interpretation Graphical User Interface (GUI). CTP is calculated at either the sampling line, or the strata or the province level, using Eq. (6).

$$P_j = \frac{\sum_{i=1}^{N} a_{ij}}{\sum_{i=1}^{N} A_i} \quad j = 1, 2, 3, \ldots, M \tag{6}$$

where P_j is the proportion of crop type j ($j = 1,\ldots,M$), a_{ij} is the proportion of crop type j in photo i ($i = 1,\ldots,N$) and A_i is the proportion of cropped arable land in photo i.

3.4. Crop acreage estimation

When CPP and CTP are estimated and inventoried, the crop acreage is calculated at the strata level using Eq. (7).

$$A_i = A_0 \times CPP_i \times CTP_i \tag{7}$$

where A_i is crop type area at stratum i; A_0 is the arable land area; CPP_i and CTP_i are the CPP and CTP values for stratum i, respectively.

At the provincial or national level, the crop acreage is calculated through summation of Eq. (8).

$$A_p = \sum_{i=1}^{n} A_i \tag{8}$$

where A_p is the crop type acreage at the provincial or national level and n is the number of strata within the province or the country.

3.5. Validation

The accuracy of CPTP method can be validated with *in situ* data. Since accuracies of the crop acreage are mainly affected by the accuracies of CPPs and CTPs, thirteen validation sites have been selected for *in situ* data collection. These validation sites, representing nearly all the agricultural landscapes in China, are located in Ningjin, Hebei Province, Dehui, Jilin Province, Jiangning, Jiangsu Province, Xinjian, Jiangxi Province, Jining and Yucheng, Shangdong Province, Kaifeng and Fengqiu, Henan Province, Xinzhou, Hubei Province, Mianyang, Sichuan Province, Lvzhou, Ningxia Autonomous Region from 2001 to 2009 (Fig. 6).

At each validation site, the truth of CPP and CTP are calculated from field crop mapping or very high-resolution image classification. At the Kaifeng and Mianyang validation sites, IKONOS and QuickBird data of about 120 km^2 and 60 km^2 are obtained respectively. Crop identification by means of a maximum likelihood classification gave an overall classification accuracy of 96.2% and 96.5% for IKONOS and QuickBird data based on validation samples selected in the ground survey, CTPs and CPPs of these two sites are then calculated by means of pixel statistics of classification. For the Dehui, Taigu, Jiangning, Xinjian, Jining, Yucheng, Fengqiu, Xinzhou, and Lvzhou validation sites, field plot boundaries are drawn from aerial images. Crop types in each field are identified by means of a field survey and crop maps are compiled for each site. Subsequently, the CPP for these sites result from cropped field area summation divided by total arable land area and the CTP results from area summation for each crop type, divided by the total cropped area.

For CPP validation, Landsat TM, IRS AWIFS and HJ-1 A/B CCD data are used, and the CPP is estimated using the flowchart given in Fig. 4 by Eq. (3). These estimated CPP values are compared with the truth of CPP. Relative errors and RMSE are calculated to evaluate the accuracy of CPP estimation with remote sensing.

For CTP validation, transect lines are also selected systematically within every validation site with the same sampling ratio as in Section 3.3.1, and the GVG surveying system is used to collect thousands of field pictures to interpret and estimate CTP values. These estimated CTP's are compared to the truth of CTP. Relative errors are calculated to evaluate the accuracy of CTP estimation with transect sampling.

4. Validation results

4.1. Accuracy of CPP estimation

The validations show that the CPP's from high-resolution data like Landsat TM, HJ-1 A/B CCD and IRS AWIFS data are close to the truth CPP's (Table 3). The average relative error is approximately 2.41% with maximum relative error of approximately 4%. The RMSE computed from regression of estimated and truth CPP equals 1.67% and the likelihood between estimated and truth CPP has passed the F test at the 95% level. Therefore, the methods used to estimate CPP is accurate enough for operational purpose at the national scale (Li and Wu, 2004).

Table 3
Comparison of estimated and *in situ* CPP values at different validation sites.

No.	Validation site	Growing season	Remote sensing data and receiving date	*In situ* CPP collection method and time	CPP estimated	CPP *in situ*	Relative errors
1	Kaifeng	Summer	Landsat TM, 2001-4-1	IKONOS, 2001-3-8	71.01%	71.85%	1.17%
3	Taigu	Fall	Landsat TM, 2003-10-14	Crop mapping, September 2003	88.83%	86.85%	2.28%
5	Jiangning	Fall	Landsat TM, 2003-7-22	Crop mapping, August 2003	92.72%	95.36%	2.64%
7	Taigu	Summer	Landsat TM, 2004-4-15	Crop mapping, June 2004	94.48%	94.73%	0.26%
8	Taigu	Fall	Landsat TM, 2004-8-5	Crop mapping, September 2004	93.24%	95.67%	2.54%
10	Ningjin	Summer	Landsat TM, 2004-4-1	Crop mapping, June 2004	79.43%	82.72%	3.29%
11	Ningjin	Fall	Landsat TM, 2004-7-4	Crop mapping, June 2004	91.45%	92.09%	0.64%
12	Xinjian	Fall	Landsat TM, 2004-8-9	Crop mapping, June 2004	93.63%	92.71%	0.92%
13	Jining I	Summer	Landsat TM, 2005-4-13	Crop mapping, May 2005	95.10%	99.06%	4.00%
14	Jining II	Summer	Landsat TM, 2005-4-13	Crop mapping, May 2005	94.99%	97.57%	2.64%
15	Mianyang	Summer	Landsat TM, 2005-4-14	QuickBird, 2005-3-5	90.35%	92.59%	2.42%
16	Taigu	Summer	Landsat TM, 2005-4-2	Crop mapping, June 2005	92.37%	95.71%	3.49%
17	Fengqiu	Summer	IRS P6 AWIFS, 2008-4-25	Crop mapping, May 2008	95.37%	98.34%	2.97%
18	Fengqiu	Fall	IRS P6 AWIFS, 2008-7-28	Crop mapping, July 2008	97.18%	99.37%	2.19%
19	Yucheng	Summer	IRS P6 AWIFS, 2008-4-25	Crop mapping, May 2008	88.25%	91.47%	3.22%
20	Yucheng	Fall	IRS P6 AWIFS, 2008-8-13	Crop mapping, August 2008	94.67%	97.08%	2.41%
21	Yucheng	Summer	HJ-1 CCD, 2009-4-16	Crop mapping, April 2009	84.45%	88.17%	3.72%
22	Yucheng	Fall	HJ-1 CCD, 2009-8-30	Crop mapping, August 2009	94.69%	97.26%	2.57%

CPP values estimated using remote sensing data are 2.05% below the *in situ* CPP values. The average relative error can be used as a systematic error to revise the original results. The revised CPP, nearly all the relative errors of the validation sites are below 2% and the average relative error is 1.42%.

The validation also shows no evident difference exists in the accuracy of CPP values in the different validation sites in different parts of China. Then, we can conclude that there is no effect of the different agricultural landscapes on the CPP estimation accuracy. Hence the method for estimating CPP as described in Section 3.2 can be used all over China if appropriate remote sensing data can be acquired.

4.2. Accuracy of CTP estimation

The accuracies of the CTP values from the transect sampling are close to the truth CTP values obtained from the crop maps (Table 4).

For most crop types, the relative errors are below 4.0% whereas the maximum relative error equals 7.64% in the Dehui validation site. The average relative error is approximately 2.63%, the RMSE computed from regression of estimated and truth CTP equals 2.25% and the likelihood between estimated and truth CPP passes the F test at the 95% level. It indicates that CTP surveys using the transect sampling and the GVG system result in results of a high accuracy. It also shows that the CTP inventory using the GVG surveying system on a transect sampling can meet the accuracy requirement of large area operational crop acreage estimation.

The accuracy of the different crop types shows that the average relative errors are 2.46% for wheat, 2.66% for maize, and 2.91% for rice. The maximum relative error is 4.04% for wheat, 7.64% for maize, and 4.73% for rice. The accuracy for wheat is best because there were almost no competing crops during the winter wheat season. For the autumn harvest crops, such as maize and rice, the relative errors were somewhat larger, as in autumn there are quite a few competing crops, including soybean, potato, vegetables and several types of beans.

There is no evidence for a difference between the relative errors in the different validation sites for wheat, maize and rice. This means that the method for CTP inventory using the GVG surveying system guided by transect sampling is suitable for most of the representative agricultural landscapes of China.

Validation shows that the method is suitable for dominant crops acreage estimation (Table 5). Table 5 gives the relative errors of CTP estimation in the Taigu validation site in 2003. The relative errors

Table 4
Validation of CTP values from transect sampling with GVG, compared with *in situ* CTP data.

No	Validation area	Year	Growing season	Validation date	Crop type	CTP from transect sampling	CTP from crop mapping	Relative errors
1	Xinzhou	2002	Fall	2002-8-1	Maddle rice	71.29%	68.07%	4.73%
2	Taigu	2003	Fall	2003-9-16	Spring maize	30.01%	30.24%	0.77%
3	Taigu	2003	Fall	2003-9-16	Vegetable	19.82%	19.29%	2.76%
4	Taigu	2003	Fall	2003-9-16	Soybean	19.07%	19.29%	1.13%
5	Dehui	2003	Fall	2003-8-1	Spring maize	64.10%	69.40%	7.64%
6	Jiangning	2003	Fall	2003-8-20	Maddle rice	74.33%	76.01%	2.31%
7	Xinzhou	2003	Fall	2003-8-15	Maddle rice	58.32%	59.18%	1.45%
8	Xinzhou	2003	Fall	2003-8-15	Vegetables	26.72%	25.27%	5.74%
9	Ningxia	2004	Fall	2004-9-10	Spring wheat	77.92%	81.20%	4.04%
10	Ningjin	2004	Summer	2004-4-25	Winter wheat	90.30%	89.51%	0.90%
11	Ningjin	2004	Fall	2004-8-15	Summer maize	90.09%	91.13%	0.30%
12	Xinjian	2004	Fall	2004-9-15	Latter rice	77.50%	80.0%	3.13%
13	Jining I	2005	Summer	2005-5-1	Winter wheat	93.03%	89.44%	4.01%
14	Jining II	2005	Summer	2005-5-4	Winter wheat	93.65%	94.48%	0.88%
15	Mianyang	2005	Summer	2005-3-27	Winter wheat	26.87%	27.74%	3.14%
16	Mianyang	2005	Summer	2005-3-27	Canola	46.85%	46.52%	0.71%
17	Taigu	2005	Summer	2005-6-20	Winter wheat	46.45%	45.33%	2.47%
18	Fengqiu	2008	Fall	2008-8-25	Summer maize	76.43%	74.56%	1.87%
19	Yucheng	2009	Summer	2009-4-30	Winter wheat	77.39%	75.58%	1.81%
20	Yucheng	2009	Fall	2009-8-30	Summer maize	81.43%	84.15%	2.72%

Table 5
Relative errors of CTP at the Taigu site in 2003.

Crop types	Survey CTP (%)	*In situ* CTP (%)	RE (%)	Crop types	Survey CTP (%)	*In situ* CTP (%)	RE (%)
Maize	31.24	30.24	3.31	Millet	0.98	0.65	50.77
Vegetables	20.61	19.29	6.84	Potato	0.95	0.86	10.47
Soybean	19.86	19.29	2.95	Pumpkin	0.57	0.65	12.31
Sorghum	3.28	3.11	5.47	Peanut	0.32	0.42	23.81
Sunflower	2.11	1.86	13.44	Flowers	0.32	0.14	128.57

increase with a decrease of the CTP value. The reason is most likely related to the sampling method, as minority crops may not have been planted along the road or seldom appears during the sampling process. Therefore, a CTP inventory based on transect sampling and GVG surveying system may not provide an unbiased estimate of the proportion of minority crops.

5. Case study

The CPTP method has been integrated into "CropWatch, a global crop monitoring system with remote sensing" and has provided reliable operational results since 2000. Here present the monitoring of the winter wheat acreage of China in 2010 as a case study.

Twenty-four scenes of HJ-B CCD data, covering almost completely the major winter wheat producing regions of China, have been used for estimating winter wheat acreage (Fig. 7).

CPP estimation was completed within 5 days in early May, *i.e.* nearly a month before the harvest. The ground survey for the CTP estimation has been carried out within 20 days from March to April. The first team, working in the southwest China sub-region team started their survey in March, while the last one, the North China sub-region team, started their survey in April. All the CTP inventory results were received before 10th May from local teams 363 counties have been surveyed during the CTP inventory (Fig. 8).

Winter wheat acreage has been calculated using an arable land dataset updated to 2008 and the estimated CTP and CPP data at the provincial level (Table 6). The results have been released on 15th, May, 1 month before the winter wheat harvest.

The province of Henan, Shandong, Hebei, Anhui, Jiangsu, and Sichuan as the main winter wheat producing regions contribute 73% of the total winter wheat area. Among these, the Henan and Shandong provinces contribute approximately 40% of the total winter wheat area. CPP values reflecting the arable land use intensity in winter. CPP are high in Henan, Shandong, Hebei, Sichuan and Chongqing (>60%), and low in Shaanxi, Gansu and Shanxi because of the colder weather. CTP values reflecting the share of winter wheat in all the crops are high in Henan, Shandong, Hebei, Jiangsu, Anhui, Shaanxi because winter wheat is the main crop in this season. These values are low in Shaanxi, Gansu and Sichuan, Hubei because of the planting of other crops like rape seed, potato and vegetables.

Great changes in cropped and non-cropped areas can be observed when comparing CPP data of the winter wheat season with those from the previous season. An example from a region covering Dezhou municipality of Shandong province is shown in Fig. 9. Winter wheat acreage has increased in the Hebei, Henan, Shandong, Shanxi, Shaanxi, Jiangsu, Anhui and Hubei provinces due to the increase of cropped areas and the CTP of winter wheat, whereas it has decreased in Gansu, Sichuan and Chongqing. The main reason for the increase is most likely that the government has increased the purchasing price of winter wheat and that the cotton

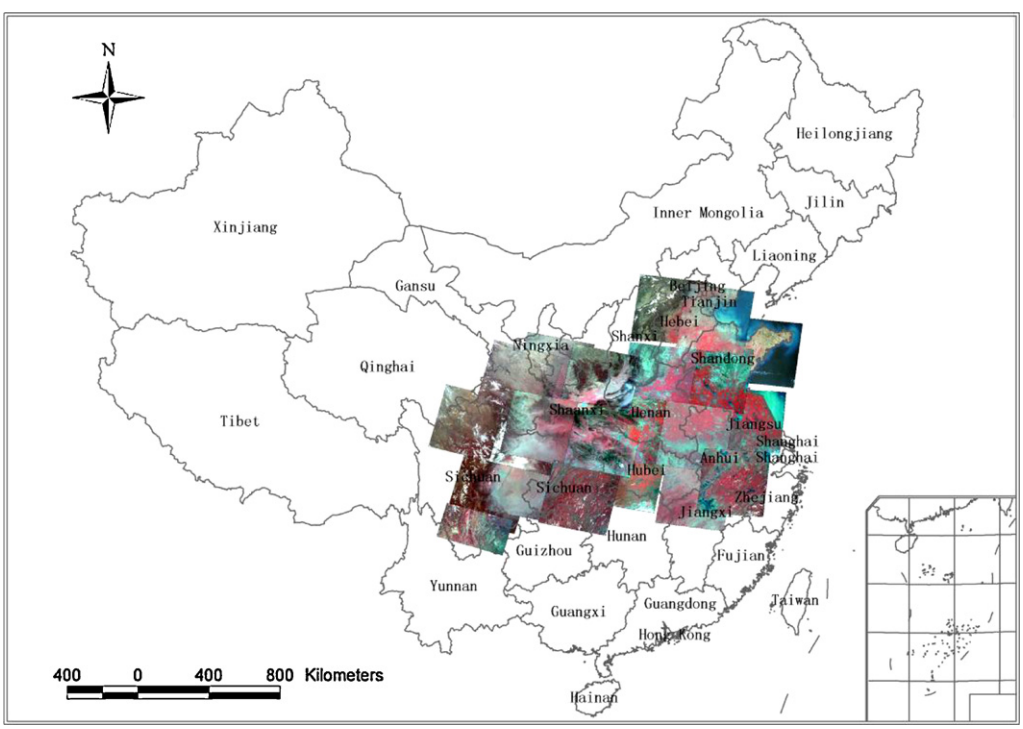


Fig. 7. HJ-1 CCD data used for the winter wheat crop acreage estimation in 2010. In this figure, one scene image is 1/4 part of one full HJ-1 CCD data.

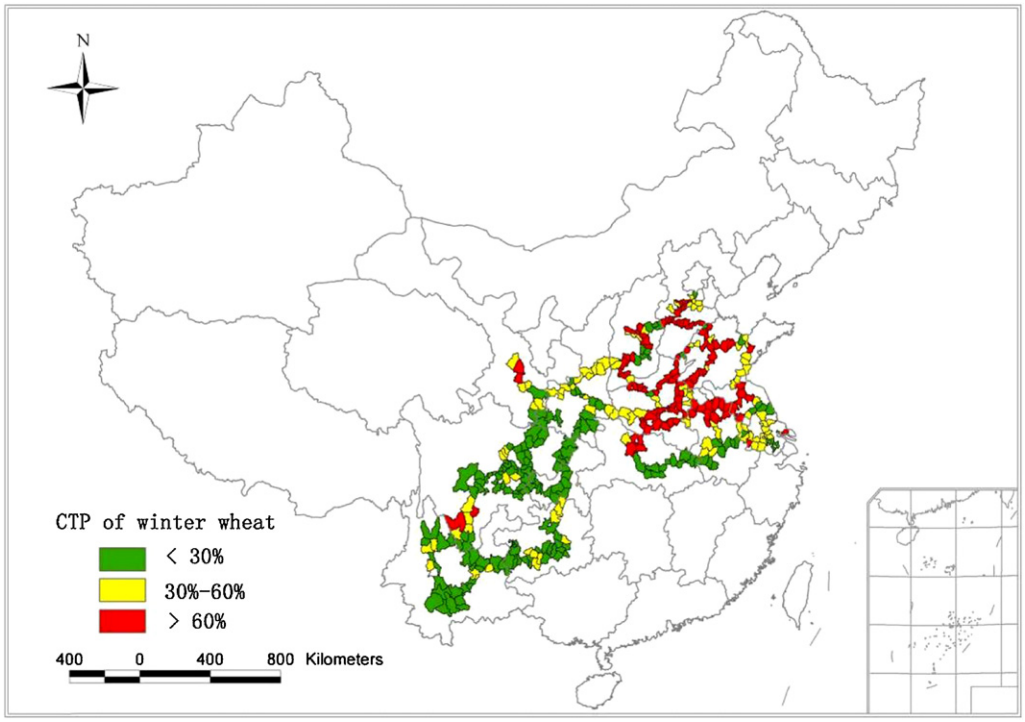


Fig. 8. Winter wheat CTP inventory survey in 363 counties in 2010.

Table 6
Winter wheat acreage of China in 2010.

Province	Arable land area (kha)	CPP (%)	Winter wheat CTP (%)	Winter wheat acreage (kha)
Hebei	4918.42	60.09	77.18	2280.97
Shanxi	2995.1	40.68	52.23	636.40
Jiangsu	5321.87	52.47	68.95	1925.32
Anhui	6240.96	49.76	71.89	2232.39
Shandong	8333.01	65.62	78.31	4282.17
Henan	8124.89	76.36	86.89	5390.49
Hubei	4912.14	49.50	32.05	779.29
Chongqing	2730.43	65.95	24.93	448.91
Sichuan	8408.15	62.09	32.41	1692.00
Shaanxi	5584.11	21.07	62.16	731.41
Gansu	4351.9	37.05	37.69	607.69
Others	–	–	–	3275.89
China	–	–	–	24,282.93

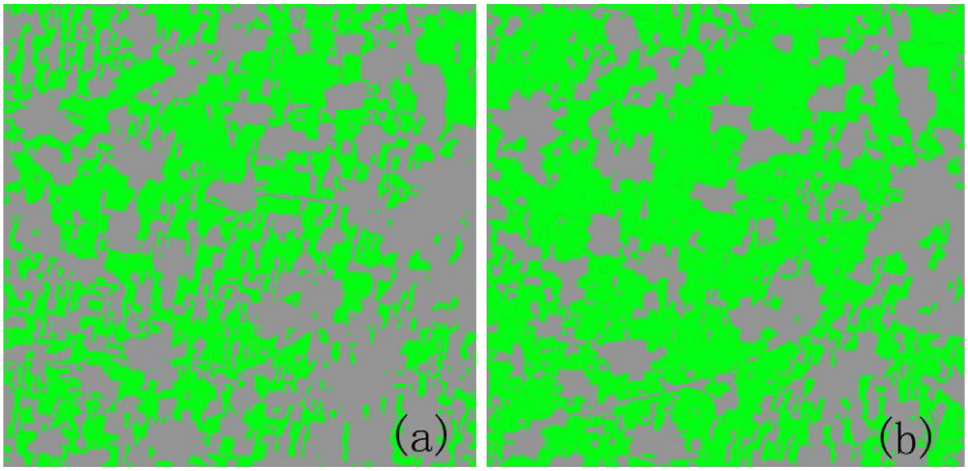


Fig. 9. Cropped (green) and non-cropped areas changed in 2010 winter wheat season compared to previous season in Dezhou of Shandong province. Classification results of HJ-1 CCD data acquired in 2009 (a) and 2010 (b).

price decreased in the previous year, thus stimulating the farmers' enthusiasm for winter wheat planting. Also, the better soil moisture during the winter wheat sowing period in 2009 stimulated the plantation of winter wheat.

6. Discussion

Agriculture plays an important role in the Chinese economy. Although China's agricultural output is the largest in the world, it only represents 10% of the world's total arable land. Reliable and timely monitoring of crop acreage at the country level is critical in China for decision making on economic policies, especially due to the big variability of off-farm works in cities. The CPTP method shows that remote sensing combined with transect sampling can provide high accuracy crop acreage estimation, as validated in the different sites. The average relative error in both CPP monitoring and CTP survey of all sites are 2.41% and 2.63% respectively, both below 4%. The RMSE computed from regression of estimated and observed CPP and CTP equals 1.67% and 2.25% respectively. However, there exists a system error in CPP estimation (Table 3), almost all the estimated CPP is slightly smaller than the observed. Take the average absolute error 2.05% as the system error to adjust the estimated CPP, which is all the estimated CPP multiply (1 + 2.05%) to get the new adjusted estimated CPP. Then the average RE of the adjusted CPP becomes 1.42%. According to the error propagation rule, the crop acreage estimation RE will be 5.10%, if consideration of system error in CPP estimation, the RE of crop acreage estimation will be 4.09%. The results indicate that CPTP method can be used for crop acreage estimation of large areas with complex crop planting systems and diverse agricultural landscapes.

Remote sensing techniques have long been used for crop acreage estimation of large areas. The Large Area Crop Inventory Experiment (LACIE) was the first experiment to demonstrate the operational capability of remote sensing for wheat monitoring (Macdonald and Hall, 1980). The results from LACIE are more reliable for the American Great Plains, but cannot meet the accuracy goal for Canada, China and other regions in the world (Dadhwal et al., 2002). The reason is that the crop classification scheme used by LACIE is only suitable for large field sizes and one single crop dominated cultivation pattern. When it concerns smaller field sizes and diverse agricultural landscapes such as that in China, the LACIE methodology cannot obtain any meaningful crop acreage information. The method developed in this paper overcomes these drawbacks by using the CPP monitoring and CTP surveys. The method makes fully use of the benefits of remote sensing, coupled with sampling techniques taking account of the low accuracy of crop type identification using remote sensing alone at the present time.

CPP information is obtained by segmenting cropped and non-cropped areas by means of unsupervised classification with full coverage of interesting regions using high spatial resolution multispectral remote sensing data. Full coverage ensures that there is no omittance of crop fields in the monitoring regions. Planted land can be exactly and accurately extracted through segmenting cropped and non-cropped areas by means of an unsupervised classification, as there is a strong contrast between vegetation and bare land. When multi-temporal remote sensing data are used, the planted area can be extracted without masking non-arable land using landuse map.

Since crop identifications using remote sensing data are difficult for the complex agricultural landscape. CTP information is acquired by ground survey with the GVG instrument and transect sampling. Validation showed that it can provide reliable and timely CTP acquisition. The GVG collects thousands of pictures along the transect routes, and each and every picture is being interpreted by people who have local experiences. CTP at the strata level can then be calculated. In the future, new methods identifying crop type using multi-temporal, multi-spectral optical data and multi-frequency SAR data are needed. Several high-resolution sensors have been launched in the last 5 years. One new sensors, *e.g.* the HJ-1 CCD can acquire high-frequency, high spatial-resolution data, two very high-resolution optical sensors (RapidEye, WorldView-2) have an increase number of spectral bands, whereas Radarsat-2, TerraSAR-X, COSMO-SkyMed provide high-resolution radar data of different radar frequency bands. These new data sources will increase the role of remote sensing data in crop identification, although their applicability to crop acreage monitoring and corresponding methodologies still need to be developed.

Data quality is sensitive to the accuracy of the method and must be pay attention. For CPP estimation, spatial resolution is a key factor that may result in miss monitoring of small fallows. Meanwhile, Small fields sparsely distributed in mountain area may also be missed using images with 30 m spatial resolution. So, new images with higher resolution (<30 m) will be more suitable for CPP estimation in China in the future. Nevertheless, uncertainty analysis should be carried out to make clear how spatial resolution and other factors affect the accuracy of CPP and CTP estimation.

The CPTP method is robust enough to meet the time requirement of operational dominant crop acreage estimation at large areas. For acreage estimation of winter wheat, maize, rice and other main grain crops in China, the CTP inventory can be finished within 20 days for any sampling region, and the CPP monitoring can be done within 1 week. Therefore, the crop acreage estimation results can be released 1 month before the harvests of any of the main crops.

The CPTP method is also affordable. 60% of total annual expense for crop acreage estimation in China is for CTP monitoring and 40% is for CPP monitoring and operational analysis, thank to free data access of HJ satellite CCD data. This method has been integrated into CropWatch (Wu, 2004) which is an operational crop monitoring system in China and has provided reliable results for the past 10 years.

The method uses just some basic characteristics of remote sensing data. It uses an unsupervised classification method to extract cropped area. The reason to use an unsupervised classification is that it is hard to assign a unique SAVI threshold for multi-date data covering the whole study area, or crops at different phenological stages.

The method needs an arable land database to support CPP estimation and final crop acreage estimation. The novelty and the accuracy of arable land data may affect the accuracy of CPP and crop acreage estimation. If arable land, however, is inaccurately defined, some arable land may not be included into the estimation, and some non-arable land may be included into the CPP estimation. Also, the arable land area of the strata are used for crop acreage estimation and its accuracy has a serious impact on the absolute crop acreage estimation, but much less on the relative values. The arable land data updated within 3–5 years was used. The changed arable land can also be detected and included into the CPP estimation and the CTP survey. Currently, high temporal and spatial resolution data such as IRS AWIFS and HJ-1 A/B CCD can provide a multi-temporal coverage of the entire study area. The multi-temporal data can extract the arable land in time. Thus it is possible to update the method by estimating crop planting acreage directly, without using land use maps or arable land databases.

This method can be used both for large areas such as for the entire China, as well as for smaller regions at the provincial or strata level. The method seems to be less suitable for minority crops like

sunflower, which have a small CTP in a stratum. Hence a low CTP value for a crop in a stratum corresponds with a large error. When using GVG in a ground survey, the road selection also has an impact on the CTP accuracy. It is recommended in the guidebook that the survey has to avoid main roads or roads with buildings along them.

7. Conclusions

This paper presents a new crop acreage estimation method, crop planting and type proportion method that integrates remote sensing data with stratified transect sampling. With a focus on China, it takes specific properties of cropping practices and agricultural landscapes into account. CPTP method has been integrated into CropWatch and has provided reliable operational results since 2000.

The CPTP method mainly consists of crop planting proportion monitoring with remote sensing data and crop type proportion survey with transect sampling and the GVG instrument. Crop acreage is calculated by multiplying the arable land area, CPP and CTP at strata level, and then summed up to provincial and country level. Validation at thirteen sites has shown high accuracies for both CPP estimation and CTP surveys. It therefore can provide reliable crop acreage information. The average relative errors of crop acreage estimation for large areas have been around 5%. It is particularly suitable for complex agricultural landscape regions with small fields. The method can also be used to monitor changes in cropping and planting structure between different years.

Conflict of interest

None.

Acknowledgements

The development of the method and its operation were supported by the Knowledge Innovation Programs of the Chinese Academy of Sciences (No. KSCX1-YW-09-01, KZCX2-313, KZCX3-SW-338-2), the National Key Technologies Research and Development Program of China (2001BA513B02), the National High-Tech Research and Development Program of China (2003AA131050), the National Extension Program (KJSX0504). The authors are grateful for the help of Rick Mueller and Zhengwei Yang from NASS, USDA in revising the paper, all of which have led to improvements in the presentation of this paper.

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