Classification of Farmland Vegetation

Subjects: Remote Sensing

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The classification and identification of farmland vegetation includes classification based on vegetation index, spectral bands, multi-source data fusion, artificial intelligence learning, and drone remote sensing.

agriculture food security remote sensing

1. Farmland Vegetation Classification Based on Vegetation Index

The classification of farmland vegetation based on vegetation index comprises the Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI). Chang et al. (2007) introduced land surface temperature (LST), combined with MODIS 7 time series single-band and time-series NDVI, as the final input feature quantity, based on a regression tree classifier to extract the spatial distribution area of corn and soybeans in the main producing areas of the United States [1]. Zhang et al. (2008) used fast Fourier transform to process the MODIS NDVI time-series curve, and selected the average value of the curve, the initial phase of the 1–3 harmonics, and the amplitude ratio as the parameters for crop identification, and realized the corn, cotton, and crop rotation in North China [2]. Zhang et al. (2008) determined four key phenological variables based on the phenological law as shown by the MODIS enhanced vegetation index (EVI) time-series curve of maize and wheat; namely, the initial growth time of the crop (T_{onset}), peak growth time (T_{peak}), EVI maximum time (EVI_{peak}), and growth termination time (T_{end}). This information was combined with expert knowledge to determine the threshold of critical period variables, and the spatial distribution and rotation of winter wheat and corn in the North China Plain were successfully identified [3]. Xiong et al. (2009) selected summer and autumn crop rotation periods and MODIS NDVI average values as standards, used a layered method to distinguish autumn harvest crop areas from other areas, and used the BP (back propagation) neural network method to classify and effectively extract three crop types of middle rice, late rice, and cotton in Jiangling District, Hubei Province [4]. Cai et al. (2009) also fused ETM+ images with time series MODIS NDVI images and used the fused 24-scene time-series NDVI data to better extract rice, rape, wheat, and their crop rotation in Zhanghe Irrigation Area [5]. He (2010) used a wavelet transform to fuseMODIS NDVI and TM NDVI. The fused NDVI not only guarantees the spectral characteristics of the original time series, but also increases the spatial resolution from 250 m to 30 m, which improves the single NDVI. Moreover, the feature quantity extracts the accuracy of the planting structure [6][7]. Huang (2010) analyzed the phenological characteristics of crops and the NDVI time series change characteristics and found the key period for the identification of the main crop types in three provinces in Northeast China. Through the phenological calendar and the agricultural field, the monitoring data iteratively revise and adjust the crop recognition threshold and build a remote sensing extraction model of crop planting structure. Hao (2011) obtained the spatial distribution of crop planting structures in three northeastern provinces by analyzing time-series MODIS NDVI images, using the ISODATA unsupervised classification algorithm and spectral coupling technology [8]. Peña-Barragán et al. (2011) performed object-oriented segmentation on Aster images and constructed the time-series vegetation index of the object (VIgreen), NDVI, etc., and another 336 feature quantities, and finally used a decision tree to realize the automatic extraction of the planting structure composed of 13 crops in Yolo County, California [9]. Zhang et al. (2012) compared the maximum, minimum, and average values of each time-series point in the MODIS EVI curve of each crop to find the critical period for each crop identification and the corresponding threshold, combined with the results of TM supervised classification, the crop planting structure in Heilong Port area was extracted [10]. Foerster et al. (2012) collaborated with 35 Landsat TM/ETM+ images of different seasons from 1986 to 2002 to construct crop NDVI time-series curves and set a reasonable range values by analyzing the difference in spectral standard deviation values of different crops at various time-series points. The spatial distribution map of 12 crops in northeastern Germany was drawn [11]. Zhong et al. (2014) used the phenological parameters EVI, phenological index, normalized difference decay index (NDSVI), normalized tillage index (NDTI), and other characteristic quantities, as well as their combinations, for testing. It was found that the participation of phenological parameters in classification can reduce the requirements of crop mapping for ground data, and the participation of four types of feature quantities in classification can obtain the highest overall classification accuracy [12].

2. Farmland Vegetation Classification Based on Spectral Band

Remote sensing recognition methods for crops based on spectral features comprises visual interpretation, supervised classification, and unsupervised classification based on image statistical classification, and various integrated classification methods based on syntactic structure classification [13].

The visual interpretation method is used to directly observe the color, shape, texture, spatial position, and other characteristics of various features in the image to interpret the remote sensing image after analysis, reasoning, and inspection based on highly experienced specialists. The advantage of this method is that it can obtain high classification accuracy, which is mostly used in early crop yield estimation research based on remote sensing technology [14], but its disadvantages are also obvious. For example, it requires interpreters to have rich experience and strong professional knowledge. Moreover, it needs to be based on a large number of on-site sampling surveys, which requires significant manpower and material resources, leading to limitations in the method. Lastly, is not suitable for crop identification research in a large area [15].

The main difference between supervised and unsupervised classification is whether there is prior knowledge of the specific classification of images. It is currently the most basic and generalized, mature, and commonly used feature information extraction technology. Among these technologies, supervised classification has high accuracy, and the classification result is in agreement with the actual category, but because it requires certain prior knowledge, the workload is relatively large. On the other hand, unsupervised classification is easier to implement; however, the accuracy of the classification results is relatively poor [16]. Both methods have their advantages, but also have certain shortcomings. With the continuous introduction and enhancement of new methods, theories, and technologies, as well as the continuous development of computer technology, the classification accuracy of supervised and unsupervised classification has also continued to improve. In order to improve some of the limitations of traditional algorithms, an increasing number of scholars are constantly improving classic algorithms and constructing new algorithms to improve the accuracy of crop recognition. Therefore, various integrated classification methods based on syntactic structure are gradually being applied [17].

However, due to the limitations in satellite image resolution, it is difficult to avoid the phenomena of “same matter with different spectrum” and “same spectrum with foreign matter” in the classification process. Therefore, it is difficult to obtain ideal results for crop classification with complex planting structures based solely on the spectral characteristics of ground objects [18].

The classification of farmland vegetation based on spectral bands can also be divided into remote sensing recognition of farmland vegetation based on (1) a single image and (2) multi-temporal remote sensing images. The remote sensing recognition of farmland vegetation based on multi-temporal remote sensing images can be divided into (1) single-feature parameter recognition, (2) multi-feature parameter recognition, and (3) multi-feature parameter statistical models. From the aspects of applicability, data sources, classification methods, advantages, and disadvantages, the remote sensing recognition of farmland vegetation based on a single image and on multi-temporal remote sensing images are compared, as shown in **Table 1**. In general, crop remote sensing recognition based on a single image is suitable for areas with relatively simple crop planting structures. Data sources include SPOT-5, IRS-1D, CBERS-02B, LANDSAT-TM, HJ-1B, HJ-1A, MODIS(Note, these are the names of sensors or satellites), and other data; classification methods include decision trees, support vector machines, neural networks, maximum likelihood, spectral angle mapping, etc. The characteristics of single-image crop remote sensing recognition include high efficiency and strong operability, but the disadvantage is that the revisit period is long, and the the accuracy is poor when key phenological period it is not obvious. The remote sensing recognition of crops based on multi-temporal remote sensing images is not only suitable for areas with relatively simple crop planting structures, but also for areas with complex crop planting structures; data sources include MODIS, AVHRR, SPOT VGT, ASTER, AWIFS, Landsat, TM/ETM+, HJ-1A/B, ETATION,(Note, these are the names of sensors) etc. The classification methods are different according to different parameter recognition. The main classification methods include fast Fourier transform, unsupervised classification and spectral coupling technology, BP neural network, threshold method, wavelet transform, minimum distance threshold method, classification regression tree, See5.0, unsupervised classification, spectral matching technology, image segmentation, random forest, temporal decomposition model, neural network model, independent component analysis model, CPPI index model, etc. The characteristics ofremote sensing recognition based on multi-temporal remote sensing images include simple operation, high efficiency, and high precision, but the disadvantages are stability, universality, and that the selection of feature quantities may be subjective. **Table 2** lists farmland vegetation remote sensing recognition methods based on spectral bands.

Table 1. Summary of remote sensing classification methods for farmland vegetation.

Remote Sensing Classification of Farmland Vegetation	Classification	
Farmland vegetation classification based on vegetation index	Normalized difference vegetation index, enhanced vegetation index, surface temperature, etc.	
Farmland vegetation classification based on spectral band	Remote sensing recognition of crops based on single image	
	Remote sensing recognition of crops based on multi-temporal remote sensing images	Single feature parameter recognition
		Multiple feature parameter recognition
		Multi-feature parameter statistical model
Farmland vegetation classification based on multi-source data fusion	Data consistency scoring	
	Regression analysis	
Farmland vegetation classification based on machine learning	Support vector machine algorithm	
	Neural network algorithm	
	Decision tree algorithm	
	Object-oriented machine learning algorithms	
	Deep learning algorithm	
Crop classification based on drone remote sensing		

Table 2. Comparison of remote sensing identification methods for farmland vegetation based on spectral bands.

Method	Applicability	Data Source	Classification	Advantages	Disadvantage
Remote sensing recognition of crops based on single image	Suitable for areas with relatively simple crop planting structure	SPOT-5	Decision tree	High efficiency and strong operability	Long revisit period and poor accuracy when the “critical phenological period” is not obvious
		IRS-1D	Support vector machines		
		CBERS-02B	Neural networks		
			Maximum		

				likelihood		
			LANDSAT-TM	Spectral angle mapping		
			HJ-1B			
			HJ-1A			
			MODIS			
Remote sensing recognition of crops based on multi-temporal remote sensing images	Single feature parameter recognition	Suitable for areas with relatively simple crop planting structure	MODIS	Fast Fourier transform	Simple operation and high efficiency	Feature selection is subjective and has limitations in areas with complex and diverse crop types
			TM/ETM+	Unsupervised classification and spectral coupling technology		
				BP neural network		
				Threshold method		
				Wavelet transform		
				Shortest distance		
	Multiple feature parameter recognition	Suitable for areas with complex crop planting structures	MODIS	Threshold method	Use multiple spectral time series feature quantities to better capture the characteristics of each type of crop that is different from other crops	Reduce the efficiency of data processing and calculation and increase the accumulation of errors
			AVHRR	Classification regression tree		
			SPOT VGT	See5.0		
			ASTER	Unsupervised classification		
			AWIFS	Spectral matching technology		
			Landsat	Image segmentation		

		TM/ETM+	Random forest		
		HJ-1A/B			
Multi-feature parameter statistical model	Suitable for areas with land consolidation, diverse terrain, and complex planting structure	MODIS	Temporal decomposition model	Higher extraction accuracy of crop planting area	Stability and universality need to be further strengthened and improved
		VHRR	Neural network model		
		SPOT-VEG	Independent component analysis model		
			CPPI index model		
		ETATION			

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The remote s based on multi-s ce remote sensing data fusion crop identification methods and crop identification methods that integrate remote sensing information and non-remote sensing information. Data from different sensors vary in space, time, spectrum, direction, and polarization. Therefore, for the same area, multiple sources of remote sensing data can be obtained. In the process of crop identification, a single datado not provide enough information to meet the needs of crop identification. Therefore, the use of multi-source data can fuse remote sensing information of different types of images to compensate for the lack of instantaneous remote sensing information and reduce the ambiguity of understanding, thereby improving the accuracy of crop recognition [19][20].

Crop recognition based on multi-source data fusion is applicable to a wide range of areas. The main data sources are radar SAR remote sensing, high score data, drone remote sensing, ground remote sensing, cultivated land data, statistical data, agricultural climate suitability data, population density, etc. The main classification methods are Principal Component Analysis (PCA) transformation method, HIS (hue, intensity, and saturation) transformation method, Brovey transformation method, Gram–Schmidt transformation fusion, NNDiffuse fusion method, SPAM (set pair analysis method) model, MIRCA2000 (global monthly irrigated and rainfed crop areas), GAEZ (global agro-ecological zones), etc. The advantages of multi-source data are high precision, high time-effectiveness and wide application range, which can compensate for the lack of instantaneous remote sensing information. The disadvantages include a large workload, difficult data acquisition, poor regional suitability of the data, and a lack of long-term sequence data sets.

Since crop area statistical data are irreplaceable and crucial in the fields of climate change, national food security, etc., scholars have integrated statistical data and natural factors such as temperature, precipitation, soil, and topography, as well as farmers' planting habits. Moreover, socio-economic factors such as population density and agricultural product prices are integrated as non-remote sensing information and remote sensing information to establish a crop spatial distribution model [21][22][23], In this way, the spatial distribution information of crops in a large range can be extracted. Distribution grid maps provide reliable basic crop spatial distribution data for global change and food security research [24][25]. For example, Leff et al. (2004) used remote sensing information to obtain agricultural land cover data, fused crop statistics at the national scale and some provincial scales, and extracted the spatial distribution results of 18 major crops around the world with a spatial resolution of 10 km [26]. Ramankutty et al. (2008) and Monfreda et al. (2008) used linear regression models to use crop statistics at different spatial scales and distributed them to farmland pixels with a resolution of 10 km around the world and obtained the spatial distribution information of 11 major crops. Some scholars—based on the cross-entropy principle of crop spatial distribution model (SPAM)—fused remotely sensed information with agricultural statistical data and obtained high-precision crop spatial distribution results on the global and regional scales [27][28]. Fischer et al. (2012), using the latest GAEZ model, comprehensively used the global cultivated land distribution map, crop suitability, population density, market distance, and other information based on the same cross-entropy theory and method to assign crop statistical information to the 5-point grid-scale pixels to obtain the spatial distribution of 23 types of crops in the world.

However, most of the current crop spatial distribution mapping technologies that integrate remote sensing information and non-remote sensing information use remote sensing to obtain land use, agricultural irrigation, and arable land suitability as auxiliary information and consider the growth mechanism and change laws of the research target crops. The crop's own remote sensing information (especially time-series remote sensing information) is not fully applied directly, which hinders the accuracy improvement of the crop spatial distribution mapping. In recent years, some scholars have shown that the introduction of remote sensing feature parameters such as NDVI into the crop spatial distribution mapping of remote sensing information and non-remote sensing information (such as statistical data) reduces the dependence of classification rules on training samples. This method is easy to understand and easy to operate. The operation can effectively improve the accuracy and efficiency of crop spatial distribution mapping [29][30].

Multi-source remote sensing data fusion is based on combining remote sensing data sets from different sources through a certain mathematical algorithm to complement and synthesize the temporal and spatial resolution and accuracy of the multi-source data to obtain a new data set. Multi-source remote sensing data usually comprise a variety of global- and regional-scale remote sensing data sets from different countries and organizations, such as the MODIS Collection 5 product developed by Boston University [31], China's land use remote sensing monitoring data developed by the Institute of Geography of the Chinese Academy of Sciences [32], and the GlobeLand30 data set developed by the National Basic Geographic Information Center [33]. These data sets come from different sensors, different spatial resolutions, and different classification algorithms, and there are large inconsistencies in space [34]. Multi-source data fusion can effectively solve the above problems and obtain data products with higher accuracy [35].

Multi-source remote sensing data fusion methods are divided into data consistency scoring methods and regression analysis methods [34]. The former are used to build a scoring table, based on the consistency of the input data set, and select high-confidence pixels for fusion. For example, Jung et al. (2006) developed a fuzzy consistency scoring method to generate a new 1 km spatial resolution global land cover product [36]. Following Jung et al. (2006), Fritz et al. (2015) used an optimized fuzzy consistency scoring method to generate a global cultivated land distribution map [37]. Lu et al. (2017) used a new hierarchical optimization method to generate China's integrated cultivated land distribution map [38]. The second method: first of all, establish the regression relationship between the training sample and the input data set, and then use it to predict the probability of cultivated land in the sample-free area. Regression models are usually based on a large number of training samples. Regression analysis has been widely used in global- and regional-scale fusion mapping. Kinoshita et al. (2014) integrated six remote sensing data products and established a global land coverage and percentage map through logistic regression [39]. See et al. (2015) used the logistic geographically weighted regression (GWR) method to establish a global model and produced a global land cover product with a spatial resolution of 1 km [35]. In addition, Schepaschenko et al. (2015) used the GWR model to generate a global forest cover map [40]. **Table 3** lists representative papers of multi-source remote sensing data fusion methods.

Table 3. Multi-source remote sensing data set synergy methods.

Fusion Method	Data Source	Research Area	Spatial Resolution	Fusion Process	Literature Source
Data consistency scoring	GLC2000, MODIS, IGBP DISCover	Global	1 km	Calculate affinity index for multi-source data set fusion mapping	[36]
	GLC-2000, MODIS VCF, GIS data, statistical data	Russia	1 km	Establish a fusion information system for multi-source data set fusion mapping	[40]
	GLC-2000, MODIS, GlobCover2005, GEOCOVER, cropland probability layer	Global	1 km	Analyze the consistency of remote sensing data products, set weights, and establish fusion rules	[37][41]
	FROM-GLC, GlobCover2009 et al. regional data set (Corine Land Cover et al.), national data set	Global	250 m	Multi-index analysis, scoring different data sets, setting weights, and fusion	[42]
Regression analysis	USGS-Hydro1k DEM, PELCOM, slope, soil data, meteorological data, land use ratio data	Belgium	1.1 km	Construct a logistic regression model of spatial autocorrelation to predict the spatial distribution of different land cover types	[43]
	GLC2000, MOD12C5, MOD12C4, GLCNMO, UMD, GlobCover	Global	5′	Using logistic regression model to predict types of land cover	[40]

Fusion Method	Data Source	Research Area	Spatial Resolution	Fusion Process	Literature Source
	GLCC, GlobCover GLC2000, UMD LC, MODIS LC, MODIS VCF,	North America	5 km	Use regression tree model to integrate global and regional land cover products	[44]
	GlobCover, GLC2000, MODIS	Global	1 km	Using GWR logistic regression model to predict the type of land cover in the sample-free area	[35]
	Land cover (MODIS LC, regional mosaics GLC2000, GlobeCover, GLCNMO), tree cover (Hansen's TC, Landsat VCF, MODIS VCF)	Global	1 km	Using GWR logistic regression model to predict the proportion of forest coverage in the sample-free area	[40]

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2. Zhang, M.; Zhou, Q.; Chen, Z.; Jia, L.; Zhou, Y.; Cai, C. Crop discrimination in Northern China with double cropping systems using Fourier analysis of time-series MODIS data. Int. J. Appl. Earth Obs. Geoinf. 2008, 10, 476–485.

3. Zhang, X.; Jiao, Q.; Zhang, B.; Chen, Z.C. Preliminary study on extracting crop planting patterns using MODIS_EVI image time series. Trans. Chin. Soc. Agric. Eng. 2008, 24, 161–165.

4. Xiong, Q.; Huang, J. Monitoring the planting area of autumn crops using the time series characteristics of NDVI index. Trans. Chin. Soc. Agric. Eng. 2009, 25, 144–148.

5. Cai, X.; Cui, Y. Extraction of crop planting structure in irrigation area based on heterogeneous multi-temporal remote sensing data. Trans. Chin. Soc. Agric. Eng. 2009, 25, 124–130.

6. He, X. Research on Remote Sensing Extraction of Corn Planting Area Based on Multi-Source Data Fusion. Ph.D. Thesis, Nanjing University of Information Science and Technology, Nanjing, China, 2010.

7. Huang, Q.; Tang, H.; Zhou, Q.; Wu, W.; Wang, L.; Zhang, L. Remote sensing extraction and growth monitoring of planting structure of main crops in Northeast China. Chin. J. Agric. Eng. 2010, 26, 218–223.

8. Hao, W.; Mei, X.; Cai, X.; Cai, X.; Jian, T.; Qin, L. Crop distribution information extraction in the three Northeast provinces based on multi-temporal remote sensing images. Chin. J. Agric. Eng. 2011, 27, 201–207.

9. Peña-Barragán, J.M.; Ngugi, M.K.; Plant, R.E.; Six, J. Object-based crop identification using multiple vegetation indices, textural features and crop phenology. Remote Sens. Environ. 2011, 115, 1301–1316.

10. Zhang, J.; Cheng, Y.; Zhang, F.; Yue, D.; Tang, H. Crop planting information extraction based on multi-temporal remote sensing images. Trans. Chin. Soc. Agric. Eng. 2012, 28, 134–141.
11. Foerster, S.; Kaden, K.; Foerster, M.; Itzerott, S. Crop type mapping using spectral–temporal profiles and phenological information. Comput. Electron. Agric. 2012, 89, 30–40.
12. Zhong, L.; Gong, P.; Biging, G.S. Efficient corn and soybean mapping with temporal extendability: A multi-year experiment using Landsat imagery. Remote Sens. Environ. 2014, 140, 1–13.
13. Tang, H.; Wu, W.; Yang, P. Research progress in remote sensing monitoring of crop spatial pattern. Chin. Agric. Sci. 2010, 43, 2879–2888.
14. Wang, N. China Wheat Remote Sensing Dynamic Monitoring and Yield Estimation; China Science and Technology Press: Beijing, China, 1996.
15. Xu, W.; Tian, Y. Research progress on remote sensing extraction methods of crop planting area. J. Yunnan Agric. Univ. Nat. Sci. 2005, 20, 94–98.
16. Zhao, C.; Qian, L. Comparison of supervised and unsupervised classification of remote sensing images. J. Henan Univ. Nat. Ed. 2004, 34, 90–93.
17. Yan, R.; Jing, Y.; He, X. Research progress on remote sensing extraction of crop planting area. Anhui Agric. Sci. 2010, 38, 14767–14768.
18. Wang, N.; Li, Q.; Du, X.; Zhang, Y.; Wang, H. Remote sensing identification of main crops in northern Jiangsu based on univariate feature selection. J. Remote Sens. 2017, 21, 519–530.
19. Bouman, B.A.M.; Uenk, D. Crop classification possibilities with radar in ERS-1 and JERS-1 configuration. Remote Sens. Environ. 1992, 40, 1–13.
20. Feng, A.; He, H.; Liu, L.; Ren, X.; Zhang, L.; Ge, R.; Zhao, F. Comparative study on identification methods of winter wheat growth period in Yucheng farmland ecosystem based on multi-source data. Remote Sens. Technol. Appl. 2016, 31, 958–965.
21. Portmann, F.T.; Siebert, S.; Döll, P. MIRCA2000—Global monthly irrigated and rainfed crop areas around the year 2000: A new high-resolution data set for agricultural and hydrological modeling. Glob. Biogeochem. Cycles 2010, 24, 1–24.
22. De Espindola, G.M.; De Aguiar, A.P.D.; Pebesma, E.; Camara, G.; Fonseca, L. Agricultural land use dynamics in the Brazilian Amazon based on remote sensing and census data. Appl. Geogr. 2012, 32, 240–252.
23. Khan, M.R.; De Bie, C.A.; Van Keulen, H.; Smaling, E.; Real, R. Disaggregating and mapping crop statistics using hypertemporal remote sensing. Int. J. Appl. Earth Obs. Geoinf. 2010, 12, 36–46.

24. Barnwal, P.; Kotani, K. Climatic impacts across agricultural crop yield distributions: An application of quantile regression on rice crops in Andhra Pradesh, India. Ecol. Econ. 2013, 87, 95–109.

25. Song, Q.; Zhou, Q.; Wu, W.; Hu, Q.; Yu, Q.; Tang, H. Research progress of multi-source data fusion in crop remote sensing identification. Chin. Agric. Sci. 2015, 48, 1122–1135.

26. Leff, B.; Ramankutty, N.; Foley, J.A. Geographic distribution of major crops across the world. Glob. Biogeochem. Cycles 2004, 18.

27. Liu, J.; Fritz, S.; Van Wesenbeeck, C.F.A.; Fuchs, M.; You, L.; Obersteiner, M.; Hong, Y. A spatially explicit assessment of current and future hotspots of hunger in Sub-Saharan Africa in the context of global change. Glob. Planet. Chang. 2008, 64, 222–235.

28. Liu, Z.; Li, Z.; Tang, P.; Li, Z.; Wu, W.; Yang, P.; You, L.; Tang, H. Analysis on the spatiotemporal changes of rice planting areas and yields in China in the past 30 years. J. Geogr. Sci. 2013, 68, 680–693.

29. Pervez, M.S.; Brown, J.F. Mapping irrigated lands at 250-m scale by merging MODIS data and national agricultural statistics. Remote Sens. 2010, 2, 2388–2412.

30. Brown, J.F.; Pervez, M.S. Merging remote sensing data and national agricultural statistics to model change in irrigated agriculture. Agric. Syst. 2014, 127, 28–40.

31. Friedl, M.; Sulla-Menashe, D.; Tan, B.; Schneider, A.; Ramankutty, N.; Sibley, A. MODIS collection 5 global land cover: Algorithm refinements and characterization of new datasets. Remote Sens. Environ. 2010, 114, 168–182.

32. Zhang, Z.; Wang, X.; Zhao, X.; Liu, B.; Yi, L.; Zuo, L.; Wen, Q.; Liu, F.; Xu, J.; Hu, S. A 2010 update of National land use/cover database of China at 1: 100000 scale using medium spatial resolution satellite images. Remote Sens. Environ. 2014, 149, 142–154.

33. Chen, D.; Chang, N.; Xiao, J.; Zhou, Q.; Wu, W. Mapping dynamics of soil organic matter in croplands with MODIS data and machine learning algorithms. Sci. Total Environ. 2019, 669, 844–855.

34. Lu, M.; Wu, W.; Zhang, L.; Liao, A.P.; Peng, S.; Tang, H.J. A comparative analysis of five global cropland datasets in China. Sci. China Earth Sci. 2016, 59, 2307–2317.

35. See, L.; Schepaschenko, D.; Lesiv, M.; McCallum, I.; Fritz, S.; Comber, A.; Perger, C.; Schill, C.; Zhao, Y.; Maus, V. Building a hybrid land cover map with crowdsourcing and geographically weighted regression. ISPRS J. Photogramm. Remote Sens. 2015, 103, 48–56.

36. Jung, M.; Henkel, K.; Herold, M.; Churkina, G. Exploiting synergies of global land cover products for carbon cycle modeling. Remote Sens. Environ. 2006, 101, 534–553.

37. Fritz, S.; See, L.; Mccallum, I.; You, L.; Bun, A.; Moltchanova, E.; Duerauer, M.; Albrecht, F.; Schill, C.; Perger, C.; et al. Mapping global cropland and field size. Glob. Chang. Biol. 2015, 21, 1980–

1992.

38. Lu, M.; Wu, W.; You, L.; Chen, D.; Zhang, L.; Yang, P.; Tang, H. A synergy cropland of china by fusing multiple existing maps and statistics. Sensors 2017, 17, 1613.
39. Kinoshita, T.; Iwao, K.; Yamagata, Y. Creation of a global land cover and a probability map through a new map integration method. Int. J. Appl. Earth Obs. Geoinf. 2014, 28, 70–77.
40. Schepaschenko, D.G.; Shvidenko, A.Z.; Lesiv, M.Y.; Ontikov, P.V.; Shchepashchenko, M.V.; Kraxner, F. Estimation of forest area and its dynamics in Russia based on synthesis of remote sensing products. Contemp. Probl. Ecol. 2015, 8, 811–817.
41. Fritz, S.; You, L.; Bun, A.; See, L.; Mccallum, I.; Schill, C.; Perger, C.; Liu, J.; Hansen, M.; Obersteiner, M. Cropland for sub-saharan Africa: A synergistic approach using five land cover data sets. Geophys. Res. Lett. 2011, 38, 155–170.
42. Waldner, F.; Fritz, S.; Di Gregorio, A.; Defourny, P. Mapping priorities to focus cropland mapping activities: Fitness assessment of existing global, regional and national cropland maps. Remote Sens. 2015, 7, 7959–7986.
43. Dendoncker, N.; Rounsevell, M.; Bogaert, P. Spatial analysis and modelling of land use distributions in Belgium. Computers, Environ. Urban Syst. 2007, 31, 188–205.
44. Song, X.; Huang, C.; Feng, M.; Sexton, J.O.; Channan, S.; Townshend, J.R. Integrating global land cover products for improved forest cover characterization: An application in North America. Int. J. Digit. Earth 2014, 7, 709–724.