

A spatiotemporal assessment of field residues of rice, maize, and wheat at provincial and county levels in China

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Abstract

China has a huge resource potential for biomass-based renewable energy development, but the resources of field residues are still not effectively used. Rice, maize, and wheat made up 89% of staple crop production in China in 2009. A comprehensive assessment of field residues of these three crops is necessary for the development of biomass-based industries. This research was based on multiyear county-level data of crop production, area and yield, as well as the crop phenology information from agrometeorological stations. Spatial and temporal analyses were conducted to quantify the spatial patterns, seasonal variations, and temporal trends of the three major field residues. The mean amount of field residue of rice, maize, and wheat was 470.8 Mt/year from 2002 to 2009. Rice residue topped the field residues at 188.5 Mt/year, followed by maize (152.6 Mt/year) and wheat (129.8 Mt/year). The resource supply of field residues varied temporally throughout the season, where peak months are May, June, September, and October. The resources of all three field residues increased from 2002 to 2009, topped by maize residues at a rate of 10.0 Mt/year. Spatially, high production counties had the fast growth rate and a strong positive spatial autocorrelation. The results showed that the intersection area of East and South Central regions has a spatially concentrated residue density and a stable supply for 5 months. The region can be considered as a suitable region for bioenergy development. A better understanding of spatial and temporal distribution of crop residues could facilitate strategic and tactical bioenergy planning.

KEYWORDS

annual trend, biomass availability, crop field residue, quantitative analysis, seasonal variation, spatial cluster, spatial correlation

1 | INTRODUCTION

Sustainable and effective provision of biomass is critical for the development of the bioenergy industry (Richard, 2010). Compared with other biomass sources such as energy crops and

forest biomass, crop residues are by-products of crop production. Crop production, influenced by the effects of crop, climate, soil, agricultural practices, and their interactions, is spatially heterogeneous in nature (Liu et al., 2013). Climate, cropping pattern, farming practices, and policy change with time, and these

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changes would alter the spatial and temporal heterogeneity of crop residue production. A comprehensive assessment of spatial characteristics and temporal variations of crop residue provision is vital not only for the resource evaluation but also for the strategical and tactical planning of bioenergy facility operations (Hiloidhari et al., 2017; Yang et al., 2014).

Strategically, maize, rice, and wheat are the top three staple crops in China, which made up 89% of Chinese staple crop production in 2009 (National Bureau of Statistics of China, 2010). Their residues are considered to be a reliable feedstock for bioenergy. The design of the biomass supply chain depends on a comprehensive understanding of spatial characteristics of feedstock provision (Hiloidhari et al., 2017). Previous studies presented state/provincial-level and national-level assessments of biomass availability (Ferreira-Leitao et al., 2010; Kim & Dale, 2004; Li et al., 2012; Matsumura, Minowa, & Yamamoto, 2005; Wang et al., 2013), county-level spatial distribution and usage of biomass in certain states (Ćosić, Stanić, & Duić, 2011; Yang et al., 2015), as well as the economic potential for biomass supply from crop residues (Chen, 2016). The distribution of crop residues has not only spatial heterogeneity but also temporal dynamics. As a result of climate change and improvement in agricultural practices, annual crop production changes with time (Hou et al., 2014; Xiong, Holman, You, Yang, & Wu, 2014). These annual changes have a close association with the cropping system and location (Osborne & Wheeler, 2013). Therefore, the availability of crop residue, even at the county level, is not constant over time.

Tactically, the uneven distribution and seasonal variations of crop residues make it difficult for biomass storage and logistics operations (Hu, Lin, Wang, & Rodriguez, 2017; Sharma, Ingalls, Jones, & Khanchi, 2013). Maize, rice, and wheat are planted in varying cropping systems in the world and have region-specific maturity times. In the United States, maize is planted as an annual crop, and is mostly harvested between September and November (USDA, 2018). In Brazil, more than half of the maize is sown as a secondary crop after soybean and harvested mainly in June to July (USDA, 2009). In China, 20 provinces have adopted multiple cropping systems, and thus have varied cropping patterns (Yan et al., 2014) and seasonal variations in crop residue availability (Han et al., 2015). A quantitative understanding of the seasonal provision patterns of crop residue is needed to support the operational design of biomass supply chain systems.

To the best of our knowledge, most studies focus on the statistical summaries of national or regional biomass resource evaluation (Table 1), without much consideration of spatial correlations or seasonal and interannual variations of the residues, especially at the county level. Spatial statistical analysis has been widely used to quantify spatial correlations in natural sciences (De Knecht et al., 2010; Fortin, James, MacKenzie, Melles, & Rayfield, 2012) and social

sciences (Gesler, 1986; Páez & Scott, 2005). Moran's *I* statistic and other similar statistics provide standard approaches to identify spatial patterns and quantify spatial correlations between spatial observations (Arthur, 1995; Getis & Ord, 1992; Moran, 1950). Spatial association includes correlation and heterogeneity: spatial correlation shows the closeness of similarity between observations, whereas heterogeneity quantifies the difference between spatial observations. Spatial associations can change under varied spatial resolutions, because spatial heterogeneity and dependency change with the resolution. Selection between provincial and county boundaries would probably result in changes in spatial patterns because of the different sizes and shapes of the sampling unit (Fortin, 1999). County-level data can reflect a more reliable and accurate analysis than province-level data to identify spatial associations such as high provision cluster regions. Therefore, we should consider both provincial and county-scale data to illustrate the global and local spatial characteristics of field residue provision.

In recent decades, residue resources have received great interest and have been widely studied in both developed and developing countries. However, a comprehensive study considering large spatial area, high spatial resolution, and long time series data analysis simultaneously is lacking (Table 1). China has an increased demand for renewable energy and a high crop residue yield potential; however, the residue resources are not used effectively (Jiang, Zhuang, Fu, Huang, & Wen, 2012). Most existing studies have only focused on the large-scale (e.g., regional or provincial level) residue provision (Hiloidhari, Das, & Baruah, 2014) or considered particular rural regions for case studies (Muth, Bryden, & Nelson, 2013; Zyadin et al., 2018). Given the complexity of its cropping systems, and a lack of quantitative understanding of the interrelations at various spatial and temporal resolutions, we take China as an example to provide a comprehensive spatiotemporal statistical analysis to quantify the spatial characteristics and temporal variations of field residue resources. This study focuses on the residues of three major field crops—rice, maize, and wheat—at provincial and county levels in China from 2002 to 2009. The objectives of this study are to (a) identify the nationwide spatial patterns of field residue production at the provincial and county levels; (b) quantify the temporal trend and seasonal variations of field residue production; and (c) analyze the spatial structures and variations of field residues in high production regions of China. The detailed spatiotemporal assessment of field residues aims to provide a new perspective on biomass resource evaluation considering spatial characteristics and temporal variations, which could facilitate sustainable planning and operational development of the bio-based industry.

TABLE 1 Summary of previous studies on biomass residue resources by various spatial resolutions, time lengths, and seasonal changes

			Data coverage		Residue type	Seasonal changes	Reference
			Spatial resolution	Time length (Year)			
Asia	China	National	Province	2	Crop and processed	No	Wang et al. (2013)
	China	Regional	County	3	Crop	Yes	Han et al. (2015)
	China	National	County	10	Crop	No	Chen (2016)
	Japan	National	National	1	Crop	No	Matsumura et al. (2005)
	China	Regional	County	3	Crop and processed	No	Yang et al. (2015)
	India	National	State	5	Crop	No	Hiloidhari et al. (2014)
	India	Regional	Village	5	Crop	No	Hiloidhari and Baruah (2011)
Europe	EU27	National	National	10	Crop	No	Scarlat, Martinov, and Dallemand (2010)
	Poland	Regional	County	1	Crop and forestry	No	Zyadin et al. (2018)
	Croatia	Regional	County	5	Crop and forestry	No	Ćosić et al. (2011)
	Five European countries	Regional	1 km × 1 km	1	Crop	No	Haase, Rosch, and Ketzer (2016)
	Germany	National	National	multi	Agricultural, forestry, municipal, industrial and other	No	Brosowski et al. (2016)
	EU	National	National	5	Agricultural	No	Searle and Malins (2016)
America	US	National	County	2	Crop	No	Muth et al. (2013)
	US	National	County	30	Crop and forestry	No	Langholtz et al. (2016)
	Canada	National	Province	10	Crop	No	Li et al. (2012)
	Brazil	National	National	1	Crop	No	Ferreira-Leitao et al. (2010)
	Argentina	Regional	District	2	Crop and forestry	No	Roberts, Cassula, Osvaldo Prado, Dias, and Balestieri (2015)
Global			National	5	Crop	No	Kim and Dale (2004)
			National	3	Crop	No	Bentsen et al. (2014)

Note: EU27: European Union, which includes 27 countries in the period of 2007–2013.

2 | MATERIALS AND METHODS

2.1 | Data source and crop residue calculation

Provincial and county-level crop production data from 2002 to 2009 were collected from the National Bureau of Statistics of China (National Bureau of Statistics of China, 2010) to quantify the spatial and temporal changes. From 2002 to 2009, data of rice, maize, and wheat from 31 provinces were collected (Figure 1). After data quality check and preprocessing, the number of counties with eight consecutive years of data for residue analysis was 1,270, 1,767, and 1,431 for rice, maize, and wheat, respectively.

The field residue availability (FRA) of each crop was calculated by Equation 1 (Wang, Xue, & Xie, 2012):

$$\text{FRA} = \text{ACP} \times \text{FRI} \quad (1)$$

where ACP is the annual crop production and FRI is a field residue index (stubble included). In our study, the FRIs of rice, maize, and wheat are 1.04, 1.07, and 1.28, respectively (Wang et al., 2012).

The provincial data of the three crops were used to estimate the total amount and the monthly provision changes in field residue from 2002 to 2009 (China Meteorological Administration, 2018). The trend of county-level field residue production from 2002 to 2009 was quantified using linear regression analysis. Data of the crop-growing period were collected from agrometeorological stations in China. The mean maturity date of all agrometeorological stations within each province was calculated as the province-level maturity time of each crop. The mean maturity time was used as the timing for monthly field residue resource supply.

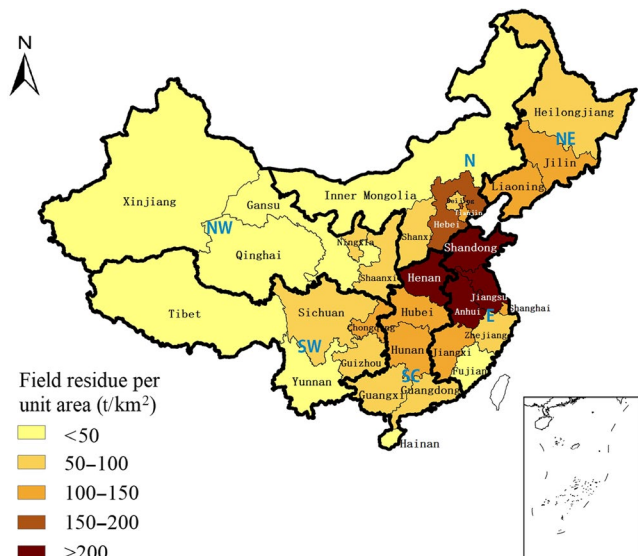


FIGURE 1 Average annual resource density of the field residues of rice, maize, and wheat in the 31 provinces in China from 2002 to 2009. The bold dark lines display the six administrative regions in China, i.e., Northeast (NE), North (N), Northwest (NW), Southwest (SW), South Central (SC), and East (E) regions

2.2 | Spatial correlation analysis

Crop production systems in China are divided into six regions according to the National Bureau of Statistics of China: North (N), Northeast (NE), East (E), South Central (SC), Southwest (SW), and Northwest (NW). The top two production regions for each crop were selected to conduct the spatial correlation analysis of field residues. After filtering the nonconsecutive county-level data for each crop, NE (132 counties) and N (288 counties) were chosen for maize analysis, SC (315 counties) and E (315 counties) for rice, and SC (256 counties) and E (254 counties) for wheat in this study. Semivariance, Moran's Index, and spatial clustering analysis were conducted to quantify the spatial correlation of crop residues. Semivariance quantifies the spatial variability of a regional field residue. Semivariance $\gamma(h)$ is computed as half the mean squared difference between the components of data pairs as shown in Equation 2 (Burrough, 2001):

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(x_i) - Z(x_i + h)]^2 \quad (2)$$

where h can be any distance of paired counties, $N(h)$ is the total number of paired counties separated by the distance h , Z represents the amount of field residue in a county, and x_i is the centroid of a county. With the equation above, a set of h and $\gamma(h)$ can be calculated. A semivariogram is plotted with $\gamma(h)$ on the y axis and h on the x axis. Range is the h value after which the $\gamma(h)$ levels off. Two counties further away

than the range value are considered as not spatially correlated in field residue amount. Range is also used in the calculations of Moran's I .

Global Moran's I is used to study the overall spatial autocorrelation, whereas Local Moran's I is used to identify the degree of spatial autocorrelation in each specific location (Anselin, 1995).

Global Moran's I is calculated by Equation 3 (Cliff & Ord, 1981):

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (z_i - \bar{z})(z_j - \bar{z})}{\sum_{i=1}^n (z_i - \bar{z})^2} \quad (3)$$

where n is the number of samples; z_i is the value of the variable at region i ; z_j is the value at other locations (where $j \neq i$); \bar{z} is the mean value of z with the sample number of n ; $S_0 = \sum_{i=1}^n \sum_{j=1}^n w_{ij}$ and w_{ij} is a spatial weighting between z_i and z_j . Z test is applied for the significance test of Global Moran's I .

1. $I = 0$ means there is no global spatial autocorrelation between observations.
2. $I > 0$ means the global spatial autocorrelation is positive.
3. $I < 0$ means the global spatial autocorrelation is negative.

Local Moran's I is calculated by Equation 4 (Getis & Ord, 1996):

$$I_i = \frac{z_i - \bar{z}}{\sigma^2} \sum_{j=1, j \neq i}^n [w_{ij} (z_j - \bar{z})] \quad (4)$$

where z_i is the value of the variable at location i ; z_j is the value at other locations (where $j \neq i$); \bar{z} is the mean value of z with the sample number of n ; σ^2 is the variance of z ; and w_{ij} is a spatial weighting between z_i and z_j . The area i is spatially associated with its neighbors when values of I_i are statistically different from 0. Z test is for significance evaluation of Local Moran's Index.

1. $I_i > 0$ means the local spatial autocorrelation is positive.
2. $I_i < 0$ means the local spatial autocorrelation is negative.

Spatial weight matrix was constructed to identify contiguous counties. When the distance between the paired counties was smaller than the range from the semivariogram, they were considered correlative and their spatial weight was calculated in ArcGIS with the inverse distance weighted model. Otherwise, the paired counties were considered to be noncorrelative and their spatial weight was 0. Both Global Moran's I and Local Moran's I were carried out on each spatial weight matrix. In this research, contiguity was defined using spatial matrix based on inverse

distance. The range according to semivariance was used as the distance parameter to calculate Global Moran's I and Local Moran's I . Local Moran's I of crop residue in different regions were also calculated in two periods, from 2002 to 2005 and 2006 to 2009. Local Indicators of Spatial Association cluster maps based on Local Moran's I were used to identify spatial cluster patterns of crop residue distribution (Harries, 2006). Cluster maps were prepared by ArcGIS10.2 based on Local Moran's I . The cluster map reflects four kinds of regions, including:

1. high–high spatial cluster: high values are surrounded by high values;
2. high–low spatial outlier: high values are surrounded by low values;
3. low–high spatial outlier: low values are surrounded by high values;
4. low–low spatial cluster: low values are surrounded by low values.

3 | RESULTS

3.1 | Spatial patterns of crop residue resources at the provincial level

The annual field residue production of rice, maize, and wheat was estimated at the mean of 470.8 million metric tonnes per year (Mt/year) from 2002 to 2009 (Table 2). Rice residue topped the biomass production at the mean of 188.5 Mt/year, followed by maize (152.6 Mt/year) and wheat (129.8 Mt/year) residues.

East and South Central were the top two regions in terms of the total field residue resource potential, where both regions produced more than 125 Mt/year (Table 2). They were also the top two regions for rice and wheat residue productions, which accounted for 69.8% and 64.8% of national production, respectively. Northeast and North regions topped the maize residue with 51.2% of national resources. At a provincial level, Henan, Jiangsu, Shandong, and Anhui had the highest amounts of residue resource (Table 2). Especially, Henan was the only province that produced more than 50.0 Mt of crop residues annually, which was close to the total production from SW and N regions.

The provinces with the highest absolute residue resource potential, Henan, Jiangsu, Shandong, and Anhui, were exactly the provinces with the highest resource density, which refers to the annual field residue production per unit area. Their potential resource densities were as high as 318.9, 286.0, 250.8, and 202.5 tonnes per square kilometer (t/km^2), respectively (Figure 2). As a reference, the national average resource density of the three field residues was only estimated at the mean of $49.3 t/km^2$. These four provinces with high residue resource density are concentrated in the northern part of East and South Central China (Figure 2).

TABLE 2 Average annual production of field residues of rice, maize, and wheat in 31 provinces of China from 2002 to 2009 (million tonnes)

Region	Source of field residue			Total
	Rice	Maize	Wheat	
East	63.02	23.56	46.18	132.76
Shandong	1.06	17.84	23.34	42.23
Jiangsu	17.69	2.23	10.48	30.39
Anhui	13.41	3.09	11.87	28.37
Jiangxi	17.48	0.07	0.03	17.57
Zhejiang	7.03	0.18	0.27	7.47
Fujian	5.43	0.13	0.03	5.59
Shanghai	0.94	0.03	0.16	1.13
South Central	68.53	20.55	38.00	127.08
Henan	3.94	14.28	34.60	52.82
Hunan	24.33	1.36	0.13	25.81
Hubei	15.47	2.15	3.24	20.86
Guangxi	12.00	2.07	0.02	14.08
Guangdong	11.36	0.64	0.02	12.01
Hainan	1.43	0.07	0.00	1.50
Northeast	22.20	44.93	1.20	68.33
Heilongjiang	12.85	14.16	1.08	28.09
Jilin	4.77	19.39	0.04	24.20
Liaoning	4.57	11.39	0.08	16.04
Southwest	31.39	17.44	8.92	57.75
Sichuan	15.31	6.18	5.56	27.04
Yunnan	6.40	5.06	1.35	12.82
Guizhou	4.61	3.79	0.79	9.18
Chongqing	5.06	2.40	0.88	8.34
Tibet	0.01	0.02	0.34	0.36
North	1.27	33.21	20.34	54.82
Hebei	0.54	13.56	14.65	28.75
Inner Mongolia	0.60	11.72	1.80	14.13
Shanxi	0.01	6.43	2.96	9.39
Tianjin	0.11	0.82	0.60	1.53
Beijing	0.01	0.68	0.33	1.02
Northwest	2.05	12.86	15.21	30.11
Shaanxi	0.83	4.78	5.02	10.63
Xinjiang	0.54	4.00	5.20	9.73
Gansu	0.04	2.67	3.44	6.15
Ningxia	0.63	1.40	0.98	3.01
Qinghai	0.00	0.02	0.58	0.59
Total	188.45	152.55	129.84	470.85

By crop, wheat residue production was the most spatially heterogeneous, and the production is concentrated in fewer, highly productive regions. The top five provinces (Henan,

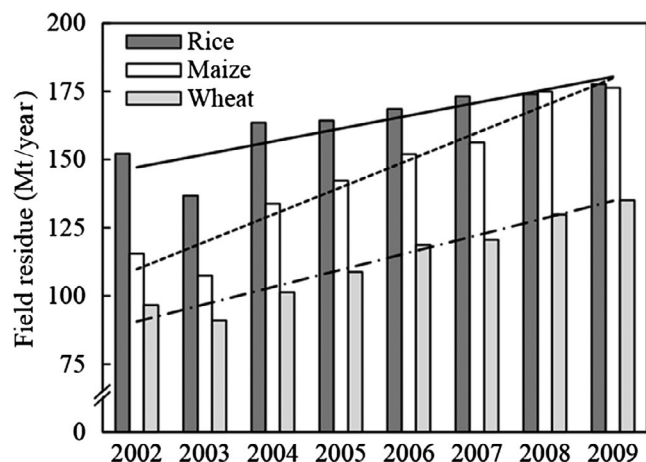


FIGURE 2 Potential resource of field residues of rice, maize, and wheat and trends during 2002–2009. Solid, dashed, and dash-dot lines stand for the trends of rice (slope = 4.7 Mt/year), maize (slope = 10.0 Mt/year), and wheat (slope = 6.3 Mt/year) residues, respectively

Shandong, Hebei, Anhui, and Jiangsu) accounted for 73.1% of national wheat residue production. Maize residue (51.9% contributed by Jilin, Shandong, Henan, Heilongjiang, and Hebei) and rice residue production (47.9% contributed by Hunan, Jiangsu, Jiangxi, Hubei, and Sichuan) were less concentrated in highly productive provinces than wheat residue production.

3.2 | Temporal variations of crop residue resources at provincial level

All three crop residues had an increased production trend from 2002 to 2009 but at different rates (Figure 2). Maize residue had the largest increase rate at 10.0 Mt/year, followed by wheat and rice residue at the rates of 6.3 and 4.7 Mt/year, respectively. The increase in rice residue was driven by the increase in both harvested area (0.30 million ha/year) and yield (68 kg ha⁻¹ year⁻¹). The increase in maize residue was mainly because of increased harvesting area (1.06 million ha/year), while the increase in wheat residue was mainly due to its yield increase (146 kg ha⁻¹ year⁻¹). In general, maize area and wheat yield contributed the most to the total residue increase of three crops together.

The major maturity time for the three crops in 20 major production provinces varied from May to November (Figure 3a). September is the most important time period, which contributes 44% of total annual residue production, followed by June (14%), May (13%), and October (12%). The highest field residue production occurred in September with 150.8 Mt, which mainly came from maize residue. A relatively small amount of field residue was harvested during the period from December to April.

Rice residue had a relatively wide harvesting range from July to November (Figure 3b). The highest rice residue production occurred in October, accounting for 36.1% of total

production, followed by September (28.8%) and July (20.7%). In China, rice is mainly planted as single rice (56.7%), whereas double rice (43.3%) can be further divided into early or late rice (52% and 48%, respectively). The maturity time varies by region for the three types of rice. Early rice was mainly grown in provinces such as Hunan, Jiangxi, Guangxi, and Guangdong, and the maturity time was July. Single rice was mostly planted in Jiangsu, Sichuan, Heilongjiang, and the other four provinces. The maturity time of single rice varied from August to October. Late rice was mature in October and November in Hunan, Jiangxi, Guangdong, Guangxi, and the other three provinces.

The maturity period of wheat production ranged from May to August. Winter wheat was mature in May and June, while spring wheat was mainly mature in June, July, and August. Wheat residue in China was mainly made up of winter wheat (122.3 Mt/year), accounting for 94.2% of all wheat residue. June was the peak month for wheat residue production amounting to 59.0 Mt, or 50.3% of the sum of wheat residues in the top ten provinces. Every year, wheat harvest along with the residue production started in May from southern provinces (Sichuan, Hubei, Henan, and Anhui) and ended in August in northern provinces (Hebei and Inner Mongolia).

3.3 | Spatiotemporal patterns of crop residue at the county level

Crop residue production had a marked spatial heterogeneity at the county level in China for all three crop residues (Table 3). The amount of crop residue production varied from less than 10 t to more than 5.0 Mt/year. Among three crop residues, rice residue had the highest mean and median values but the lowest standard deviation at the county level (Table 3). The results indicated that rice residue had the relatively more stable distribution when compared with maize and wheat residues. The mean value of maize residue was double of its median value, whereas the mean value of wheat residue was triple of its median value. In particular, the county with the largest amount of wheat residue produced more than 5.5 Mt/year, which is much higher than that produced by the county with largest maize (2.0 Mt/year) and rice (0.95 Mt/year) residue production.

The county-level distributions of rice, maize, and wheat residues varied spatially (Figure 4). Rice residue had a relatively distributed spatial pattern of high production, with 70 counties providing rice residue over 400 kt annually amounting to 36.7 Mt (22.4% of total rice residues). The high production counties of rice residue were mainly located in South Central, East, and part of Northeast regions. The wide spread of high production counties demonstrated the relative distributed pattern of rice straw production.

For wheat residue, there were 51 counties where the annual average production was over 400 kt, with 28.2 Mt in total. The high production counties of wheat residue were mainly located in the western region of E and northern region of SC,

FIGURE 3 Maturity time and quantity of field residues of rice, maize, and wheat in high production provinces from 2002 to 2009: (a) sum of three crop residues from top 20 provinces; (b) rice residue from top 10 provinces; (c) maize residue from top eight provinces; (d) wheat residue from top 10 provinces. SW, Southwest; NE, Northeast; NW, Northwest; N, North; SC, South Central; E, East region; Mt, million tonnes

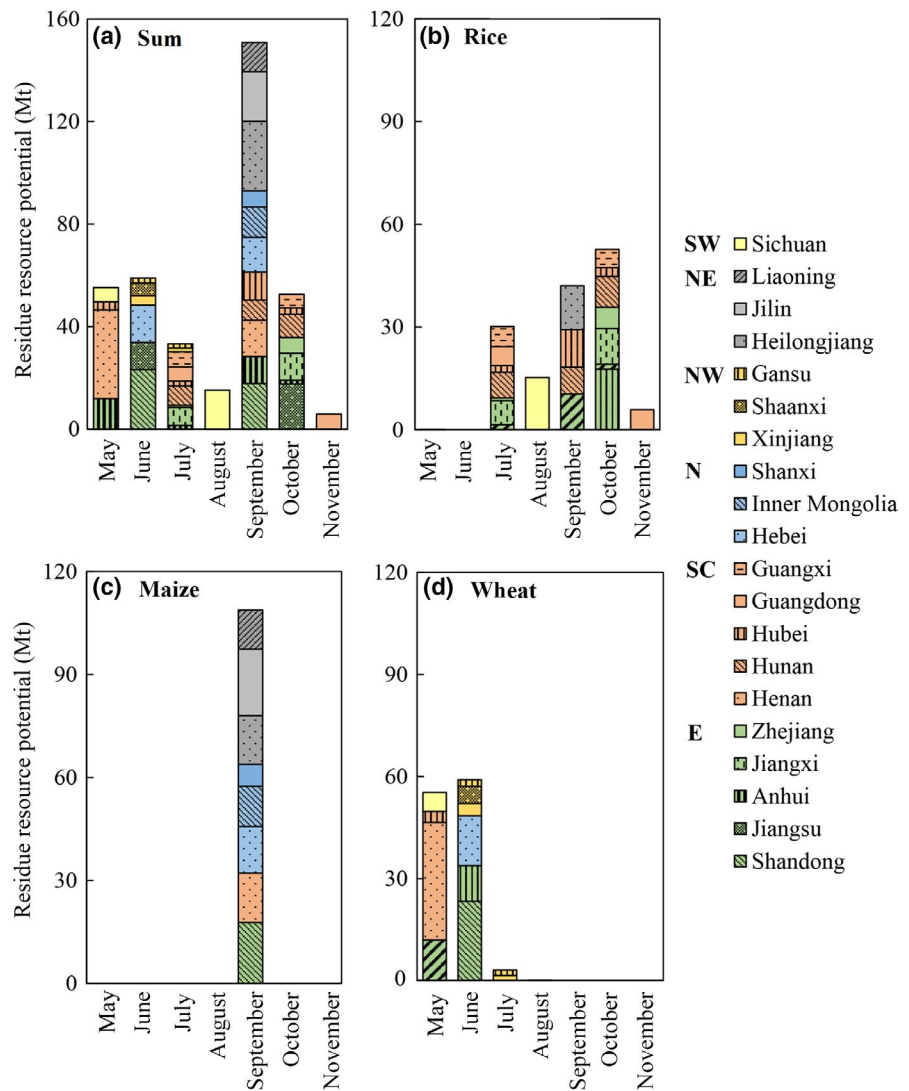


TABLE 3 Descriptive statistics for county-level field residues of rice, maize, and wheat in China during 2002–2009 (kilotonnes)

Field residue	Number of counties	Min	Median	Max	Mean	SD
Rice	1,270	0.03	83.00	950.27	128.71	137.85
Maize	1,767	0.01	36.22	2,041.75	79.91	152.59
Wheat	1,431	0.02	23.36	5,536.03	82.51	190.30

accounting for 23.9% of national wheat residue production. For maize residue, only 44 counties could produce more than 400 kt/year, with the total amount of 36.0 Mt/year, contributing to 25.5% of the total maize residue. These high production counties are mainly concentrated in the central area of NE.

The results showed that 78.7% of the counties with maize residue production increased their production from 2002 to 2009. Among them, 112 counties, or 6.3% of the counties, had a rapid increase with over 20 kt/year, which mainly were located in the NE region and east of Inner Mongolia. Sixty percent of counties had an increase in rice residue. About 6.3% of counties, which were located in the

central area of SC and NE, had an increase with more than 20 kt/year. For wheat, 54.2% of counties had an increased field residue from 2002 to 2009, with 7.1% of counties with production increases of more than 20 kt/year. The counties with high increasing rates were located in the northern and central area of E.

3.4 | Spatial correlation and clustering analysis of crop residue

In both 2002–2005 and 2006–2009, all the Indexes of Global Moran for the three crop residues in different regions were

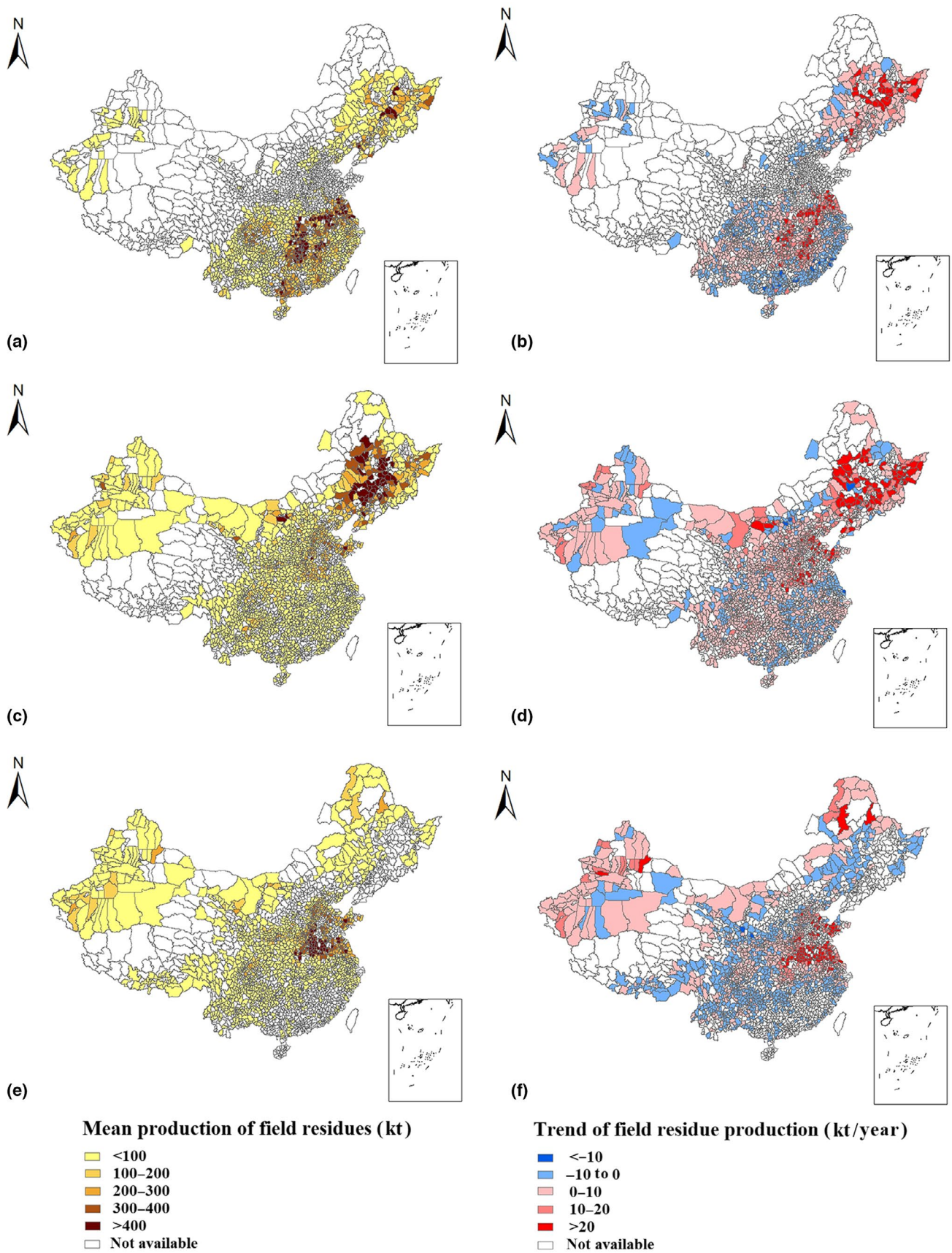


FIGURE 4 Mean and trend of crop residue (rice, maize, and wheat) production at the county level during 2002–2009: (a) mean production of rice residue; (b) trend in production of rice residue; (c) mean production of maize residue; (d) trend in production of maize residue; (e) mean production of wheat residue; (f) trend in production of wheat residue

TABLE 4 Global Moran's Index of field residue resources of rice, maize, and wheat in top two production regions in China

Crop	Region	Year	Global Moran's <i>I</i>	Z value	<i>p</i> -value
Rice	East	2002–2005	0.25	21.90	<0.001
		2006–2009	0.38	21.33	<0.001
	South Central	2002–2005	0.29	26.91	<0.001
		2006–2009	0.30	26.93	<0.001
Maize	Northeast	2002–2005	0.33	12.00	<0.001
		2006–2009	0.29	10.87	<0.001
	North	2002–2005	0.42	16.88	<0.001
		2006–2009	0.11	2.60	<0.01
Wheat	East	2002–2005	0.29	45.76	<0.001
		2006–2009	0.29	44.47	<0.001
	South Central	2002–2005	0.44	47.84	<0.001
		2006–2009	0.31	42.60	<0.001

positive (Table 4). The results demonstrated that there was a significant ($p < 0.01$) positive spatial autocorrelation of each crop residue in high production regions, meaning that adjacent counties inside the same region had similar production level. For rice residue, the results showed that there was a remarkable increase in Global Moran's Index in the East from 2002–2005 to 2006–2009, whereas the South Central region had a slight increase. Both increases in Global Moran's Index demonstrated an increased concentration of rice residue resource during the two time periods, which also corresponds to the pattern in the trend analysis shown in Figure 4. For maize residue in the North region and wheat residue in the South Central region, the values of Global Moran's Index had a drop, suggesting that the distribution of residue resources became less concentrated.

Local Moran's *I* revealed the clustering patterns of the county level residue production. The results showed that spatial cluster patterns of the three crop residues remain relatively stable from 2002 to 2009. High–high clusters, referring to the high residue production regions that aggregated together, remained mostly unchanged in different regions over years for all crop residues except maize (Figure 5). For rice residue, high–high cluster areas were mainly in Hunan and Hubei provinces in the South Central region and in the middle of Jiangxi, Anhui, and Jiangsu provinces of the East region over the two periods. The number of counties in high–high cluster regions increased in the South Central region whereas it decreased in the East region during the two periods. For maize residue, unchanged high–high cluster areas were only located in the middle of Jilin and southwest of Heilongjiang provinces. Local spatial autocorrelation in the North region changed over time. The high–high clusters of maize residue in N in 2002–2005 no longer occurred in 2006–2009 (Figure 5c,d). For wheat residue, high–high cluster regions concentrated in the north of East and South Central regions,

mainly in Henan, Shandong, north of Anhui and Jiangsu provinces.

Unlike the interlaced distribution of provinces with high or low residue productions, the results of spatial clustering analysis on county-level residue productions showed that both rice and wheat residues had a relatively steady and locally concentrated field residue resource in high production regions from 2002 to 2009 (Table 5). Maize residue, however, had an unsteady spatial concentration patterns in the North region.

4 | DISCUSSION

4.1 | Provincial level crop residue resources

Provinces with high resource densities, such as Henan, Jiangsu, Shandong, and Anhui, are favorable as locations for biomass plants and markets, mainly due to the comparatively low transportation costs. As the bulk densities of field residues are low, their overall cost can be sensitive to the distance required for road transport, which, for long distance transportation, can be 25%–30% of the total cost (Bentsen, Nilsson, & Larsen, 2018). High resource density and well-established local facilities can reduce the cost of bioenergy and improve its competitiveness to other energy sources.

Multiple cropping is common in the provinces with a high resource density. Multiple cropping systems are designed to efficiently use the environmental resources throughout the growing season. Field residue supply is therefore less concentrated in terms of quantity and time. This feature is very different as compared to the cropping systems in the United States, where most areas adopt a single cropping system and corn stover contributes approximately 70% of total crop residues (Langholtz, Stokes, & Eaton, 2016). Multiple cropping not only reduces biomass storage requirement and the associated losses but also provides

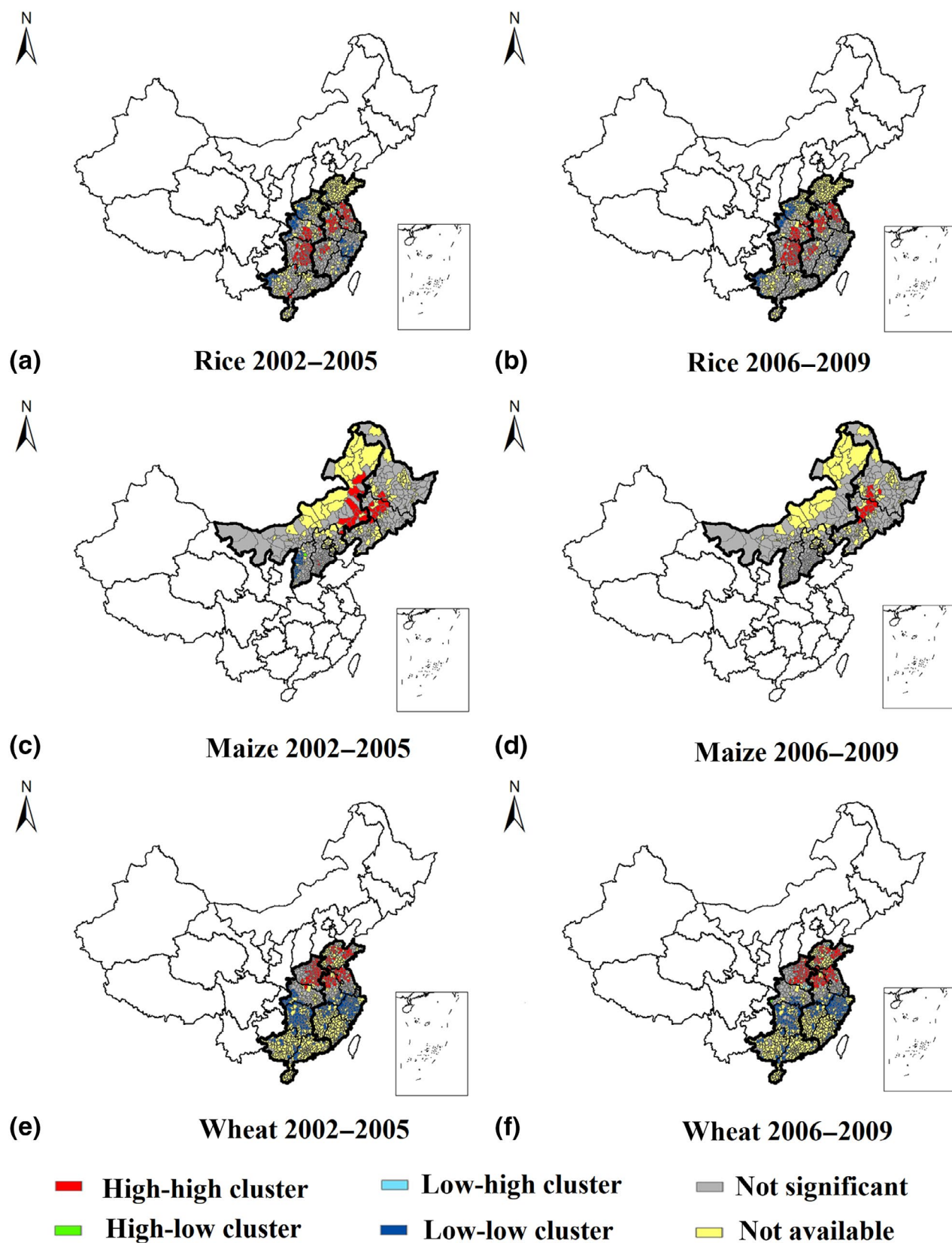


FIGURE 5 Spatial cluster maps of three field residues of (a, b) rice (East and South Central China), (c, d) maize (North and Northeast China), and (e, f) wheat (East and South Central China) in main production regions in 2002–2005 and 2006–2009

TABLE 5 Number of counties in the high–high clusters in the top two regions with highest field residue resource in China from 2002 to 2009

Field residue	Region	Number of counties	
		2002–2005	2006–2009
Rice	East	52	47
	South Central	57	64
Maize	Northeast	13	15
	North	13	0
Wheat	East	71	72
	South Central	66	64

a stable supply potential to the biomass based energy facilities. However, the pressure for timely harvests in multiple cropping regions would increase demand for harvesting machinery and logistics management. At the provincial level, due to its high density of crop field residues and relatively steady supply potential throughout the year, Anhui province is viewed as having an advantage for developing crop residue-based bioenergy systems.

4.2 | County-level crop residue resources

The results of our county-level analysis demonstrated that field residues had a varied spatial correlation structure even within the same province or high production region. This complexity indicated the necessity to understand the distribution of county-level residue resource. During 2002–2009, there was a specialization of crop production in the Northeast region. Maize and rice residues had increased during this period with a decreased wheat residue, indicating a replacement of wheat by maize and rice. Meanwhile, some high–high cluster disappeared, such as the rice residue cluster in the southern ends of Guangxi and Guangdong provinces and the maize cluster in Inner Mongolia.

The distribution pattern of residue resource can strongly influence the development of bioenergy market and industry. It is critical for the government and business to consider where and how to develop biomass supply chain systems, including the number and capacity of storage and processing facilities and associated logistics infrastructure such as road or rail transportations (Jonker et al., 2016; Lin et al., 2016; You, Tao, Graziano, & Snyder, 2012; Zhang, Osmani, Awudu, & Gonela, 2013). A more spatially concentrated pattern of residue resource would reduce the logistics complexity and costs for biomass-based industry and support the development of large-scale facilities to achieve economies of scale (Hu et al., 2017; Lin, Rodríguez, Shastri, Hansen, & Ting, 2013; Zhang et al., 2013).

Overall, the counties around the intersection of East and South Central regions (Shandong, Henan, Anhui, and Jiangsu provinces) have spatially concentrated high

productivity and resource density, fast increasing trends of production, and stable supply potentials of crop residues in 5 months. The counties could be considered as a suitable region for bioenergy production. On the demand side, this region has a relatively high population and therefore a high energy demand. Developing bioenergy industry in this region would be able to take advantage of processing crop residue locally to meet an increased energy demand. Furthermore, the spatial characteristics of county-level biomass availability could provide decision support for the supply chain optimization of biomass facility locations and biomass flow patterns.

A detailed spatiotemporal analysis of field residue provides a foundation to support sustainable bio-based industry development. This study estimated the potential of residue provision based on the assumption that all residues could be collected and used. A more realistic estimation of residue provision should further consider the variations on the removal ratio of different crop residues in different regions due to soil conditions and tillage practices, as well as the loss during harvest and transportation. With the advances in crop breeding, future increase in grain yield may possibly result in a decrease in straw yield (Bentsen, Felby, & Thorsen, 2014). A spatiotemporal explicit residue harvest index should be considered in future studies on field residue resources.

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