

Original Research

Spatio-Temporal Variation, Regional Imbalance, and Spatial Dynamics of Straw Resource Economic Pressure in China's Crop Sector

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Abstract

Crop straw, as a major agricultural residue, poses both environmental challenges and opportunities for sustainable resource utilization. This study introduces the concept of “straw pressure”, defined as the amount of straw generated per unit of agricultural output, to evaluate the coupling between crop residue generation and agricultural development in China. Using panel data from 31 provinces during 2014-2023, we applied the Tapio decoupling model, Dagum Gini coefficient decomposition, spatial autocorrelation analysis, and a spatial Markov chain to examine the spatiotemporal dynamics and regional disparities of straw pressure. The results indicate that while China's total straw output continued to increase, overall straw pressure declined only slightly and exhibited pronounced spatial heterogeneity, with higher values in major grain-producing regions and lower levels in coastal provinces. Tapio results reveal that most regions experienced weak decoupling, with strong decoupling yet to emerge. Dagum decomposition shows that inequality is primarily driven by between-region gaps, which have widened over time. Spatial analysis indicates insignificant global autocorrelation but shifting local hot and cold spots, while the spatial Markov chain highlights strong lock-in effects for extreme states and significant neighborhood influence on transitions of intermediate states. These findings confirm the value of straw pressure as a diagnostic metric, providing evidence-based insights for region-specific policies to promote high-value utilization, cross-regional diffusion, and the green transformation of agriculture.

Keywords: straw pressure, decoupling, Dagum Gini coefficient, spatial autocorrelation, spatial Markov chain, green agriculture

Introduction

Crop residues such as straw are generated in enormous quantities worldwide as a byproduct of agriculture. Global production of crop residues is on the order of 5 billion tonnes per year [1], exceeding the mass of grain harvested and representing a vast potential resource. In many developing regions, these residues play crucial roles as livestock fodder and domestic fuel. Studies estimate that roughly 15-20% of the feed for ruminant livestock globally comes from crop residues [2], underscoring their importance for food production and rural livelihoods. At the same time, mismanagement of straw poses serious environmental challenges. Open-field burning of excess straw remains common in parts of South Asia, releasing smoke and greenhouse gases that degrade air quality and endanger public health [3]. In India – the world’s second largest crop producer – approximately 500 million metric tonnes of agricultural residues are generated annually, of which around 100 Mt are burned each year [3]. This practice has been linked to severe episodic smog, elevated PM_{2.5} pollution, and tens of thousands of premature deaths in the Indo-Gangetic Plain [3]. Even on a global scale, an estimated 400-500 Mt of crop residues are still burned in fields each year, emitting on the order of 1.2 Mt of methane and 30-40 kt of nitrous oxide – potent greenhouse gases that drive climate change [4]. Such open burning not only causes hazardous air pollution but also wastes the biomass’s nutrient content: virtually all the carbon and nitrogen in the straw are lost during combustion. These problems highlight the need for more sustainable management of straw and other residual biomasses [5].

Around the world, researchers and policymakers are exploring ways to transform straw from an environmental liability into a valued resource. A broad array of utilization pathways has been developed. Bioenergy production is a major avenue: technologies now exist to convert straw into heat, electricity, biogas, or liquid biofuels. For example, Denmark and Sweden have both incentivized the use of cereal straw in large-scale energy systems; Denmark today uses about 1.3 Mt of straw per year for power and heating, whereas Sweden – with abundant wood biomass and fewer straw-focused policies – uses only ~0.1 Mt, illustrating how policy and resource economics shape straw’s energy prospects [6]. Soil amendment and fertilizer use is another critical pathway: returning straw to the field recycles nutrients and organic carbon, improving soil structure and fertility over time. Long-term agronomic trials in Europe have shown that retaining or incorporating cereal straw can raise soil organic carbon and enhance soil health, whereas removing straw for many years tends to deplete soil carbon and negatively affect soil properties [2]. Accordingly, many countries, including China, India, and those in the EU, promote “straw return” programs, sometimes providing incentives or equipment to facilitate in-situ incorporation [7, 8]. Material utilization and industry constitute a further set

of approaches: straw can be used as livestock bedding, as a raw material in paper and fiberboard industries, as a substrate for mushroom cultivation, or processed into bioproducts. For instance, chemical pretreatment can render straw more palatable as cattle feed or convert straw cellulose into bio-based plastics [9]. These diverse strategies being implemented internationally demonstrate that crop residues are increasingly seen not as waste to be disposed of, but as a renewable resource to be harnessed for economic and environmental benefit. Nevertheless, significant challenges remain in scaling up these solutions. Common barriers include the high cost of collecting and transporting bulky straw, the short time-window between crop harvest and planting of the next crop, and the need for technologies or incentives that make straw valorization profitable for farmers [4]. Thus, managing straw sustainably is a global issue that requires both technological innovation and supportive policy frameworks.

China exemplifies both the immense potential and the acute urgency of straw management. As the world’s largest agricultural producer, China generates an extraordinary quantity of crop residues – recent estimates put China’s annual straw production at roughly 700-800 million tonnes [10]. This output has been rising modestly alongside improvements in crop yields and expansion of grain production. Historically, a large fraction of Chinese straw was disposed of by open burning, contributing to severe seasonal haze. In the early 2000s, for example, over half of China’s straw was reportedly burned on farms, releasing choking smoke and reactive gases that led to hazardous smog episodes during harvest seasons. Remote sensing data show that straw burning emissions in some regions spiked dramatically before stricter controls were implemented – one study noted a 245% increase in northeast China’s straw-burning PM_{2.5} between 2012 and 2016 [11]. Recognizing the environmental and public health toll, the Chinese government enacted a series of strong policies in the 2010s to curb open-field burning and promote straw utilization. These include outright bans on burning, alongside substantial investments in straw recycling programs, pilot projects, and subsidies for straw-based bioenergy, forage, and fertilizer uses [12]. As a result, China’s straw utilization rate has sharply increased in the past decade. Official statistics indicate that over 90% of crop straw is now collected or repurposed rather than burned. In absolute terms, China’s Ministry of Agriculture reported that about 820 Mt of crop residues were produced in 2021 and that the vast majority was effectively utilized under the no-burn policy regime [13]. This rapid transition has mitigated the fire incidents and improved seasonal air quality in many farming areas. At the same time, it has created new challenges: managing such a high volume of straw through alternative pathways requires significant infrastructure and coordination across the supply chain. Agronomically, returning large quantities of straw to soils must be done carefully – if too much

straw is incorporated without sufficient decomposition time, it can impede seedling emergence and even lead to pest or disease carryover. In waterlogged paddy fields, heavy straw incorporation can also generate methane during anaerobic decay. These nuances underscore that while straw is a major carbon and nutrient reservoir for China's agriculture, it can become an environmental liability if not managed properly. Balancing the benefits and risks of straw utilization remains a key sustainability challenge for China's agricultural sector.

In the context of these global and national imperatives, there is a growing need for metrics that can quantitatively assess the coupling between agricultural production and residue generation. Most conventional indicators used in straw management focus on the absolute scale of residues handled – for instance, the total amount of straw recycled, or the percentage of straw put to beneficial use. While such metrics are useful, they do not capture how efficiently a farming system is performing in terms of residue generation relative to its productive output. In other words, if one region produces twice as much grain as another, is it also producing twice as much straw waste, or has it managed to decouple agricultural growth from waste production? This question is central to sustainable intensification and circular economy approaches, yet standard measures have not directly addressed it. Environmental performance indicators in agriculture often examine resource or emission intensity to evaluate sustainability. However, there has been no widely adopted metric for crop residue intensity – the amount of straw generated per unit of agricultural output value. The absence of such an indicator represents a notable gap in both research and policy assessment, making it difficult to compare regions or track progress in “producing more with less waste”. To fill this gap, this study introduces the concept of “straw pressure”. We define straw pressure as the quantity of crop straw generated per unit of agricultural output. This novel indicator is proposed as a means to evaluate how tightly linked straw generation is to agricultural production, and whether that linkage is weakening over time – i.e., whether there is spatiotemporal decoupling between crop output growth and straw output growth.

The purpose of this research is to develop the straw pressure metric and use it to analyze spatial and temporal dynamics of straw-resource burdens in China's planting sector. Concretely, we ask whether China has achieved improvements in straw generation efficiency as its agricultural economy grows, and how straw pressure varies across different regions of the country. To answer these questions, we construct a panel dataset of 31 Chinese provinces for the period 2014-2023 and employ several analytical tools. First, we apply a Tapio decoupling analysis to measure the elasticity between straw output and agricultural output over time. This allows us to categorize the straw-production relationship in each region/year based on whether straw pressures are rising or falling relative to economic

growth. Next, we utilize the Dagum Gini coefficient decomposition method to quantify regional inequalities in straw pressure and to distinguish the contributions of intra-regional vs. inter-regional disparities. We then examine spatial autocorrelation to determine whether high- or low-straw-pressure provinces exhibit clustering on the map. Finally, we employ a spatial Markov chain modeling approach to evaluate the dynamic evolution of straw pressure levels, accounting for neighborhood effects, whether a province's transitions in straw pressure category are influenced by the straw pressure of its neighbors. By integrating these methods, our analysis provides a comprehensive assessment of both the temporal decoupling trends and the spatial distribution patterns of straw pressure in China.

Materials and Methods

Data Sources

This study integrates multi-dimensional authoritative datasets, adhering to open science principles. Crop production data (2015-2024) for staple crops and cash crops were extracted from the China Statistical Yearbook and cross-validated via the official portal.

Straw Yield Estimation

The total amount of straw resources was estimated based on the yield of major crops and their respective straw-to-grain ratios. This approach follows the biomass coefficient method, which assumes that the quantity of straw produced is proportional to the grain output of each crop [14]. The accounting framework is expressed as:

$$S_{i,t} = \sum_{j=1}^n Y_{i,j,t} \times R_j \times C_j$$

Where, $S_{i,t}$ represents the total straw resources in province i in year t ; $Y_{i,j,t}$ denotes the yield of crop j in province i and year t ; R_j is the straw-to-grain ratio of crop j , reflecting the biomass relationship between grain and straw; C_j is the collectable coefficient, which accounts for the proportion of straw that can be effectively collected and utilized after deducting field losses or non-recoverable portions. Considering the cropping structure of China, nine major crops were selected, including rice, wheat, maize, soybean, potato, cotton, peanut, rapeseed, and sugarcane. Based on agricultural statistics and relevant literature, the straw-to-grain ratios were set as follows: rice 1.01, wheat 1.37, maize 1.10, soybean 1.44, peanut 1.26, potato 0.77, cotton 3.10, rapeseed 2.71, and sugarcane 0.10. These coefficients reflect the biomass relationship between grain and straw for different crops with reasonable accuracy.

Tapio Decoupling Analysis

To characterize the relationship between straw resource output and the growth of the planting industry, this study applied the Tapio decoupling model [15]. The Tapio decoupling index measures the elasticity between the change rate of environmental pressure and the change rate of economic growth. The formula is defined as:

$$D_{i,t} = \frac{\Delta S_{i,t}/S_{i,t-1}}{\Delta G_{i,t}/G_{i,t-1}}$$

where $D_{i,t}$ represents the decoupling index for province i in year t , $\Delta S_{i,t}$ denotes the change in total straw resources, and $\Delta G_{i,t}$ refers to the change in planting industry output. Essentially, the index reflects the responsiveness of straw resource changes to economic fluctuations.

Within the Tapio framework, this study employs the ratio of straw pressure change to agricultural output change as decoupling elasticity, using 0.8 and 1.2 as thresholds to categorize the interaction into eight distinct types. When agricultural output increases while straw pressure decreases, the relationship is defined as strong decoupling; if straw pressure grows but at a much slower pace than output ($0 < D_{i,t} < 0.8$), it is weak decoupling; when both grow almost proportionally ($0.8 \leq D_{i,t} \leq 1.2$), it is expansive decoupling; and if straw pressure grows faster than output ($D_{i,t} > 1.2$), it is negative decoupling. Under conditions of declining agricultural output, if straw pressure rises, it represents strong recoupling; if both decline but straw pressure decreases less than output ($0 < D_{i,t} < 0.8$), it is weak recoupling; when they decline nearly proportionally ($0.8 \leq D_{i,t} \leq 1.2$), it is expansive recoupling; and if straw pressure decreases faster than output ($D_{i,t} > 1.2$), it is considered negative recoupling. This refined classification provides a nuanced understanding of the dynamic link between agricultural growth and the burden of straw resources.

Construction of the Straw Pressure Indicator

To capture the environmental burden associated with agricultural economic development, this study constructed a ‘‘straw pressure’’ indicator, defined as the amount of straw generated per unit of planting industry output. The formula is given as:

$$P_{i,t} = \frac{S_{i,t}}{G_{i,t}}$$

where $P_{i,t}$ denotes the straw pressure in province i during year t , $S_{i,t}$ represents the total straw resources, and $G_{i,t}$ indicates the planting industry output. This indicator reflects the resource pressure borne by each unit of agricultural economic growth. A higher value of straw pressure implies a heavier ecological burden

for the same level of economic output, whereas a lower value indicates higher efficiency and more sustainable utilization of straw resources.

Dagum Gini Coefficient and Its Decomposition

To examine the regional inequality and its sources in straw pressure, this study adopted the Dagum Gini coefficient and its decomposition. Unlike the traditional Gini index, the Dagum approach not only measures the overall degree of inequality but also decomposes it into three distinct components: intra-regional inequality, inter-regional inequality, and transvariation intensity. This decomposition enables a more precise understanding of the structural sources of disparity [16].

The overall Gini coefficient is defined as:

$$G = \frac{1}{2n^2\mu} \sum_{i=1}^n \sum_{j=1}^n |P_i - P_j|$$

where n is the total number of observations, μ is the mean value of straw pressure, and P_i and P_j represent the values of straw pressure in different provinces.

When decomposed, the total inequality can be expressed as:

$$G = G_w + G_{nb} + G_t$$

where G_w captures intra-regional inequality, G_{nb} measures inter-regional inequality, and G_t represents transvariation intensity caused by distributional overlapping among regions.

The intra-regional inequality is computed as:

$$G_w = \sum_{k=1}^K G_k \times \frac{n_k \mu_k}{n\mu}$$

where K is the number of regions, G_k is the Gini coefficient within region k , and n_k and μ_k are the number of provinces and the mean straw pressure in region k .

The inter-regional inequality is given by:

$$G_{nb} = \sum_{k=1}^K \sum_{h=1, h \neq k}^K G_{kh} \times \frac{n_k \mu_k + n_h \mu_h}{2n\mu}$$

where G_{kh} is the between-region Gini coefficient, reflecting the mean difference between regions k and h .

Finally, the transvariation intensity is defined as:

$$G_t = \sum_{k=1}^K \sum_{h=1, h \neq k}^K D_{kh} \times \frac{n_k \mu_k + n_h \mu_h}{2n\mu}$$

where G_{kh} denotes the index of transvariation, which measures the extent of overlapping between

the distributions of two regions when provinces in a relatively low-level region outperform those in a relatively high-level region.

Spatial Autocorrelation Analysis

After measuring the regional disparities of straw pressure, this study further investigated its spatial distribution patterns and dependencies by applying spatial autocorrelation analysis. Both the global Moran's I and the local Moran's I (LISA) indices were employed. The global Moran's I tests whether straw pressure exhibits an overall clustering or dispersion pattern across the country [17]. The formula is expressed as:

$$I = \frac{n}{\sum_{i=1}^n \sum_{j=1}^n w_{ij}} \times \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (P_i - \bar{P})(P_j - \bar{P})}{\sum_{i=1}^n (P_i - \bar{P})^2}$$

where n is the number of provinces, P_i and P_j represent the straw pressure values of provinces i and j , \bar{P} is the national mean, and w_{ij} is the element of the spatial weight matrix, usually constructed based on contiguity or distance. The value of Moran's I ranges between -1 and 1 . A significantly positive Moran's I indicates spatial clustering of high or low values, while a significantly negative value suggests a checkerboard pattern of high-low mixing. A value close to zero implies a random spatial distribution.

Beyond the global pattern, the local Moran's I (LISA) was also calculated to identify hot spots and cold spots of straw pressure. It is defined as:

$$I_i = \frac{(P_i - \bar{P})}{m_0} \sum_{j=1}^n w_{ij} (P_j - \bar{P})$$

$$m_0 = \frac{1}{n} \sum_{i=1}^n (P_i - \bar{P})^2$$

where I_i denotes the local autocorrelation statistic for province i , and m_0 is a standardization term. A significantly positive I_i indicates a province is surrounded by neighbors of similar values (high-high or low-low clusters), whereas a significantly negative I_i reveals spatial heterogeneity between a province and its neighbors (high-low or low-high outliers).

Spatial Markov Chain Analysis

To capture the dynamic evolution of straw pressure under spatial neighborhood conditions, this study employed the spatial Markov chain model. Compared with the traditional Markov chain, the spatial Markov chain incorporates neighborhood effects, meaning that a province's transition depends not only on its own initial state but also on the states of its neighbors [18].

First, straw pressure values were classified into four levels using the quantile method: very low (LL), low

(L), high (H), and very high (HH). This classification ensures comparability and highlights the distributional characteristics across different levels of straw pressure.

In the traditional Markov chain framework, the transition probability is defined as:

$$P = \{p_{ij}\}$$

$$p_{ij} = \Pr(x_{t+1} = j | x_t = i)$$

$$\sum_j p_{ij} = 1$$

where p_{ij} represents the probability of transitioning from state i to state j .

In the spatial Markov chain framework, the transition probability is further conditioned on the neighborhood state. Let the neighborhood state at time t be denoted by q . The conditional transition probability matrix is defined as:

$$P(q) = \{p_{ij}(q)\}$$

$$p_{ij}(q) = \Pr(x_{t+1} = j | x_t = i, N_t = q)$$

where N_t denotes the neighborhood state at time t , and $p_{ij}(q)$ is the probability of moving from state i to state j given that the neighborhood state is q .

By comparing the transition matrices under different neighborhood conditions, the model can identify how "high-value neighbors", "low-value neighbors", or "mixed neighbors" influence the evolution path of straw pressure, thereby revealing the role of spatial interactions in shaping its dynamic changes.

Regional Classification

To highlight the regional disparities of straw pressure, this study followed the conventional classification by the National Bureau of Statistics of China, dividing the 31 provinces into three major regions: eastern, central, and western. The eastern region consists of 11 provinces and municipalities, namely Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. This region is characterized by higher levels of economic development and agricultural modernization. The central region covers 6 provinces, including Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan. As a key transitional zone between east and west, it is an important grain-producing area with a solid agricultural foundation. The western region includes 12 provinces and autonomous regions: Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. With vast territory and diverse natural conditions, the western region is rich in straw resources, though significant disparities exist in regional development.

Results

Total Straw Resources

Between 2014 and 2023, the total amount of straw resources in China remained at a high level with a slightly increasing trend. At the national level, straw output increased from 7.95×10^8 t in 2014 to 8.67×10^8 t in 2023, representing a growth of about 9.1% over the decade. This indicates that the continuous expansion of the planting sector and improvements in crop yields provided sustained support for straw resource supply. Regionally, the central region consistently served as the major contributor, with straw output rising from 3.70×10^8 t to 3.96×10^8 t, accounting for approximately 46-47% of the national total throughout the study period. This highlights the dominant role of the central provinces, known as China's major grain-producing area, in straw supply. The western region experienced an increase from 2.17×10^8 t to 2.42×10^8 t, showing relatively faster growth, which reflects structural optimization and yield improvements in western agriculture. In contrast, the eastern region rose modestly from 2.08×10^8 t to 2.29×10^8 t, with limited fluctuations, suggesting a stable agricultural production pattern. In sum, China's straw resources during the study period exhibited a pattern of "steady overall growth with pronounced regional disparities". The central region remained the dominant supplier, the western region demonstrated accelerated growth, and the eastern region showed

relatively stable increases. These findings provide a solid foundation for subsequent analyses of straw pressure, regional inequality, and spatial dynamics (Fig. 1).

Decoupling Relationship Analysis

Based on the Tapio model, the results indicate that between 2015 and 2023, the relationship between straw resource output and the growth of the planting industry in China was consistently characterized as "weak decoupling". The national decoupling index fluctuated within a narrow range (from -0.15 to 0.60), suggesting that while the agricultural economy continued to grow, changes in straw output were relatively moderate, implying a certain degree of relative independence between the two. Regionally, the eastern region exhibited mostly positive decoupling indices (0.10-0.43), reflecting that economic growth outpaced the increase in straw output, a typical weak decoupling pattern. This implies that in the eastern region, improvements in agricultural output value were more closely linked to technological progress and structural upgrading rather than to increases in straw production. The central region showed greater fluctuations. In 2016 (-1.07) and 2023 (-1.96), the decoupling indices recorded stronger negative values, indicating that straw output decreased more sharply than economic growth. Nevertheless, the remaining years still fell within the weak decoupling range, meaning the overall classification remained "weak decoupling". This suggests that as the primary

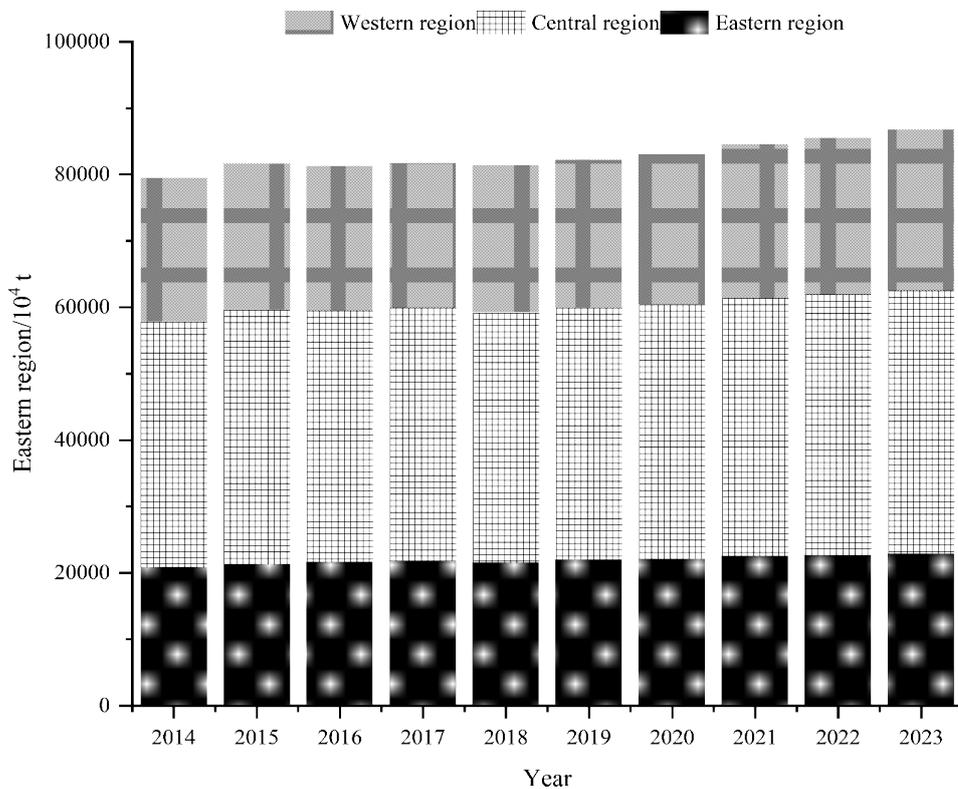


Fig. 1. Total crop straw production in China.

grain-producing area, the central region's straw output was more susceptible to variations in cultivated area and climatic conditions, weakening the coordination between resource supply and economic growth. The western region maintained relatively stable decoupling indices, mostly between 0.00 and 0.45, consistently showing weak decoupling with limited fluctuations. This indicates a relatively balanced relationship between straw output and economic development in the west, with agricultural structural adjustments exerting only minor influence (Table 1).

Straw Pressure Analysis

Between 2014 and 2023, the unit straw output per agricultural output value (straw pressure) in China showed a clear declining trend. This indicates that during the process of agricultural economic development, the efficiency of straw resource utilization continuously improved, and the dependence of economic growth on straw supply gradually weakened. In most provinces, straw pressure decreased by 20%-40% over the study period, which is consistent with the advancement of agricultural modernization and improvements in resource efficiency.

Spatially, straw pressure displayed a distinct stratified pattern. The northeastern provinces (e.g., Jilin, Heilongjiang, and Inner Mongolia) consistently maintained the highest levels, ranging between 2.0 and 5.0 t/10⁴ yuan, with notable fluctuations. This is closely associated with their role as China's grain production bases, where large-scale planting leads to higher straw generation relative to economic output. The central

region (including Henan, Anhui, Hunan, and Jiangxi) exhibited medium levels of straw pressure, mostly between 1.0 and 2.0 t/10⁴ yuan. As these provinces are also major grain producers but have made progress in mechanization and large-scale operations, their straw pressure steadily declined, indicating a gradual coordination between economic growth and resource constraints. The eastern and southern coastal provinces (such as Jiangsu, Zhejiang, Guangdong, Fujian, and Shanghai) showed the lowest levels, generally between 0.3 and 1.0 t/10⁴ yuan, and continued to decline throughout the study period. By 2023, some provinces had dropped below 0.5 t/10⁴ yuan, suggesting that in economically advanced areas, the marginal pressure of straw resources has been significantly alleviated, with agricultural growth increasingly driven by technology and capital rather than resource consumption.

It is also noteworthy that several western provinces (such as Sichuan, Yunnan, Guizhou, and Shaanxi) recorded substantial decreases, with values falling below 1.0 t/10⁴ yuan by 2023. This demonstrates that agricultural restructuring and economic transformation have played important roles in reducing resource pressures in these regions. Overall, straw pressure in China exhibited a pattern of "general decline, pronounced regional differentiation, higher pressure in grain-producing areas, and lower pressure in developed areas" during the study period (Fig. 2).

Gini Coefficient Analysis

Between 2014 and 2023, the overall Dagum Gini coefficient of straw pressure in China increased from

Table 1. Decoupling relationship between crop straw production and planting industry output value in China.

Year	Eastern region		Central region		Western region		China	
	Decoupling index	Type						
2015	0.43	Weak decoupling	2.06	Weak decoupling	0.27	Weak decoupling	0.60	Weak decoupling
2016	-11.56	Weak decoupling	-1.07	Weak decoupling	-0.13	Weak decoupling	-0.15	Weak decoupling
2017	0.32	Weak decoupling	0.15	Weak decoupling	-0.04	Weak decoupling	0.11	Weak decoupling
2018	-0.29	Weak decoupling	-0.23	Weak decoupling	0.27	Weak decoupling	-0.06	Weak decoupling
2019	0.38	Weak decoupling	0.11	Weak decoupling	0.00	Weak decoupling	0.13	Weak decoupling
2020	0.10	Weak decoupling	0.09	Weak decoupling	0.15	Weak decoupling	0.12	Weak decoupling
2021	0.22	Weak decoupling	0.20	Weak decoupling	0.21	Weak decoupling	0.20	Weak decoupling
2022	0.05	Weak decoupling	0.16	Weak decoupling	0.22	Weak decoupling	0.14	Weak decoupling
2023	0.36	Weak decoupling	-1.96	Weak decoupling	0.45	Weak decoupling	0.46	Weak decoupling

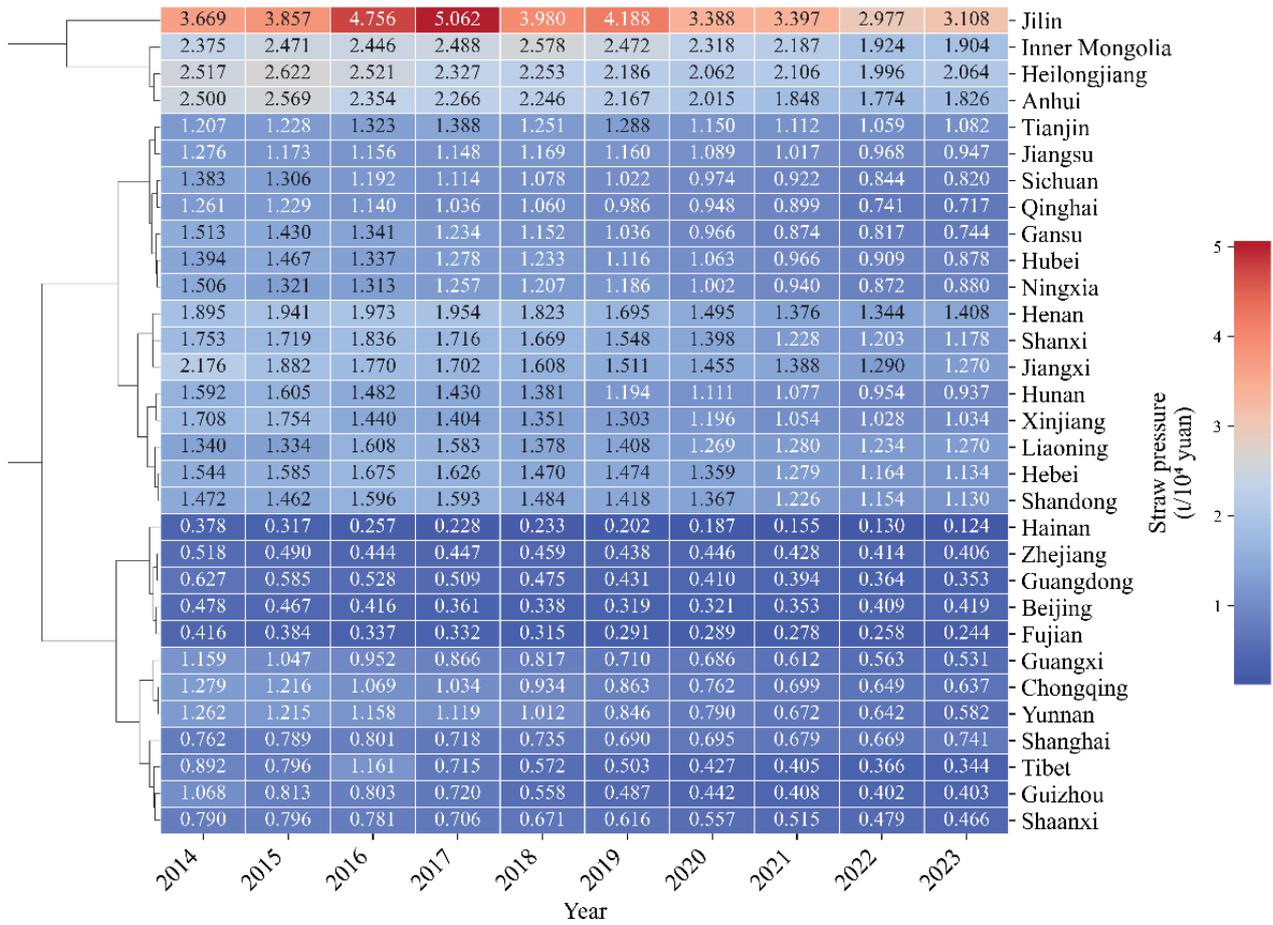


Fig. 2. Temporal variation of straw pressure across 31 Chinese provinces.

0.266 to 0.334, showing a rising trend and indicating widening disparities among provinces. While regional differences were relatively modest at the beginning of the study period, they gradually expanded over time, reflecting a growing divergence in the relationship between resource utilization efficiency and economic output across provinces.

The decomposition results show that inter-regional inequality has consistently been the primary source of overall disparity. In 2014, the inter-regional component was 0.185, accounting for nearly 70% of the total, and by 2023 it remained high at 0.176. This suggests that differences in economic development levels, cropping structures, and straw utilization patterns among eastern, central, and western regions are the decisive factors shaping the overall inequality. Intra-regional inequality remained relatively low but increased slightly, rising from 0.061 in 2014 to 0.085 in 2023. This indicates that disparities among provinces within the same region have become more pronounced. The trend is particularly evident in the central and western regions, where some provinces achieved faster progress in straw utilization efficiency, while others lagged behind, leading to rising internal imbalances. The contribution of transvariation intensity (cross-regional overlapping) grew steadily, from 0.020 in 2014 to 0.073 in 2023.

This reflects the emergence of a “catch-up” effect, in which some provinces from traditionally low-level regions surpassed or approached those in high-level regions, thereby increasing distributional overlap across regions. In terms of intra-regional disparities, the eastern region maintained a relatively high Gini coefficient (0.26-0.33), consistently above the national average, indicating substantial internal differences among developed provinces. The central region fluctuated between 0.165 and 0.232, showing an upward trend in recent years, suggesting a gradual rise in internal inequality. The western region recorded the most significant increase, with its Gini coefficient rising from 0.154 to 0.255, making it the main contributor to expanding intra-regional disparities. This highlights the growing divergence in agricultural development levels and resource utilization efficiency across western provinces (Table 2).

Global Spatial Autocorrelation Analysis

The results of the global Moran’s I index for straw pressure across 31 provinces in China from 2014 to 2023 reveal that no significant spatial autocorrelation was detected during the study period (Table 3). In 2014 and 2015, Moran’s I values were relatively

Table 2. Regional disparities of straw pressure in China.

Year	Gini coefficient				Intra-group Gini coefficient		
	Total	G_w	G_b	G_t	Eastern region	Central region	Western region
2014	0.266	0.061	0.185	0.02	0.267	0.165	0.154
2015	0.285	0.066	0.193	0.026	0.284	0.173	0.179
2016	0.302	0.072	0.192	0.038	0.324	0.215	0.159
2017	0.323	0.079	0.195	0.049	0.333	0.232	0.193
2018	0.317	0.078	0.189	0.05	0.318	0.198	0.225
2019	0.334	0.085	0.187	0.062	0.331	0.229	0.245
2020	0.322	0.083	0.176	0.064	0.321	0.205	0.248
2021	0.329	0.085	0.177	0.067	0.316	0.224	0.252
2022	0.323	0.083	0.172	0.069	0.311	0.215	0.246
2023	0.334	0.085	0.176	0.073	0.313	0.23	0.255

Table 3. Global spatial autocorrelation results of straw pressure in China.

Year	Moran's I	E(I)	Sd(I)	z	p
2014	0.122	-0.033	0.114	1.31	0.095
2015	0.112	-0.033	0.112	1.228	0.110
2016	0.062	-0.033	0.105	0.803	0.211
2017	0.040	-0.033	0.101	0.620	0.268
2018	0.048	-0.033	0.112	0.689	0.245
2019	0.021	-0.033	0.111	0.456	0.324
2020	0.021	-0.033	0.106	0.457	0.324
2021	0.036	-0.033	0.109	0.587	0.278
2022	0.038	-0.033	0.114	0.602	0.274
2023	0.041	-0.033	0.110	0.627	0.265

higher at 0.122 and 0.112, with corresponding z-scores of 1.31 and 1.228, approaching statistical significance at the 10% level. This suggests a weak spatial clustering tendency in the early years, although it was not significant at the 5% level. From 2016 to 2023, Moran's I values declined and stabilized within a narrow range of 0.02-0.06, with all z-scores below 1.0 and p-values well above 0.05. This indicates that straw pressure across provinces was essentially randomly distributed at the national scale, without strong global spatial dependence. In other words, provinces with high or low levels of straw pressure did not form persistent "high-high" or "low-low" clusters nationwide. Overall, the global Moran's I of straw pressure exhibited a gradual shift from weak positive correlation toward near zero. This pattern suggests that as agricultural restructuring and regional economic differentiation intensified, the spatial distribution of straw pressure became more dispersed, with disparities increasingly shaped by local rather than nationwide spatial effects.

Local Spatial Autocorrelation (LISA) Analysis

The LISA maps for 2014, 2019, and 2023 show that straw pressure in China did not form large-scale or persistent spatial clusters nationwide, but several provinces exhibited significant local spatial dependence.

In 2014, Jilin, Heilongjiang and Inner Mongolia displayed "low-low" clustering, indicating that these provinces, together with their neighbors, maintained relatively low levels of straw pressure, reflecting their comparative advantage in resource efficiency per unit of agricultural output. Meanwhile, parts of the central and southeastern regions (e.g., Anhui, Henan, Jiangxi, Guangdong) were identified as "high-low" or "low-high" outliers, suggesting strong spatial heterogeneity compared with their neighboring provinces. By 2019, the northeastern "low-low" cluster was no longer significant, while Sichuan emerged as a new "low-low" cluster in the west, suggesting that certain western provinces

exhibited low levels of straw pressure in spatially homogeneous patterns. At the same time, southeastern coastal provinces such as Guangdong and Fujian continued to present “high-low” outlier characteristics, reflecting higher straw pressure levels compared with their neighbors. In 2023, Sichuan maintained its “low-low” cluster, while Zhejiang emerged as a “high-low” outlier, and Guangdong continued to demonstrate persistent “high-low” features. This pattern indicates that China’s straw pressure has not converged spatially but instead shows a coexistence of localized hot spots and cold spots. Particularly in the southeastern coastal region, rapid economic development combined with heterogeneous agricultural practices has amplified differences with adjacent provinces (Fig. 3).

Spatial Markov Chain Analysis

The spatial Markov transition probability matrix of straw pressure reveals strong path dependence and state stability across different categories (Table 4). First, examining the diagonal elements shows that HH (very high) and LL (very low) states exhibit the greatest stability. Under HH neighborhood conditions, the probability of remaining in the HH state is 91.2%, with only 8.8% transitioning to H. Similarly, under L or H neighborhood conditions, the HH state retains over 79% stability. For LL, the probability of remaining in the same state exceeds 97% in most neighborhood scenarios. This indicates that once extreme high or low states emerge, they are difficult to alter fundamentally, reflecting a strong “lock-in effect”. Second, the intermediate states (L and H) are more dynamic and prone to change. For example, under L neighborhood conditions, the L state has an 88.7% probability of persistence but also an 11.3% chance of declining

to LL. Likewise, the H state under L neighborhoods shows a 68% probability of moving downward. This suggests that mid-level regions are more vulnerable to neighborhood influences, with fluctuations reflecting adjustments in agricultural efficiency and economic development. Third, there is clear spatial dependence in the transition dynamics. The neighborhood context significantly influences the direction of transitions. For instance, when the neighborhood is HH, H states have a 20.7% chance of upgrading to HH, whereas under L neighborhoods, H states are more likely to downgrade (68% shifting to L). This implies that high-level regions are “pulled up” when adjacent to very high states but “pulled down” when surrounded by low-level states.

Discussions

Our results reveal significant regional disparities in straw resource pressure across China, alongside clear temporal shifts. Straw pressure – the burden of managing surplus crop residues – varies widely: major grain-producing provinces in the eastern and central regions exhibit much higher pressure than less intensive agricultural areas in the west. This pattern aligns with disparities in agricultural activity and resource use noted in other studies; for instance, one recent assessment found agricultural carbon pressures significantly higher in eastern coastal provinces than in western or northeastern regions [19]. Over time, China’s total straw output has risen dramatically, from roughly 700 million tons in 2012 to 827 million tons by 2017 [20], exacerbating disposal pressures. Indeed, the expansion of straw production has outpaced utilization capacity in many areas, leading to growing volumes of unutilized straw. Nationally, straw management has

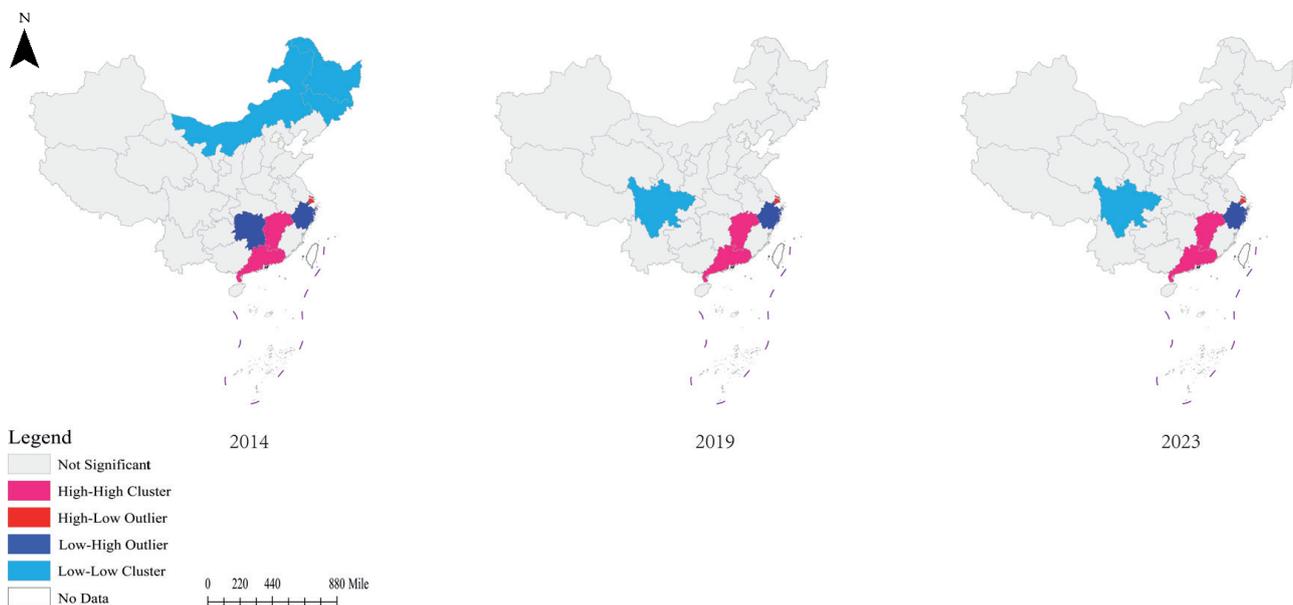


Fig. 3. Local spatial autocorrelation results of straw pressure in China.

Table 4. Spatial Markov transition probability matrix of straw pressure in China.

Adjacency type	Local type	LL	L	H	HH
LL	LL	1.000	0.000	0.000	0.000
	L	0.000	1.000	0.000	0.000
	H	0.000	0.000	0.000	0.000
	HH	0.000	0.000	0.000	0.000
L	LL	0.972	0.028	0.000	0.000
	L	0.113	0.887	0.000	0.000
	H	0.000	0.320	0.680	0.000
	HH	0.000	0.000	0.182	0.818
H	LL	1.000	0.000	0.000	0.000
	L	0.091	0.818	0.091	0.000
	H	0.000	0.143	0.857	0.000
	HH	0.000	0.000	0.207	0.793
HH	LL	1.000	0.000	0.000	0.000
	L	0.000	1.000	0.000	0.000
	H	0.000	0.000	0.818	0.182
	HH	0.000	0.000	0.088	0.912

become a more urgent environmental issue in the past decade, as highlighted by the 18% share of straw in total agricultural waste and rising concern over disposal [21]. Our analysis confirms that, without intervention, regions with already high straw pressure tend to see that pressure persist or increase, whereas some lower-pressure regions have made modest improvements. This echoes patterns observed in broader agricultural sustainability metrics, where initial regional gaps can widen if technological diffusion and policy support are uneven [22]. The temporal evolution of straw pressure in China thus reflects both the overall surge in straw generation and the uneven capacity of different regions to manage this biomass sustainably.

Importantly, our findings suggest an emerging convergence in certain regions as straw utilization efforts take effect. Some high-pressure provinces have recently begun to stabilize or even slightly reduce their straw burden, likely due to policy-driven improvements in utilization. Meanwhile, previously low-pressure areas experiencing agricultural intensification have seen straw pressure creep upward. Overall, however, the spatial imbalance remains pronounced: a clear east–west divide persists, mirroring China’s broader rural resource and economic disparities. Similar regional imbalance phenomena are documented in other contexts of China’s green agricultural development [23]. Factors such as climate, crop types, and farming practices also play roles. For example, cold northern provinces like Heilongjiang face unique challenges – a very short window for field incorporation of straw before winter, and uneven machinery access – which intensify local straw pressure despite high overall production [24]. In contrast, southern provinces with year-round cropping may have more continuous straw utilization cycles

but often struggle with the sheer volume of residues from double-cropping. Taken together, these patterns underscore that China’s straw management challenge is highly region-specific. Any meaningful reduction in straw pressure will require recognizing these spatial differences and tailoring interventions accordingly.

Encouragingly, our analysis of the Tapio decoupling index indicates that many regions are beginning to decouple straw generation from agricultural economic growth. In several provinces, the growth rate of straw output has become lower than the growth rate of agricultural GDP, reflecting a shift toward more efficient, sustainable production. Such trends are a positive sign of agricultural green transition, as they suggest improvements in resource use efficiency – through technologies like straw mulching, bioconversion, and shorter-stalk crop varieties – are mitigating the traditionally tight link between output and residue generation. Our findings mirror those in recent studies of agricultural emissions decoupling, which report that many Chinese provinces have shifted from weak to strong decoupling of farm outputs from environmental burdens over the past decade. In particular, regions like Anhui and Shandong have been noted to achieve the most favorable decoupling statuses, leveraging better farming practices and straw utilization technologies [25–27].

Comparatively, the decoupling of agricultural growth from resource and waste pressures is a focal point in global sustainable agriculture research. Internationally, organizations like the FAO emphasize that boosting productivity while reducing environmental impacts is key to the “green transformation” of agriculture [28, 29]. Our evidence of straw-economic decoupling aligns with this principle, indicating that Chinese agriculture

is beginning to follow a path seen in some developed countries where growth is achieved without proportional increases in waste. For example, improved harvest machinery and crop breeding in Western countries have effectively reduced straw residues per unit of grain, contributing to a form of decoupling [30, 31]. These examples resonate with our findings: regions that invest in straw utilization infrastructure, such as bio-refineries, composting facilities, and straw-based product industries, are achieving better decoupling outcomes. On the other hand, areas that have not modernized straw management show continued coupling, underlining how technology and policy are decisive in bending the straw-output curve downward relative to economic growth.

From a theoretical standpoint, the decoupling we observe can be seen as part of China's agricultural sustainability transition. It reflects movement toward what some scholars term "sustainable intensification", wherein productivity increases while resource inputs and wastes are controlled or reduced. This shift is crucial for meeting China's dual goals of food security and environmental protection. Our results contribute empirical support to the notion that targeted improvements – such as promoting straw-as-resource rather than waste – can enable an agriculture sector to grow economically without a parallel rise in pollution or resource pressure. Such progress is especially notable given China's scale; it reinforces that even in a large, rapidly developing agricultural system, decoupling is achievable with concerted efforts. Going forward, maintaining and accelerating this decoupling trend will be vital. It requires continued innovation in straw utilization.

To quantitatively assess the inequity in straw pressure across regions, we employed the Dagum Gini coefficient and its decomposition. The analysis confirms pronounced regional imbalance in straw pressure and reveals that this imbalance has a persistent structure. Specifically, the between-group differences are the dominant source of inequality, more so than within-group variation. In our case, when China's provinces are grouped, the disparities between these macro-regions account for the majority of the overall Gini coefficient, indicating that regions as broad units are on very different trajectories. This finding is consistent with other recent studies of China's agricultural sustainability indicators. For instance, Yao et al. found that for agricultural green development levels, the contribution of between-region disparities has grown over time and, since around 2019, has exceeded other sources to become the primary cause of overall regional inequality [22]. Our results echo that pattern in the context of straw pressure: structural gaps between China's developed agricultural heartlands and its peripheral or less-developed regions are driving most of the inequality.

Notably, the Dagum decomposition showed an increasing trend in the between-region Gini component over our study period. In other words, the straw pressure gap between leading and lagging regions has widened

somewhat, even as some internal disparities narrowed. This suggests a form of spatial divergence or club formation: high-pressure regions are in a different "club" than low-pressure regions, with relatively little overlap. Indeed, the Gini between the eastern and western provinces was the highest among regional pairings, underscoring a large East-West gulf in straw management outcomes. These findings reinforce the argument that broad regional factors – such as economic development level, technological input, and policy support – heavily influence straw utilization efficiency. Developed regions tend to have better access to straw processing enterprises and technologies, whereas less-developed regions often lack these, causing a stark performance divide. Such regional inequality in environmental and resource indicators is not unique to straw; it parallels patterns in income and industrial development. In China's case, our analysis highlights that group-wise disparity must be addressed if the overall national performance on straw utilization is to improve. The dominance of inter-regional inequality indicates that national targets could be undermined by a few large regions lagging behind. Therefore, bridging the gap between regions – by uplifting the weaker regions' straw utilization capacity – is a strategic priority.

Our spatial Markov chain analysis provides a dynamic perspective on how regional straw pressure levels evolve over time, accounting for spatial context. The results reveal a notable path dependence in the evolution of straw pressure: regions already in a high-pressure state show a strong tendency to remain in that state in subsequent periods, especially if their neighboring regions also have high straw pressures. In effect, a "high-pressure club" has formed, where membership is self-perpetuating. Once a province falls into the highest category of straw pressure, the probability of it transitioning to a lower category is quite small unless significant external changes occur. This dynamic suggests a lock-in effect, akin to what is seen in other socio-environmental phenomena. For instance, studies of regional poverty and development often find that areas with entrenched disadvantages tend to sustain their status over time, contributing to persistent spatial stratification [32]. Similarly, in our context, provinces with severe straw management challenges, due to factors like huge crop production, limited utilization capacity, and weak policy enforcement, are effectively stuck in a high-pressure equilibrium year after year.

Crucially, the spatial Markov approach highlights not only temporal persistence but also neighborhood effects. We observed that a region's likelihood to improve or worsen its straw pressure status is influenced by the straw pressure state of its neighbors. High-pressure regions clustered together reinforce a regional pattern of stagnation, whereas an isolated high-pressure province surrounded by lower-pressure neighbors had a slightly better chance to escape its state. This kind of spatial interaction aligns with the findings of Wang

et al., who noted that in agricultural green development efficiency, spatial Markov analysis showed significant path dependence and neighborhood effects, underlining the role of cross-regional diffusion of innovations [23]. In our case, the implication is that without diffusion of straw utilization technologies and policies across provincial borders, the current high-pressure regions could remain trapped. There appears to be a spatial clustering of performance: a few leading provinces continuously exhibit low straw pressure, and a cluster of lagging provinces continuously exhibit high pressure – a pattern reminiscent of “convergence clubs” or polarization in spatial economics.

From a theoretical lens, this path-dependent behavior suggests increasing returns and cumulative causation at work in straw resource management. Regions that got an early start in building straw utilization infrastructure have reaped benefits that allow them to further invest and stay ahead. Conversely, regions that remained reliant on rudimentary straw handling suffer environmental costs and foregone income that hamper their ability to improve, thereby reinforcing the original state. This lock-in is problematic, but not insurmountable. International experiences show that targeted policy can break such path dependence. For example, addressing “energy poverty” in rural areas has required external investments to kick-start a virtuous cycle where local improvements become self-sustaining. In our study, the spatial Markov findings point to the need for concerted interventions in high-pressure clusters – essentially jolting the system out of its current equilibrium through innovation transfer, increased funding, and stricter enforcement. Otherwise, market forces alone may perpetuate the current spatial pattern for the foreseeable future. High-pressure provinces, especially those contiguous to each other, may continue to share practices that reinforce their status quo, a phenomenon akin to a negative neighborhood spillover. Recognizing this, policymakers should encourage cross-regional learning and assistance: successful straw utilization models from low-pressure regions should be introduced into high-pressure regions as a means of altering their trajectory.

Our findings on China’s straw utilization challenges resonate with international research in several ways. First, the concept of improving resource use efficiency – using straw as a resource rather than treating it as waste – is universal in sustainable agriculture. Studies worldwide have emphasized that crop residues hold significant value and that improving their utilization efficiency can yield win-win outcomes for climate and farm incomes [2]. Our discussion of decoupling and green transformation parallels these themes. For instance, researchers have pointed out that using residues for bioenergy can replace fossil fuels and reduce greenhouse emissions [33], and that returning more straw to fields can sequester carbon and improve soil health. In China, these principles are being applied through programs encouraging straw-based biofuel and

straw returning, much like bioeconomy initiatives in the EU or the US. Second, the push for agricultural green transformation is a global endeavor. Foreign studies often discuss sustainable intensification, regenerative agriculture, and circular economy approaches – all of which involve better residue management. Our observation that technology and innovation drive green outcomes aligns with findings in other countries: for example, cross-country research has shown that green technology innovation (GTI) improves environmental quality by enabling renewable energy use and efficient resource utilization [34, 35]. This is directly relevant to straw, as turning straw into biogas or ethanol is essentially deploying renewable energy tech to farm waste.

Despite these similarities, there are notable differences between China’s straw challenge and those documented abroad. In many developed countries, the straw utilization issue was largely resolved decades ago – either through mechanization that chops and spreads straw back into fields, or through well-established markets for straw. For instance, Japan’s strict law requiring straw recycling and a high-tech approach means straw is hardly considered a “waste” anymore [36]. In Denmark, straw has become a significant energy resource, with over 13 dedicated straw-fired power plants contributing 80%+ of Denmark’s renewable energy output – a scenario very different from China, where straw-to-power is still nascent [6]. These cases highlight that foreign research often examines straw utilization from the standpoint of optimizing an already functional system rather than from the standpoint of eliminating pervasive open burning. China’s situation is more acute due to the sheer volume of straw and the rapidity of its growth, which few other countries have experienced. While countries like Canada and the UK report straw recycling rates of around 67%-73%, China has only in the last few years reached a similar overall utilization rate [37]. It’s important to note, however, that even at 87% utilization, the remaining unused straw in China is enormous in absolute terms, often burnt or left to rot, causing significant emissions. Foreign literature seldom deals with tens of millions of tons of residues being openly burned each year – a scale that is uniquely Chinese to some extent. This means China must draw on foreign best practices but also innovate solutions proportional to its scale. For example, while European farms can plow residues back on relatively small fields easily, in China, the logistics on vast farms or among millions of smallholders make it more challenging – hence the interest in industrial-scale utilization as part of the solution.

Another difference lies in the spatial evolution mechanisms studied. In Western contexts, one doesn’t often find studies applying spatial Markov chains to agricultural environmental indices; the Chinese literature is at the forefront of using such advanced spatial analysis for agriculture. Western research on spatial dynamics might focus on broader issues like

land-use change or rural development disparities, but the fine-grained analysis of something like “straw pressure” transitioning over time in different regions is a novel contribution of our study. Thus, our work extends the international discourse by examining the dynamics of resource-utilization efficiency geographically, a perspective that could be valuable for other large countries dealing with regional disparities in agricultural sustainability. In summary, while the core goals – improving straw utilization efficiency, achieving green agricultural transformation, and understanding spatial mechanisms – are shared globally, the scale and specific expressions of these issues in China provide both a challenging scenario and a learning laboratory. We have shown that China’s progress and problems can be contextualized with foreign experiences, learning from successes and avoiding pitfalls.

Conclusions

This study introduced the concept of straw pressure as a novel indicator to evaluate the coupling between agricultural output and residue generation in China’s planting sector. Using panel data from 31 provinces during 2014-2023, the analysis demonstrated that the chosen time horizon captures both the period of rapid policy intervention against open-field burning and the subsequent expansion of straw utilization programs, ensuring data consistency and policy relevance. Results showed that while total straw output continued to rise, straw pressure declined modestly, indicating partial decoupling of residue generation from agricultural growth. Regional disparities remained significant, with central grain-producing provinces facing persistently high straw pressure. Spatial analyses further revealed heterogeneous clustering and path dependence in provincial transitions. By clearly defining and empirically validating the straw pressure metric, the study achieved its research objective: to provide a practical tool for assessing residue burdens relative to economic gains. The findings not only enrich the methodological toolkit for sustainability analysis but also offer policy-relevant insights to guide differentiated strategies for residue management and agricultural green transformation.

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Conflict of Interest

The authors declare no conflict of interest.

References

1. CHERUBIN M.R., DA SILVA OLIVEIRA D.M., FEIGL B.J., PIMENTEL L.G., LISBOA I.P., GMACH M.R., VARANDA L.L., MORAIS M.C., SATIRO L.S., POPIN G.V., DE PAIVA S.R., BELARMINO DOS SANTOS A.K., SOARES DE VASCONCELOS A.L., AMARAL DE MELO P.L., PELLEGRINO CERRI C.E., CERRI C.C. Crop residue harvest for bioenergy production and its implications on soil functioning and plant growth: A review. *Scientia Agricola*. **75** (3), 255, **2018**.
2. SMERALD A., RAHIMI J., SCHEER C. A global dataset for the production and usage of cereal residues in the period 1997-2021. *Scientific Data*. **10** (1), 685, **2023**.
3. LAN R., EASTHAM S.D., LIU T., NORFORD L.K., BARRETT S.R.H. Air quality impacts of crop residue burning in India and mitigation alternatives. *Nature Communications*. **13** (1), 6537, **2022**.
4. LIN M., BEGHO T. Crop residue burning in South Asia: A review of the scale, effect, and solutions with a focus on reducing reactive nitrogen losses. *Journal of Environmental Management*. **314**, 115104, **2022**.
5. CHI H., ZHANG W., LIU Z., LIU X. Estimation of carbon emission reduction potential from fertilized utilization of crop straw in China. *Journal of Shanxi Agricultural University (Natural Science Edition)*. **45** (5), 100, **2025** [In Chinese].
6. BENTSEN N.S., NILSSON D., LARSEN S. Agricultural residues for energy - A case study on the influence of resource availability, economy and policy on the use of straw for energy in Denmark and Sweden. *Biomass & Bioenergy*. **108**, 278, **2018**.
7. CHANG F., YUE S., LI S., WANG H., CHEN Y., YANG W., WU B., SUN H., WANG S., YIN L., DENG X. Periodic straw-derived biochar improves crop yield, sequesters carbon, and mitigates emissions. *European Journal of Agronomy*. **164**, 127516, **2025**.
8. WELDESEMAYAT SILESHI G., BARRIOS E., LEHMANN J., TUBIELLO F.N. An organic matter database (OMD): consolidating global residue data from agriculture, fisheries, forestry and related industries. *Earth System Science Data*. **17** (2), 369, **2025**.
9. GASIOREK M., STEFANSKA B., PRUSZYNSKA-OSZMALEK E., KOMISAREK J., NOWAK W. Effects of the straw inclusion in the diet of dairy calves on growth performance, rumen fermentation, and blood metabolites during pre- and post-weaning periods. *Journal of Animal Physiology and Animal Nutrition*. **106** (1), 33, **2022**.
10. SONG Y., GAO M., LI Z. Impacts of straw return methods on crop yield, soil organic matter, and salinity in saline-alkali land in North China. *Field Crops Research*. **322**, 109752, **2025**.
11. FANG T. The Impact of Straw Burning on Mortality Rate: A Case Study of Northeast China. *Highlights in Business, Economics and Management*. **32**, 92, **2024**.
12. LIANG J., PAN S., XIA N., CHEN W., LI M. Threshold response of the agricultural modernization to the open crop straw burning CO₂ emission in China’s nine major agricultural zones. *Agriculture, Ecosystems & Environment*. **368**, 109005, **2024**.
13. BAI W., ZHANG L., YAN L., WANG X., ZHOU Z. Crop Straw Resource Utilization as Pilot Policy in China: An Event History Analysis. *International Journal of Environmental Research and Public Health*. **20** (5), **2023**.

14. LIU Z., ZHAO Y., LI Y., LIU X. Spatiotemporal Evolution and Regional Disparities in the Carbon Reduction Potential of Fertilized Straw Utilization in China. *Polish Journal of Environmental Studies*. **2025**.
15. ZHANG Z., SHARIFI A. Analysis of decoupling between CO₂ emissions and economic growth in China's provincial capital cities: A Tapio model approach. *Urban Climate*. **55**, 101885, **2024**.
16. MA T., LIU Y., YANG M. Spatial-Temporal Heterogeneity for Commercial Building Carbon Emissions in China: Based the Dagum Gini Coefficient. *Sustainability*. **14** (9), **2022**.
17. WANG F., PEI X., ZHOU L. Trend and inequality in livestock CO₂ emission intensity: Evidence from 341 prefecture-level cities from 2006 to 2022 in China. *Environmental Research*. **284**, 122209, **2025**.
18. WANG N., QU Z., LI J., ZHANG Y., WANG H., XI H., GU Z. Spatial-temporal patterns and influencing factors of carbon emissions in different regions of China. *Environmental Research*. **276**, **2025**.
19. ZHOU J., WANG G. Evaluating the Carbon Pressure of China's Agricultural Development on Ecological Sustainability. *Polish Journal of Environmental Studies*. **2025**.
20. YANG W., LI X., ZHANG Y. Research Progress and the Development Trend of the Utilization of Crop Straw Biomass Resources in China. *Frontiers in Chemistry*. **10**, 2022, **2022**.
21. CONG H., YAO Z., ZHAO L., MENG H., WANG J., HUO L., YUAN Y., JIA J., XIE T., WU Y. Distribution of crop straw resources and its industrial system and utilization path in China. *Transactions of the Chinese Society of Agricultural Engineering*. **35** (22), 132, **2019**.
22. YAO S., LIU S. Y., WU G. S. Regional differences spatiotemporal evolution, and convergence of agricultural green development in China: A comparison based on two types of regional divisions. *Applied Ecology and Environmental Research*. **23** (1), 1071, **2025**.
23. WANG L., LI M., ZHANG P. Regional differences and distributional dynamic evolution of science and technology innovation driven green development efficiency in Chinese agriculture. *Frontiers in Sustainable Food Systems*. **9**, 2025, **2025**.
24. GUO C., LI M., CHEN H. Study on the Influencing Factors of Green Agricultural Subsidies on Straw Resource Utilization Technology Adopted by Farmers in Heilongjiang Province, China. *Agriculture*. **15** (1), 93, **2025**.
25. JIA L., WANG M., YANG S., ZHANG F., WANG Y., LI P., MA W., SUI S., LIU T., WANG M. Analysis of Agricultural Carbon Emissions and Carbon Sinks in the Yellow River Basin Based on LMDI and Tapio Decoupling Models. *Sustainability*. **16** (1), **2024**.
26. DONG B., MA X., ZHANG Z., ZHANG H., CHEN R., SONG Y., SHEN M., XIANG R. Carbon emissions, the industrial structure and economic growth: Evidence from heterogeneous industries in China. *Environmental Pollution*. **262**, **2020**.
27. CHEN J., JIA J., LIU C., MAO D. Decoupling analysis of the carbon emissions' change and the economic growth in Jiangxi's agricultural sector. *Electr Network*, **2020**.
28. ZHAO X., LI S. Artificial intelligence and public environmental concern: Impacts on green innovation transformation in energy-intensive enterprises. *Energy Policy*. **198**, **2025**.
29. XIAO Y., ZHANG B., WANG H. Research on the impact of environmental regulations on green technological innovation in China from the perspective of digital transformation: a threshold model approach. *Environmental Research Communications*. **6** (3), **2024**.
30. PENAILILLO K.A., FERNANDA AEDO M., CAROLINA SCORCIONE M., MATHIAS M.L., JOBET C., VIAL M., LOBOS I.A., SALDANA R.C., ESCOBAR-BAHAMONDES P., ETCHEVERRIA P., UNGERFELD E.M. Effect of Oats and Wheat Genotype on In Vitro Gas Production Kinetics of Straw. *Animals*. **11** (6), **2021**.
31. DERYCKE V., LANDSCHOOT S., DEWITTE K., WAMBACQ E., LATRE J., HAESAERT G. Straw Yield and Quality: An Extra Motivation for the Introduction of Triticale in Mixed Farming Systems. *Cereal Research Communications*. **46** (1), 158, **2018**.
32. SILVER D., SILVA T.H. A Markov model of urban evolution: Neighbourhood change as a complex process. *PLoS One*. **16** (1), e0245357, **2021**.
33. SANDSTRÖM V., CHRYSAFI A., LAMMINEN M., TROELL M., JALAVA M., PIIPPONEN J., SIEBERT S., VAN HAL O., VIRKKI V., KUMMU M. Food system by-products upcycled in livestock and aquaculture feeds can increase global food supply. *Nature food*. **3** (9), 729, **2022**.
34. WANG X., ELAHI E., ZHANG L. Mandatory Environmental Regulation and Green Technology Innovation: Evidence from China. *Sustainability*. **14** (20), **2022**.
35. LIN T., WANG L., WU J. Environmental Regulations, Green Technology Innovation, and High-Quality Economic Development in China: Application of Mediation and Threshold Effects. *Sustainability*. **14** (11), **2022**.
36. NGUYEN T.T, SASAKI Y., KAKUDA K., FUJII H. Comparison of paddy soil fertility under conventional rice straw application versus cow dung compost application in mixed crop-livestock systems in a cold temperate region of Japan. *Soil Science and Plant Nutrition*. **68** (5-6), 594, **2022**.
37. SUN N., GAO C., DING Y., BI Y., SEGLAH P. A., WANG Y. Five-Dimensional Straw Utilization Model and Its Impact on Carbon Emission Reduction in China. *Sustainability*. **14** (24), 16722, **2022**.