Enhancing the local enforcement of straw-burning regulation by digital technology: evidence from China

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Abstract

Open-air straw burning (OSB) is a practice prevalent in developing countries that presents substantial risks to public health. However, the prevalence of OSB in these countries is not due to the absence of regulations but the insufficient enforcement of existing regulations at the local level. This study investigates a reform of open-air straw-burning (OSB) management in China, which aims to leverage digital technology, specifically satellite, to enhance the local enforcement of OSB regulations. Specifically, this reform utilized satellite data of OSB numbers as an indicator for evaluating the performance of local governments in regulation enforcement. We evaluate the effectiveness of this reform by exploring a unique county-level satellite-based dataset and employing a staggered Difference-in-Differences approach combined with a two-part model. We found that using satellite data as a measure of local governments' performance led to a reduction in counties' OSB numbers by 56.50%. Furthermore, favorable conditions for straw utilization in counties and their financial dependence enhanced the reform's effectiveness. These findings underscore the importance of digital technology in OSB governance and other related environmental governance areas by enhancing transparency and information flow in the local enforcement of regulations.

Keywords: open-air straw burning, digital technology, regulation enforcement, muti-level government, principle–agency model

JEL codes: H77, K42, Q18, Q53

1. Introduction

Agricultural production is considered a significant cause of environmental pollution (Korontzi, et al., 2006, Wada, et al., 2010, Long, et al., 2021), and economists have recommended the implementation of environmental regulations and fines to mitigate this effect by internalizing the farmers' external costs (Shortle, et al., 2001, Blackman, et al., 2018, Smith, 2019). However, countries with multiple levels of government face challenges in inadequate local enforcement of regulations (Oates, 2002, UNEP, 2019). This issue arises due to the information asymmetry between higher-level and local governments (Zhang, et al., 2018). Since higher-level governments cannot directly observe local governments' efforts in the regulation enforcement, assessing their performance and implementing appropriate rewards and penalties becomes challenging. As a result, the information asymmetry contributes to the irresponsibility of local governments, hindering the effective enforcement of regulations at the local level.

The widespread occurrence of open-air straw burning (OSB) in developing countries is a representative example of inadequate local enforcement of regulations. Burning straws in the open air after harvest generates numerous air pollutants, posing significant risks to public health (Rangel and Vogl, 2019, He, et al., 2020, Guo, 2021, Lai, et al., 2022). It is a long-standing practice across the world, especially in developing countries. In China, 25% of total crop straws were burnt by farmers on their farms in 2016 (Fang, et al., 2019), whereas this number was about 21% in India in 2008 (Jain, et al., 2014). Russia and some Southeast Asian countries have experienced similar issues with OSB (Theesfeld and Jelinek, 2017, Sereenonchai and Arunrat, 2022). However, the prevalence of OSB is not due to the absence of regulations but the lack of local enforcement. Many developing countries, including China, India, and Russia, introduced national regulations on straw burning as early as the turn of the millennium, around the year 2000 (Theesfeld and Jelinek, 2017, Bhuvaneshwari, et al., 2019, Huang, et al., 2021). However, the success of these regulations has been limited. For example, in China, satellite data revealed a substantial threefold surge in OSB events between 2000 and 2014 after regulation introduction (Yin, et al., 2021). Additionally, some empirical and descriptive studies have provided evidence indicating that regulations have limited effectiveness in reducing OSB in developing countries (Theesfeld and Jelinek, 2017, Bhuvaneshwari, et al., 2019, Cao and Ma, 2023, Nian, 2023).

The above studies have sufficiently revealed the negative impact of OSB and the prevalent issue of inadequate local enforcement of its regulations. However, the effective way to address the inadequate local enforcement is largely unexplored. This paper fills this gap by focusing on an OSB reform in China introduced in 2013 known as Grid Management (GM), specifically targeting this challenge. This reform's essence is to enhance the information-collection capacity of high-level government by integrating digital technology, i.e., remote-sensing satellite. More specifically, the reform utilized satellite-based OSB data as the key indicator for evaluating the performance of local governments in enforcing these regulations.

This study aims to assess the effectiveness of GM in enhancing local enforcement of OSB regulations. We first developed a principal-agent model to elucidate utilizing satellite technology as an indicator of performance can mitigate the information asymmetry between higher-level and local governments, thereby promoting regulation enforcement at the local level. As empirical evidence, we collect satellite-based OSB data spanning from 2009 to 2017 across eight provinces with the highest OSB numbers. To estimate the effects of GM on counties' OSB numbers, we employed a staggered Difference-in-Differences design, considering that provinces introduced GM at different times. Furthermore, to address the issue of numerous zero values in the OSB data, we integrated a two-part model with the staggered Difference-in-Differences design.

This study makes three important contributions to the current literature. First, this work is linked to Cao and Ma (2023) and Nian (2023), which provided empirical evidence on insufficient local enforcement of OSB regulations in China. This research delves deeper into subsequent reforms, offering evidence of their effectiveness. This enriches the perspective of observing OSB management in China. Second, given the pervasive issue of inadequate local enforcement of OSB regulations in developing countries, our study becomes crucial in offering effective approaches that integrate digital technology, such as satellite, with policy design. Third, our study contributes to an emerging research field regarding digital technology in environmental governance. These studies have provided insights indicating that digital technology improves information dissemination and transparency in environmental governance (Lovett, et al., 2007, Ascui, et al., 2018, Toonen and Bush, 2020, Kloppenburg, et al., 2022). Our study contributes by presenting a theoretical model and quasi-experimental evidence based on OSB management in China.

The remainder of this paper is organized as follows. Section 2 provides an overview of the policy design of GM, showing how the Chinese government integrates satellite technology into the policy framework. Section 3 presents the theoretical framework of the mechanism by which digital technology mitigates information asymmetry among multiple levels of government. Sections 4 and 5 outline the data collection and present the empirical strategy, respectively. Section 6 presents the empirical results, focusing on the effects of GM on counties' OSB numbers and its heterogeneous effectiveness. Finally, Section 7 concludes the study and discusses the results.

2. Institutional setting

2.1 The national open-air straw-burning (OSB) regulations

Huang, et al. (2021) categorized the evolution of OSB regulations in China into three distinct phases. The first phase, spanning from 1999 to 2007, saw the issuance of the "Management Measures for Prohibiting Straw Burning and Promoting Comprehensive Utilization" by six national departments. This policy marked the inaugural establishment of regulations on straw burning, mandating farmers to abstain from burning straw near airports and transportation arteries. The second phase, extending from 2008 to 2012, witnessed an institutional upgrade in the department responsible for policy formulation. During this period, the State Council issued the "Opinions on Accelerating the Comprehensive Utilization of Crop Straw," which provided detailed supplements and explanations regarding the comprehensive utilization of straw based on the 1999 policy. The third phase commenced after 2013. In that year, the State Council issued the "Notice on Strengthening the Comprehensive Utilization and Prohibition of Crop Straw Burning." This policy highlighted persistent issues from previous policies before 2013, including inadequate attention from local governments, insufficient incentive mechanisms, and incomplete implementation of responsibilities. Moreover, it mandated each province to establish a system of accountability for preventing OSB.

2.2 Inadequate local enforcement of open-air straw-burning (OSB) regulations

The widespread occurrence of uncontrolled OSB could not be attributed to the fact that national OSB regulations had not been communicated to farmers. For instance, Hou, et al. (2019) collected panel household data covering the period from 2003 to 2013 in three provinces: Liaoning, Jilin, and Heilongjiang. They discovered that the proportion of villages with OSB regulations increased from 21.5% in 2008 to 53.7% in

2013. However, findings from the fixed-effect model indicated that these regulations did not have a significant effect on farmers' engagement in OSB activities.

The limited effectiveness of regulations was attributed to the lack of efficient enforcement at the local level. Monitoring farmers' OSB activities necessitates real-time surveillance, leading to high monitoring costs for local governments (Cao and Ma, 2023). Consequently, higher-level governments should design effective incentive mechanisms to encourage local governments to put more effort into monitoring farmers. However, there was a lack of effective indicators for assessing local governments' efforts in managing OSB (Wang, et al., 2021). Relying solely on self-reports from local governments for evaluation was deemed inaccurate, as local authorities might exaggerate their efforts to gain favor from higher-level government.

2.3 The Grid Management (GM) reform

To address inadequate local enforcement of OSB regulations, Jiangsu pioneered GM in 2013, integrating remote sensing satellite technology with the policy framework. And other provinces followed in subsequent years (More details are shown in Table A1). This innovation enabled higher-level governments to bypass local government and directly access information from farmers. GM employed a geographical grid-based approach to demarcate jurisdictions and manage OSB in grid-based units (Figure 1). Each grid level established a management committee comprising members from various departments, with the head of the jurisdiction, such as the county head, serving as the committee leader.

The committee was responsible for the outcome of their OSB management, with their performance evaluation criteria being based on satellite data. For example, in Jiangsu, a 100-point evaluation mechanism was established for each jurisdictional leader, with each satellite-detected OSB spot resulting in a deduction of 5 points from their score[1]. These assessment outcomes directly influenced the promotion prospects of leaders and determined the financial allocation of the organization for the following year.

Moreover, village committees built the bridge between the government and farmers, directly monitoring OSB activities[2]. Their supervision method entailed conducting regular physical patrols to detect and discourage OSB practices among farmers. When farmers engaged in small-scale OSB, village committees took persuasion and criticism as penalties. However, when OSB occurred on a large scale, the police department intervened, imposing fines or even administrative detention on farmers.

[Figure 1 insert here]

[1]The document source is indicated in Table A1.
[2] We delineated the role of village committees in GM , drawing insights from Wang, F., Wang, M., Yin, H., 2021. Can campaign-style enforcement work: When and how? Evidence from straw burning control in China, *Governance*.

3. Theoretical framework

We developed a model to understand how satellite utilization in GM can align the interests of local governments and farms with policy objectives. This model refers to the theoretical framework developed by Zhang, et al. (2018), examining the influence of central supervision on a firm's chemical oxygen demand emissions.

[Figure 2 insert here]

2.1 Model setting

Top-down regulation is implemented in a principal–agent structure (Figure 2). Three types of players are involved in the game: high-level governments (principal), local governments (agent), and farmers (agent). High-level governments are legislators, introducing environmental regulations and setting standard pollution levels to constrain farmers' emissions. Furthermore, they entrust local governments to supervise farmers and assess local governments' execution of the contract to ensure effective enforcement of regulations. To simplify the model without sacrificing generality, our model assumes one high-level government, one local government, and one farmer. All players are considered risk-neutral.

First, we analyzed the farmer's decision concerning compliance with regulation. His payoff matrix is shown in Table 1. The farmer has two actions: compliance and noncompliance. For farmer compliance with regulation, we denoted the compliance cost (or abatement cost) as c, signifying the amount the farmer must pay to keep his emissions below the pollution standard. Under noncompliance, the farmer does not need to consider the compliance cost. However, he faces the risk of the local government monitoring his noncompliance. If caught, the local government would impose a fine f ($f > c$) on the farmer. However, the local government cannot always identify and punish noncompliance due to asymmetric information between the local government and the farmer. The probability ρ ($\rho \in [0,1]$) of the farmer being caught in noncompliance depends on the local government's monitoring efforts. The local government has two actions: high effort and low effort. When the government exerts high effort, the probability of the farmer being caught is denoted as ρ_h, whereas with low effort, it is denoted as ρ_l ($\rho_h > \rho_l$).

[Table 1 insert here]

Next, we analyzed the local government's decisions, and his payoff matrix is shown in Table 2. The cost of the local government's supervision is determined by their efforts. The cost of high effort is denoted as $\omega\rho_h$, whereas the cost of low effort is denoted as $\omega\rho_l$. Moreover, the assessment of the local government's performance is conducted by the high-level government. Since the high-level government cannot observe the local government's efforts, the assessment conducted by the high-level government is outcome-oriented. In this approach, the high-level government directly detects farmer compliance and evaluates the local government's performance based on these observations. Upon detecting the farmer's noncompliance, the high-level government imposes a penalty π on the local government, irrespective of the local government's efforts in supervising the farmer. The probability of the farmer being detected is denoted as σ ($\sigma \in [0,1]$). This probability represents the high-level government's detection capacity to capture the farmer's information from the bottom up. For example, if the high-level government employs effective digital technology, such as remote sensing satellite and camera equipment, to capture the farmer's information, the accuracy of detection is considered high, and σ approaches 1. Conversely, if the high-level government lacks effective instruments to gather information, σ approaches 0.

[Table 2 insert here]

2.2 The play order and strategies

The order of play is that the local government first acts, then the farmer acts considering the local government's action (Figure 3). Specifically, the local government decides whether to exert high effort in supervision. The strategy set of the local government is denoted as $s_{LG} = (H, L)$. Subsequently, the farmer can observe this action. For instance, if the local government exerts a high effort, the farmer can easily notice an increase in the intensity of physical patrols or policy propaganda. The farmer has four strategies to respond to the local government's strategies: (1) unconditional compliance, regardless of whether the government exerts high or low effort; (2) compliance when the local government exerts high effort but noncompliance when effort is low; (3) noncompliance when the local government exerts high effort but compliance when effort is low; and (4) unconditional noncompliance, regardless of the level of effort exerted by the local government. The strategy set of the above strategies is donated as $s_F = (\{C, C\}, \{C, N\}, \{N, C\}, \{N, N\})$.

[Figure 3 insert here]

2.3 Nash equilibrium

We first assume $\rho_l f < c < \rho_h f$ to exclude two extreme scenarios where noncompliance or compliance become farmer's dominant strategies (Table 3). Specifically, when $c > \rho_h f$, noncompliance emerges as the farmer's dominant strategy, $\{N, N\}$, which means the farmer consistently receives higher payoffs for noncompliance compared to compliance, irrespective of the local government's action between high- or low-effort strategies. In this scenario, the farmer contends with prohibitive compliance costs, surpassing even the penalties imposed by the high-effort local government. As a result, it is futile that the high-level enhance detection capability, as the actions taken by the local government have no bearing on the farmer's decision.

When $c < \rho_l f$, compliance emerges as the farmer's dominant strategy, $\{C, C\}$, which means the farmer consistently receives higher payoffs for compliance compared to noncompliance, irrespective of the local government's action between high- or low-effort strategies. In this scenario, the farmer incurs minimal compliance costs, even lower than the penalties imposed by the low-effort local government. As a result, there is no imperative for the high-level government to enhance detection capability, as the farmer has already opted for compliance.

Then, we analyze the Nash equilibrium based on the given assumption. The assumption of $\rho_l f < c < \rho_h f$ makes the farmer's decision hinges on the local government's strategy, denoted as {C, N}. When the local government exerts high effort, the farmer opts for compliance. Conversely, when the local government exerts low effort, the farmer chooses noncompliance. Given the farmer's strategy, the local government's payoffs of high and low efforts are $-\omega\rho_h$ and $-\pi - \omega\rho_l$, respectively. The critical condition driving the local government's high effort is:

$$-\omega\rho_h > -\sigma\pi - \omega\rho_l$$

$$\rightarrow \sigma > \frac{\omega\rho_h - \omega\rho_l}{\pi}. \tag{1}$$

Equation 1 suggests two potential Nash equilibria. When $\sigma > \frac{\omega\rho_h - \omega\rho_l}{\pi}$, the Nash equilibrium is (H, {C, N}), indicating that the local government exerts high effort, and the farmer chooses compliance. Conversely, when $\sigma < \frac{\omega\rho_h - \omega\rho_l}{\pi}$, the Nash equilibrium is (L, {C, N}), indicating that the local government exerts low effort, and the farmer chooses noncompliance.

The Nash equilibrium suggests that the alignment between policy objectives and the interests of both farmers and local governments depends on the high-level government's detection capacity (σ). When the high-level government possesses effective digital technology, resulting in a probability of detection (σ) higher than the critical value ($\frac{\omega\rho_h-\omega\rho_l}{\pi}$), both the farmer and local government are incentivized to engage in environmental governance. Hence, the detection capacity of the high-level government determines the local enforcement of regulations.

[Table 3 insert here]

Finally, we utilize the insights derived from the theoretical model to hypothesize the potential impact of GM. The GM's utilization of satellite data as the performance indicator of local governments (i.e., prefecture, county, town governments, as well as even village committees) substantially enhanced the detection capacity of high-level government (i.e., province government). And it gave clearer standards for penalties imposed on local governments. Additionally, the compliance costs for farmers were not sufficiently prohibitive for them to prefer enduring punishment from the local government over refraining from burning straws. In accordance with the theoretical model's findings, GM has the potential to shift farmers' strategies from noncompliance to compliance.

Hypothesis: using satellite data as a measure of local governments' performance has the potential to incentivize farmers to shift away from noncompliance.

4. Data

This study compiled the most comprehensive county-level panel data file on OSB for analysis. We focused on provinces in the northeastern plain—including Heilongjiang, Jilin, and Liaoning—and the northern plain—including Anhui, Jiangsu, Hebei, Henan, and Shandong[3]. Additionally, the research period for this study spanned from 2009 to 2017[4].

4.1 Year of Grid Management (GM) introduction

The year in which GM was introduced in the province is the key independent variable. The timeline of the GM introduction is presented in Figure 4. Data on policies were obtained from Beidafabao, a Chinese legal search database including laws and policy documents, primarily at the national, provincial, and prefecture levels, established by Peking University. We searched for the keyword "straw" in the policy title and filtered the policy based on the following principles:

(1) Geographical division: The policy stated that the province established a multilevel grid system to divide the area geographically.

(2) Performance evaluation: The policy explicitly took the number of OSB spots detected by satellite as the performance assessment standard for evaluating cadre performance.

(3) Penalty/reward rules: The policy established an incentive system for penalties or rewards based on OSB numbers.

The detailed principles in GM documents are presented in Online Appendix Table A1.

[3] These two regions, as depicted in Online Appendix Figure A2, largely encompass China's plain territories, making them the principal hubs for grain production and the areas of the most severe OSB.
[4] We selected the year 2009 to ensure that the research period followed the introduction of the second-round national regulations, which were strengthened in 2008. We selected the year 2017 to set Jilin and Heilongjiang as the control group, as they were the final provinces in our dataset to adopt GM, which occurred in 2018.

[Figure 4 insert here]

4.2 Open-air straw-burning (OSB) data

The key dependent variable is the OSB number at the county-month level, which denotes the frequency of OSB events in each county by month. This data was obtained using remote sensing satellites provided by the NASA website. We used MOD14A2 production data on OSB during the daytime (approximately 10:30 and 13:30 local time) from the satellite TERRA. [5] Moreover, we aggregated daily OSB numbers into monthly data. We combined the daily counts of OSB pixels with county boundary data to calculate the total number of OSB spots in each county for the entire month. OSB seasons vary in the northeastern and northern plains. The northeastern plain grows grains once per year, and farmers burn straws in March, April, October, and November (Yin, et al., 2021). In contrast, the northern plain grows grain twice per year, and farmers burn straw mainly between the two growing seasons in the summer (May–July) (Yin, et al., 2021). Therefore, we collected OSB data in March, April, October, and November in the northeastern plain and from May to July in the northern plain (spatial distribution of OSB is shown in Online Appendix Figure A1).

4.3 Air pollution

Another dependent variable is particulate matter, including $PM_{2.5}$ and PM_{10}. We employed monthly satellite-based ground-level data for $PM_{2.5}$ and PM_{10} from the National Tibetan Plateau Data Center (Wei and Li, 2023a, Wei and Li, 2023b). The temporal coverage of this dataset spans from 2000 to 2021. We extracted monthly $PM_{2.5}$ and PM_{10} data from 2009 to 2017 in the northern and northeastern plains. These spatial data, combined with county boundary data, were used to obtain $PM_{2.5}$ and PM_{10} for each county at the month level during the OSB seasons.

[5] The NASA website has two satellites to detect OSB, TERRA and AQUA. We did not use the nighttime (approximately 22:30 and 1:30 local time) data from AQUA because the satellite passed over too late.

4.4 Control variable

We collected climate data at the month-county level, including temperature, precipitation, and wind as control variables. We obtained county-level daily meteorological data from the National Meteorological Information Center of China. We then calculated the monthly temperature, precipitation, and wind speed by averaging the daily values over a given month. Additionally, we also collected the socioeconomic data at the year-county level, and these data were from two sources: (1) the China County Statistical Yearbook, which provides information on agriculture machine power, livestock production, fiscal expenditure on revenue, and the proportion of the first and secondary industries; and (2) the National Tibetan Plateau Data Center (Lixian, et al., 2021), which provides remote sensing data on nighttime light.

[Table 4 insert here]

5. Empirical strategies

5.1 Basic setting

We followed Chen, et al. (2022) and used a staggered difference-in-difference (DID) design to assess the causal effect of GM on counties' OSB numbers based on the following regression setup:

$$Y_{itm} = \alpha + \beta_1 D_i + \boldsymbol{x\delta} + A_i + B_t + C_m + \varepsilon_{imt} \quad (2)$$

where Y_{imt} is the OSB numbers at the month-county level. The variable of interest is D_i, a dummy variable that equals one in the years after county *i* introduced GM (Online Appendix Figure A3). The coefficient of D_i, β_1, indicates the effect of GM on OSB numbers. Finally, $\boldsymbol{x}$ is the vector of climate and economic factors, and ε_{imt} is the error term. A_i, B_t, and C_m are vectors of county, year, and month dummy variables that accounted for county, year, and month fixed effects, respectively.

5.2 Parallel trend test

To alleviate concerns about pre-existing trends between GM and non-GM counties, we examined the dynamics of the relationship between GM and OSB numbers, following Beck, et al. (2010). We included a series of dummy variables in the standard regression to trace the year-by-year effects of GM on OSB numbers:

$$Y_{itm} = \alpha + \beta_1 D_i^{-5} + \beta_2 D_i^{-4} + \cdots \beta_6 D_i^{0} + \cdots \beta_{10} D_i^{+4} + \boldsymbol{x\delta} + A_i + B_t + C_m + \varepsilon_{imt} \quad (3)$$

where D_i^{-j} equals one for counties in the *j*th year before GM introduction; D_i^{+j} equals one for counties in the *j*th year after they GM introduction; and D_i^{0} equals one for counties in the year when GM is introduced. In terms of the interval of j, we selected a 10-year window, where j ranges from -5 to +4.[6] Moreover, we excluded the variable D_i^{-1} to set it as the benchmark year. Thus, the vector of $\boldsymbol{\beta}$ coefficients estimate the

[6] At the first point, D_i^{-5} equals one for all points that are five or more years before GM introduction.

dynamic effect of GM on the OSB numbers relative to the first year before GM introduction.

5.3 Two-part model

The challenge in employing a staggered DID design is that the dependent variable, OSB numbers, exhibits a mix of both discrete ($Y = 0$) and continuous ($Y > 0$) characteristics. In other words, this dataset includes a mass point at zero. As shown in Figure 5, over 40% of the OSB observations are recorded as a value of zero. The zero values have a unique interpretation distinct from the non-zero values, indicating that the county does not require OSB, likely due to the minimal cultivation of major straw-producing crops such as grains. Hence, an appropriate empirical strategy necessitates estimating the values for zero and non-zero observations separately rather than aggregating them using the conventional staggered DID design.

[Figure 5 inserts here]

To address the challenge, we adopted the two-part model proposed by Belotti, et al. (2015) to extend the staggered DID design. When OSB occurs, one observes a positive random variable. Conversely, when OSB does not occur, the observed dependent variable is recorded as zero and constitutes a zero-censored variable. Thus, zero and non-zero values are generated using different densities as a special type of mixture model. The first part of the two-part model estimates the probability of OSB events occurring at the county-month level.

$$\Pr(y > 0|\boldsymbol{x}) = F(\boldsymbol{x\sigma}) \tag{4}$$

where $\boldsymbol{x}$ and $\boldsymbol{\delta}$ represent the independent variables in Equation (2) and their new coefficients, respectively; and $F(.)$ is the cumulative distribution function of OSB, which is typically obtained from an extreme value (logit) or normal distribution (probit). Our study used a normal distribution as the cumulative distribution.

The second part of the two-part model estimates the OSB number under the conditions where the OSB event occurs.

$$E(y|y>0,\boldsymbol{x}) = g^{-1}(\boldsymbol{x\gamma}) \quad (5)$$

where $\boldsymbol{x}$ and $\boldsymbol{\gamma}$ represent the independent variables in Equation (2) and their new coefficients $\boldsymbol{\gamma}$. g (.) is the density function for $y|y>0$. We utilized the Poisson distribution as a specific density function for g (.). Thus, the overall mean OSB could be written as the product of expectations from the first and second parts of the model, [7]as follows:

$$E(y|\boldsymbol{x}) = \Pr(y>0|\boldsymbol{x}) \times E(y|y>0,\boldsymbol{x}) \quad (6)$$

6 Result

6.1 Parallel trend test

We initially performed tests to identify any pre-existing trends between GM and non-GM counties, as depicted in Figure 6. The figure visually emphasizes two critical observations: first, the reduction in OSB did not precede the introduction of GM. As shown, in comparison with the benchmark year (-1), the coefficients associated with GM dummy variables in Equation (3), β_{-j}, do not exhibit statistical significance from zero for all years preceding GM introduction. Second, the effect of GM on OSB numbers became rapidly evident after the introduction of GM. Specifically, β_0 is negative and significant at the 1% level, and in subsequent years, the coefficients β_{+j} gradually inflate. The empirical evidence indicates that although the trend of OSB in GM counties initially aligned with the overall average OSB trend before GM introduction, a noticeable year-on-year reduction in OSB occurred following GM introduction.

[Figure 6 inserts here]

[7] The method for estimating Equation (6) is detailed in Online Appendix 2

6.2 The effect of Grid Management (GM)

Table 5 presents the results of the OLS model compared with those of the two-part model. The marginal effects of the OLS model are represented by the coefficients of independent variables, denoted β_1 and $\boldsymbol{\delta}$, in Equation (2). The marginal effects of the two-part model are calculated using the method outlined in Online Appendix 2. Standard errors are clustered at the prefecture level.

The results indicate that GM significantly decreased OSB numbers by 2.65 spots, representing 56.50% of the total value. Specifically, the OLS coefficient of *D* in column (3) is 4.76, whereas the coefficient estimated by the two-part model is comparatively lower, at 2.65 in column (1). This suggests that the OLS model tends to overestimate the effect of GM on OSB numbers. However, in terms of significance, the significance obtained from both estimation methods is consistent. After controlling the economic factors, the coefficients of *D* in columns (2) and (4) show slight inflation but remain statistically significant. Additionally, the following process was followed to convert reduced OSB numbers to percentages. The average of the OSB numbers in countries after implementing GM was 2.04 spots, as calculated by our OSB dataset. Assuming these counties did not implement GM, the average number of OSB numbers would reach 4.69 (2.65+2.04) spots. Therefore, reducing OSB numbers from 4.69 to 2.04 was equivalent to reducing it by 56.50%.

[Table 5 inserts here]

When comparing the statistical significance of *D* between the first and second models, GM appeared more effective in decreasing the frequency of OSB events than the likelihood of their occurrence (Table 6). The statistical significance of *D* in the former is only 10% (columns 1 and 2), whereas in the latter, it is 1% (columns 3 and 4). This phenomenon may be attributed to GM's evaluation mechanism. Assessment standards for evaluating local governments' efforts allowed for a limited number of OSB events within their jurisdiction. While these standards motivated local governments to exert more effort when OSB was widespread, they may have resulted in decreased vigilance when dealing with only a small number of such events.

[Table 6 inserts here]

6.3 Robustness test

To mitigate concerns regarding the potential influence of unobservable confounders, we conducted a placebo test by randomly selecting GM counties. First, a placebo group of GM counties was generated. If n counties implemented GM in year t based on the actual database (Figure A7), the placebo group should randomly select n counties from all the counties in that year. Moreover, in year t+1, the counties previously selected in year t were excluded to avoid re-election. Second, the effect of GM was estimated based on a new database. We estimated the coefficients of variable D using an updated database that incorporates the placebo GM group. Third, we recorded the coefficients and p-value of D. Fourth, we replicated the above steps 500 times and illustrated the distribution of the coefficients and p-values. Figure 7 illustrates the results of the placebo test, revealing that the average value of coefficients across 500 iterations approaches zero, with corresponding p-values exceeding 10%. These results suggest that the effects of GM on OSB numbers, as assessed in the benchmark regression in Table 5, are unbiased.

[Figure 7 insert here]

Another robustness test we conducted involved estimating the indirect effect of GM on air pollution, specifically focusing on $PM_{2.5}$ and PM_{10}. This test provides an alternative perspective for assessing the impact of GM on OSB by examining the changes in air pollution during the OSB season attributable to GM. Since the datasets for $PM_{2.5}$ and PM_{10} do not have zero values and exhibit a normal distribution (as shown in Online Appendix Figure A4), we employed the OLS approach to estimate the effect of GM on $PM_{2.5}$ and PM_{10} using Equation (2). The results demonstrated that GM significantly reduced $PM_{2.5}$ and PM_{10}. The coefficient of D in column (1) indicated that GM significantly decreased $PM_{2.5}$ by 5.60 μg/m³ during the straw-burning season. After controlling for economic factors, the coefficient of D in column (2) decreases to 4.28 while remaining statistically significant at the 1% level. The coefficient of PM_{10} in columns (3) and (4) indicated that counties with GM experienced a significant decrease of 5.66–6.68 μg/m³ in PM_{10} during the straw-burning season. These reductions in air pollution offer indirect evidence of GM's effect on straw burning. Additionally, they underscore the influence of GM on public benefits, given that air pollution poses a significant risk to public health.

[Table 7 insert here]

6.4 Heterogeneity analysis

A heterogeneity analysis can provide key factors that may improve policy effectiveness and allow researchers to deepen their understanding of the prerequisites for policy to function (Hou, et al., 2021). We chose key factors influencing GM's effectiveness based on the perspectives on farmers' compliance costs and local government's efforts. The perspective on farmers' compliance cost focuses on the local conditions at the county level that support straw utilization. Counties offering favorable conditions for straw utilization will alleviate the burden of compliance costs on farmers. Sustainable straw utilization encompasses two pathways: on-farm straw recycling, which necessitates robust agricultural machinery, and industrial-level utilization, primarily as animal feed (further details are shown in Online Appendix 1). Therefore, we chose the counties' agricultural machine power and livestock production as the proxy for the local conditions that supported straw utilization. Higher values suggest higher levels of favorable conditions for straw utilization in the respective counties.

The perspective on local government's efforts focuses on the financial dependence of county governments on provincial governments. As depicted in the online appendix Table A1, the deduction of financial allocations for the following year served as a penalty mechanism for evaluating county governments' performance in managing OSB. Consequently, counties relying more heavily on financial allocations were more likely to prioritize OSB management and input more effort. We selected the rate of counties' fiscal expenditures to revenue as a proxy for financial dependence. A higher rate indicates greater financial dependence.

Table 8 represents the heterogeneous effects of GM, and the method for estimating heterogeneous effects is detailed in Online Appendix 3. The first finding is counties characterized by higher levels of agricultural machine power, livestock production, and fiscal expenditure relative to revenue exhibited a heightened capacity to reduce the frequency of OSB events following GM introduction. This finding is supported by the coefficients of the cross-term variables in columns (2), (4) and (6) of Table 8. All coefficients of the cross-term variables have a significant negative effect on the frequency of OSB events. These results imply that all three variables—total agricultural machine power, livestock production, and fiscal expenditure relative to revenue—are likely to enhance GM's effectiveness in reducing OSB numbers when OSB events occur.

Moreover, Table 8 illustrates that counties with limited agricultural machinery power and fiscal expenditure relative to revenue continued to witness an escalation in OSB events despite the introduction of GM initiatives. This finding is supported by the coefficients of D in columns (2) and (6) of Table 8. These two coefficients of D have significant positive effects on the frequency of OSB events. These results implied that the effectiveness of GM initiatives was constrained in counties with limited agricultural machinery supply and financial dependence.

[Table 8 insert here]

7. Conclusion and discussion

This study presents an empirical examination of the effectiveness of the Grid Management (GM) reform for the management of open-air straw burning (OSB) in China. This reform utilized satellite data of OSB numbers as an indicator for evaluating the performance of local governments in regulation enforcement. We found that GM substantially decreased OSB events detected by remote-sensing satellites at the county level. Specifically, counties implementing GM exhibited a notable 56.50% reduction in OSB numbers compared to those that either did not adopt GM or did so later. Moreover, the robust test of the effect of GM on air pollution suggests that the decrease in OSB attributed to GM led to a reduction of 4.28 μg/m³ and 5.66 μg/m³ in $PM_{2.5}$ and PM_{10}, respectively. Finally, friendly straw-utilization conditions and county governments' financial dependence enhanced the effectiveness of GM.

Two farm survey research studies corroborated our findings regarding the differences in the effectiveness of OSB regulation before and after GM implementation. Hou, et al. (2019) surveyed householders in Liaoning, Jilin, and Heilongjiang in 2013, before GM was implemented. They found that the regulation of OSB had limited effects on farmers' OSB activities. In contrast, Sun, et al. (2019) conducted a survey in Jiangsu in 2015, where GM was established two years prior. They found that the regulations had significant negative effects on farmers' OSB activities.

The policy implication of our findings is that the capability of high-level governments to collect grassroots-level information from the bottom up is a critical condition for the effective top-down enforcement of agri-environmental regulations. Digital technology serves as the means to enhance this capability, thereby further improving the efficiency of regulatory enforcement (Rothe, 2017, Zhang, et al., 2018, Kloppenburg, et al., 2022). However, our results also highlight the significance of farmers' compliance costs (Vatn, 2015, Tang, et al., 2020). Excessive costs borne by farmers can lead to regulatory failure. In such situations, mandatory compliance measures may not achieve police targets. Therefore, high-level governments should prioritize reducing compliance costs in such situations before imposing intense monitoring pressure on farmers.

The limitation of this study is that the study does not reveal the negative effects of GM on the farmers' benefits. The assessment standards for evaluating the local government's efforts to monitor OSB are one-size-fits-all across most provinces, neglecting the distinct challenges encountered by counties in their efforts to control OSB. Consequently, this standardized approach may prompt counties with a surplus of straw to implement extreme measures, restricting farmers from burning straw even when local conditions do not necessitate such measures. Due to the county-level analysis using remote sensing data, we were unable to provide more detailed insights into these adverse effects at the household level.

Figures

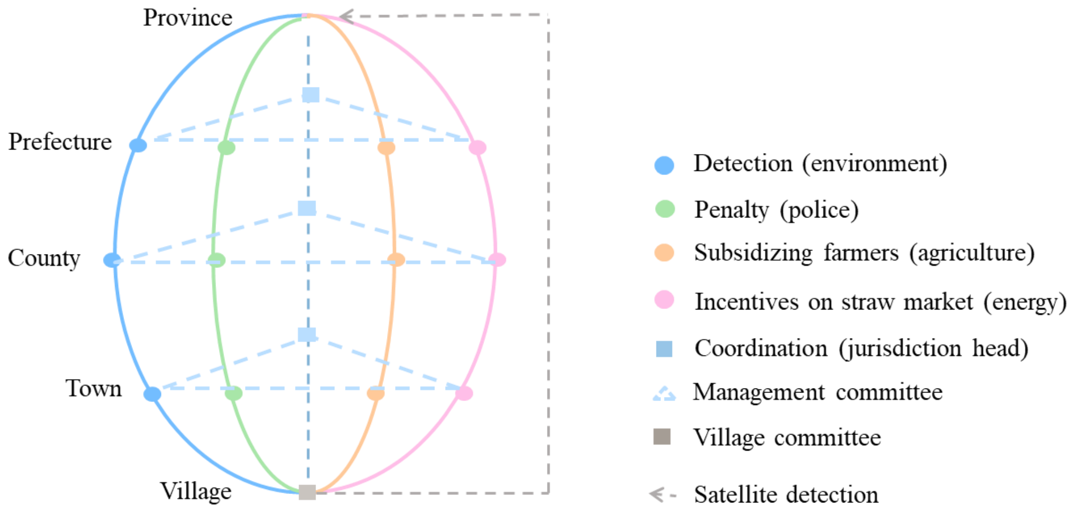


Figure 1. Grid Management (GM)

Note: The authors summarize the governance structure of GM

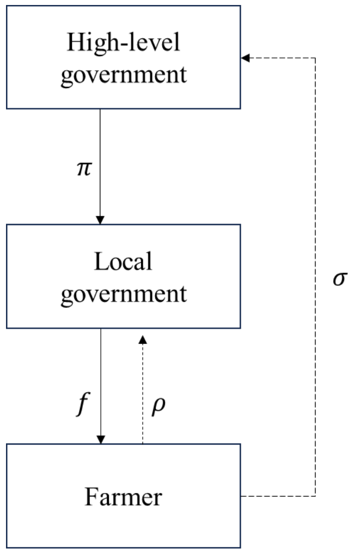


Figure 2. Principal-agent structure

Note: (a) The structure is developed by Zhang, B., X. Chen, and H. Guo. "Does central supervision enhance local environmental enforcement? Quasi-experimental evidence from China." Journal of Public Economics, Vol. 164, (2018) pp. 70-90. (b) π represents the imposition of penalties by the higher-level government on the local government. (c) f represents the imposition of penalties by the local government on the farmer. (d) ρ presents the probability of the farmer being caught in noncompliance by the local government. (e) σ represents the probability of the farmer being detected in noncompliance by the high-level government.

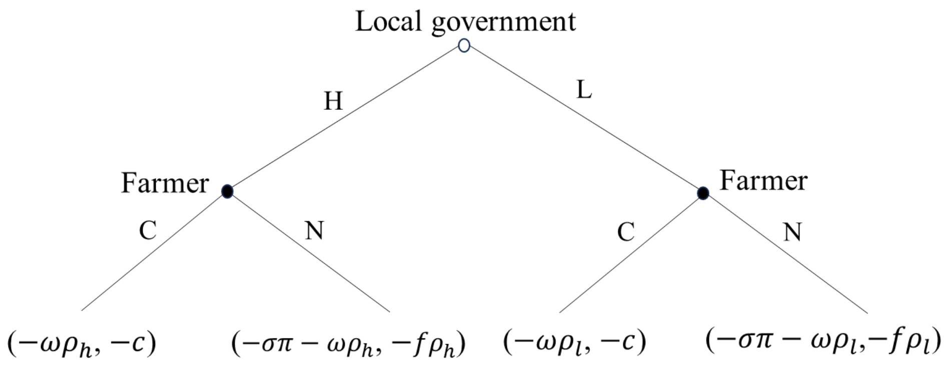


Figure 3. Game tree

Note: (a) H: High effort; L: low effort; C: compliance; N: noncompliance (b) The expected payoffs associated with each strategy are enclosed in parentheses. The values on the left side of the parentheses represent the payoffs for the local government, while those on the right side represent the payoffs for the farmer.

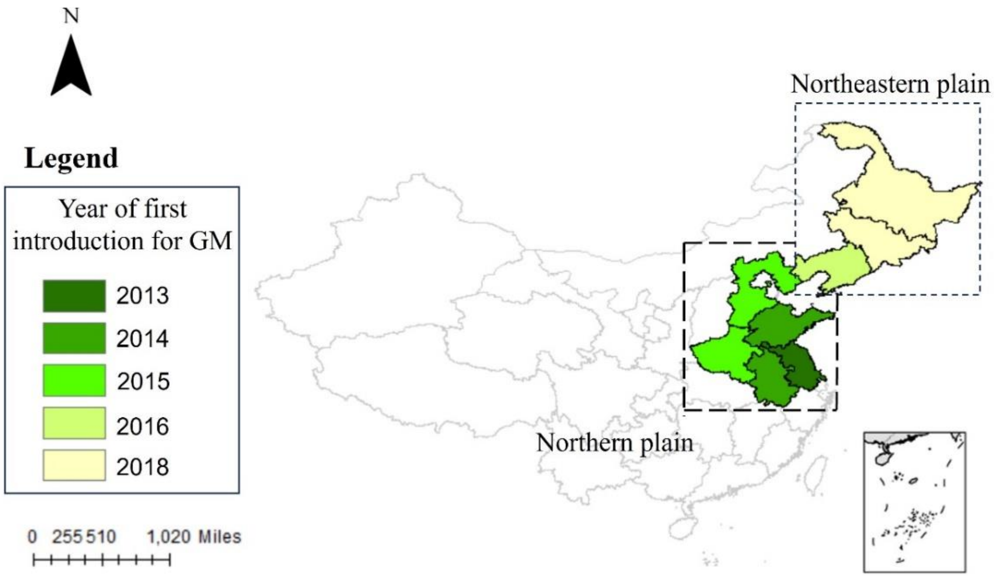


Figure 4. The timeline of Grid Management (GM) establishment

Note: (a) The data comes from the Beidafabao website and is organized by the authors. (b) Details of GM documents are presented in Online Appendix Table A1.

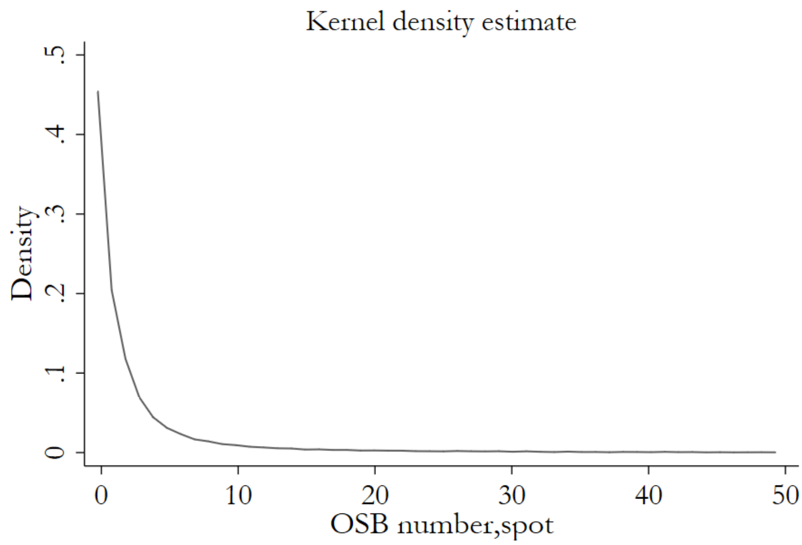


Figure 5. Density of open-air straw-burning (OSB) number

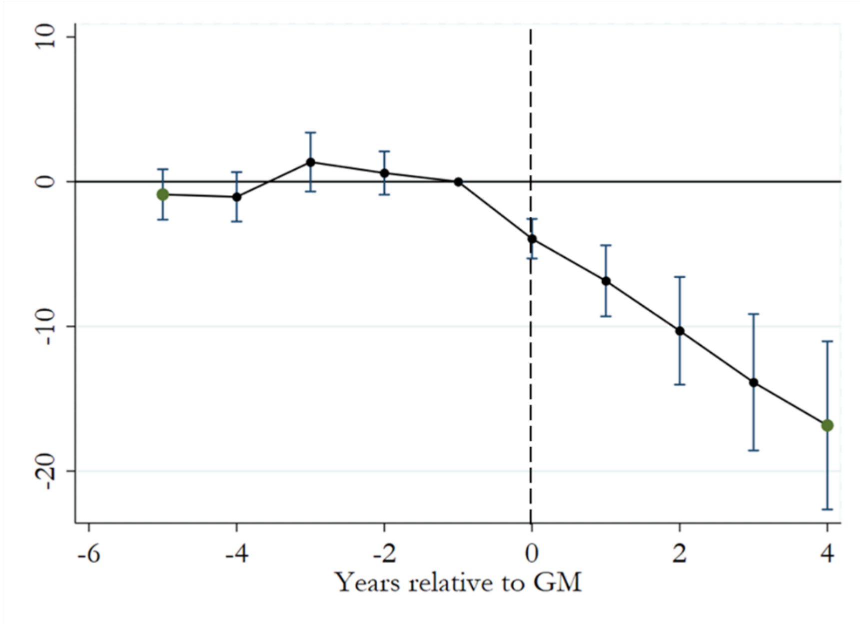
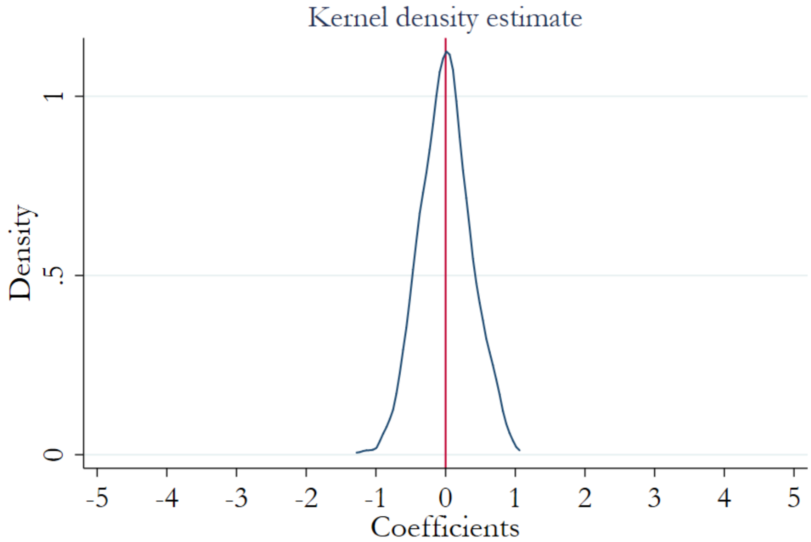


Figure 6. The dynamic impact of Grid Management (GM) on open-air straw-burning (OSB) number

Note: (a) We considered a 10-year window, spanning from 5 years before GM introduction until four years after GM implementation. (b) The value "0" indicates the year in which GM was introduced. (c) The benchmark year is one year before GM introduction (the value "-1"). (d) The solid line represents the dynamic change in deviation of OSB from the county's average relative to the benchmark year. The confidence intervals are at the 95% level and clustered at the prefecture level. (e) The control variables include climate factors and socioeconomic factors. (f) Year, county, and month-fixed effects are controlled.

Panel a: density of placebo-test coefficients



Panel b: distribution of p-value

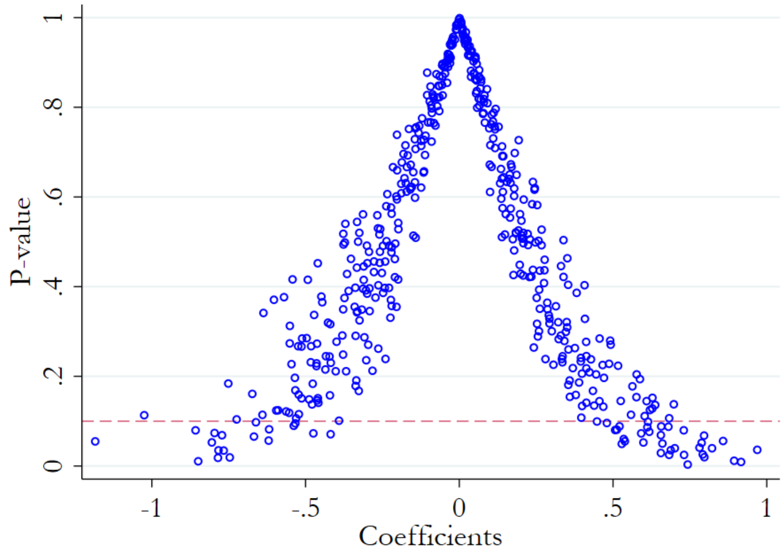


Figure 7. Placebo test

Note: (a) The placebo test is replicated 500 times. (b) The solid line in panel a represents the mean of placebo-test coefficients, which is -0.001. (c) The dashed line in panel b represents the critical points of the 10% confidence interval. Blue dots above the dashed line imply non-significant coefficients. (d) The mean of p-value = 0.496

Tables

Table 1. The farmer's payoff matrix given the local government's actions

	High effort		Low effort	
	Caught by local government	Not caught by local government	Caught by local government	Not caught by local government
	ρ_h	$1 - \rho_h$	ρ_l	$1 - \rho_l$
Payoffs				
Compliance	$-c$	$-c$	$-c$	$-c$
Noncompliance	$-f$	0	$-f$	0
Expected payoffs				
Compliance	$-c$		$-c$	
Noncompliance	$-f\rho_h$		$-f\rho_l$	

Table 2. The local government's payoff matrix given the farmer's actions

	Compliance		Noncompliance	
	Detected by high-level government	Not detected by high-level government	Detected by high-level government	Not detected by high-level government
	σ	$1-\sigma$	σ	$1-\sigma$
Payoffs				
High effort	$-\omega\rho_h$	$-\omega\rho_h$	$-\pi-\omega\rho_h$	$-\omega\rho_h$
Low effort	$-\omega\rho_l$	$-\omega\rho_l$	$-\pi-\omega\rho_l$	$-\omega\rho_l$
Expected payoffs				
High effort	$-\omega\rho_h$		$-\sigma\pi-\omega\rho_h$	
Low effort	$-\omega\rho_l$		$-\sigma\pi-\omega\rho_l$	

Table 3. The Nash equilibrium in different scenarios

	$\sigma < \dfrac{\omega\rho_h - \omega\rho_l}{\pi}$	$\sigma > \dfrac{\omega\rho_h - \omega\rho_l}{\pi}$
$c < \rho_l f$	(L, {N, **N**})	(L, {N, **N**})
$\rho_l f < c < \rho_h f$	(L, {C, **N**})	(H, {**C**, N})
$c > \rho_h f$	(L, {C, **C**})	(L, {C, **C**})

Note: The bold represents the farmer's response to the local government's action.

Table 4. Summary description

Variables	Level	Obs. [ab]	All data Mean	Std. Dev.	Min	Max	Northeastern plain Mean	Std. Err.[d]	Northern plain Mean	Std. Err.
Dependent variables										
OSB numbers, spot	Month	27,405	3.81	[12.19]	0	311	6.68	(1.13)	2.21	(0.18)
$PM_{2.5}$, ug/m^3	Month	27,405	54.64	[16.05]	15.13	143.84	50.00	(1.48)	57.24	(1.38)
PM_{10}, ug/m^3	Month	27,405	97.84	[28.42]	29.20	274.94	86.18	(2.70)	104.36	(2.71)
Climate factors										
Precipitation, mm	Month	27,405	89.76	[76.20]	0.00	779.75	27.45	(1.21)	124.60	(4.33)
Temperature, celsius	Month	27,405	16.46	[11.32]	-20.91	32.15	2.55	(0.50)	24.24	(0.14)
Wind speed, m/s	Month	27,405	2.51	[0.62]	0.90	7.49	2.87	(0.07)	2.30	(0.04)
Socioeconomic *factors*[d]										
Agricultural machine power, thousand kilowatts	Year	19,109	688.73	[506.66]	0	3360	441.22	(44.00)	822.12	(45.44)
Livestock production, thousand tons	Year	20,180	57.90	[57.90]	0.02	729.19	67.58	(8.57)	53.14	(3.38)
Fiscal expenditure to revenue, 100%	Year	21,249	3.36	[2.640]	0.22	23.31	3.98	(0.50)	3.02	(0.21)
The rate of the first industry, 100%	Year	19,376	0.19	[0.13]	0.00	0.75	0.23	(0.03)	0.17	(0.01)
The rate of the second industry, 100%	Year	19,496	0.46	[0.15]	0.04	0.89	0.40	(0.02)	0.50	(0.01)
Night light	Year	27,405	1289.55	[1475.24]	-7049.56	6298.74	1061.65	(152.76)	1416.97	(98.92)

Note: (a) We have a total of 924 counties (273 counties in the northeastern plain and 651 counties in the northern plain) over the period of 2009 to 2017 (for nine years). (b) The observation in the northeastern is 9,828, while the observation in the northern pain is 17,577 (c) Provinces within the northeastern plain encompass Heilongjiang, Jilin, and Liaoning, while those in the northern plain comprise Anhui, Jiangsu, Hebei, Henan, and Shandong. Notably, although the southern parts of Anhui and Jiangsu do not fall within the northern plain geographically, we also consider these regions in our database to ensure the integrity of the provinces. (d) Due to some counties failing to report their economic data in the China County Statistical Yearbook, it has many missing values for the socioeconomic factors. (e) Standard errors are clustered by prefecture.

Table 5. Marginal effects of Grid Management (GM) on open-air straw-burning OSB) numbers

	Two-part model		OLS	
	(1)	(2)	(3)	(4)
Key independent variable				
D, 1=in years after the county introduces GM[a]	-2.645***	-3.492***	-4.760***	-6.084***
	(0.285)	(0.389)	(1.007)	(1.302)
Climate factors				
Precipitation, mm	-0.008***	-0.013***	-0.002	-0.003
	(0.002)	(0.003)	(0.002)	(0.003)
Temperature, celsius	0.580***	0.757***	0.944***	1.346***
	(0.077)	(0.102)	(0.249)	(0.357)
Wind speed, m/s	0.926***	1.240***	1.655***	2.587***
	(0.221)	(0.294)	(0.463)	(0.686)
Socioeconomic *factors*				
Log (agricultural machine power, thousand kilowatts)		-0.363		2.078**
		(1.019)		(1.047)
Log (livestock production, thousand tons)		0.162		0.998
		(0.358)		(0.696)
Fiscal expenditure to revenue, 100%		0.079		0.336*
		(0.070)		(0.187)
The rate of the first industry, 100%		-4.078		2.067
		(3.617)		(8.114)
The rate of the second industry, 100%		0.740		6.985
		(2.655)		(5.285)
Log (night light)		-1.380***		-1.134*
		(0.475)		(0.601)
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Observation	27,405	17,659	27,405	17,659
R^2			0.325	0.337

Note: (a) The key independent variable, *D*, a dummy variable that equals one in the years after the county introduced GM and zero otherwise. The timeline illustrating the introduction of GM is presented in Figure 4. (b) The dependent variable is the satellite-based OSB numbers at the county and monthly levels. (c) The standard errors are clustered by prefecture-level and are listed in parentheses., *** p<0.01, ** p<0.05, * p<0.01

Table 6. Two-part model results

	First part: the occurrence of OSB ($Y = 0$)[a]		Second part: OSB number ($Y \mid Y > 0$)[b]	
	(1)	(2)	(3)	(4)
	Probit	Probit	Poisson	Poisson
Key independent variable				
D, 1= in years after the county introduces GM	-0.104*	-0.116*	-0.659***	-0.702***
	(0.057)	(0.063)	(0.073)	(0.080)
Climate factors[c]	Y	Y	Y	Y
Socioeconomic factors[d]		Y		Y
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Log pseudolikelihood	-13,611	-8,816	-60,878	-47,952
Observation	27,405	17,659	15,503	10,918

Note: (a) The independent variable is whether county *i* occurred OSB in month *m* and year *t*. The coefficients of the dependent variables are estimated using the probit model. (b) The independent variable is the number of OSB spots, conditional to counties occurring OSB. The coefficients of the dependent variables are estimated using GLM given Poisson distribution. (c) The climate factors include precipitation, temperature, and wind speed. (d) The socioeconomic factors include log (agricultural machine power), log (livestock production), log (fiscal expenditure to revenue), the rate of the first and second industry, and log (night light) (e) The standard errors are clustered by prefecture-level and are listed in parentheses., *** p<0.01, ** p<0.05, * p<0.1.

Table 7. The impact of Grid Management (GM) on $PM_{2.5}$ and PM_{10}

	$PM_{2.5}$[a]		PM_{10}[b]	
	(1)	(2)	(3)	(4)
Key independent variable				
D, 1= in years after the county introduces GM	-5.602***	-4.277***	-6.679***	-5.656***
	(0.671)	(0.630)	(1.101)	(1.133)
Climate factors[c]	Y	Y	Y	Y
Socioeconomic factors[c]		Y		Y
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Observation	27,405	17,659	27,405	17,659
R^2	0.725	0.747	0.820	0.830

Note: (a) The dependent variables in columns (1) and (2) are the density of $PM_{2.5}$ at the county and monthly level. (b) The dependent variables in columns (3) and (4) are the density of PM_{10} at the county and monthly level. (c) Climate and socioeconomic factors are the same as those in Table 6. (d) The standard errors are clustered by prefecture-level and are listed in parentheses., *** p<0.01, ** p<0.05, * p<0.1.

Table 8. Heterogeneous effect of Grid Management (GM) on open-air straw-burning (OSB) numbers

	First part[b]	Second part[b]	First part	Second part	First part	Second part
	(1)	(2)	(3)	(4)	(5)	(6)
Log (agriculture machine power) × D	0.015	-0.372***				
	(0.052)	(0.070)				
Log (livestock production) × D			-0.037	-0.234***		
			(0.037)	(0.058)		
Fiscal expenditure to revenue × D					0.030	-0.048*
					(0.019)	(0.155)
D, 1= in years after the county introduces GM	0.213	1.816***	0.026	0.286	-0.207***	0.563***
	(0.342)	(0.463)	(0.152)	(0.250)	(0.088)	(0.111)
Climate factors[a]	Y	Y	Y	Y	Y	Y
Socioeconomic factors[a]	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
Observations	17,315	10,918	17,315	10,918	17,315	10,918
Log pseudolikelihood	-8816	-47738	-8815	-47829	-8813	-47925

Note: (a) Climate and socioeconomic factors are the same as those in Table 6. (b) The first and second parts represent the dependent variables as the likelihood of OSB occurrence ($Y = 0$) and frequency ($Y > 0$), respectively. (c) Standard errors are clustered by prefecture-level and are listed in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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Appendix

Online Appendix 1: Straw utilization in China

The paramount approach for straw utilization, as an alternative to burning, is returning straw to the fields (Figure A6). Returned straw accounted for 35.19% of total straws in 2016 in China (Figure A5). Straw returning involves using straw mulching, deep plowing, or crushing implements and other agricultural machines so that the remaining straw can be left in the field. This technology can reduce farmers' chemical fertilizer inputs (Yin, Zhao et al., 2018; Hu, Liu et al., 2020) and increase crop yields (Wang, Jia et al., 2018; Huang, Yang et al., 2021). Another significant approach is feeding livestock. Straw fed to livestock accounted for 20.89% (Figure A5). This method entails farmers either manually collecting straw or hiring straw-baling services to create straw bales, which can then be fed to farm livestock or sold to livestock enterprises. Other straw utilization accounted for less than 6%.

The initial compliance costs for farmers lie in their access to machinery (Table A2). Farmers must cover service fees for hiring straw-returning or baling machines from cooperatives. In some villages, the absence of such machinery deprives farmers of the opportunity to use straw. Additionally, another compliance cost arises from the adverse effects of returning straws. Despite being a primary technology, excessive straw returning can lead to pest, weed damage, and other agronomy issues (Table A2).

Online Appendix 2: Two-part model

(1) Estimation method

The log-likelihood contribution of an observation was

$$\ln\{E(y|\boldsymbol{x})\} = i(i=0)\{1-F(\boldsymbol{x\sigma})\} + i(i>0)\big[\ln\{F(\boldsymbol{x\sigma})\} + \ln\big(g(\boldsymbol{x\gamma})\big)\big] \quad (1)$$

where i (.) denotes the indicator function that distinguishes whether the values of the straw-burning numbers are zero. The models for zeros and non-zero were estimated separately, as $\boldsymbol{\sigma}$ and $\boldsymbol{\gamma}$ coefficients were separated in the log-likelihood contribution for each observation.

Estimating $\boldsymbol{\sigma}$ and $\boldsymbol{\gamma}$ coefficients of the two-part model was a straightforward process. The threshold, $\Pr(y > 0|\boldsymbol{x})$, was modeled using probit regression for binary outcomes. The positives of straw burning, $E(y|y > 0, \boldsymbol{x})$, were modeled using a generalized linear model (GLM) for a continuous outcome, with g (.) function adopting the Poisson distribution. Subsequently, we employed the maximum likelihood estimation (MLE) to calculate the estimations $\widehat{\boldsymbol{\sigma}}$ and $\widehat{\boldsymbol{\gamma}}$ based on the probit and GLM models.

(2) The marginal effect

Regarding the independent variable j, the expected overall outcome $E(y|\boldsymbol{x})$,[8] with respect to x_j, is

$$\frac{\partial E(y|\boldsymbol{x})}{\partial x_j} = \frac{\partial F(x, \widehat{\sigma}, \widehat{\gamma})}{\partial x_j}, j = 1, \ldots\ldots J \quad (2)$$

where $\widehat{\boldsymbol{\sigma}}$ and $\widehat{\boldsymbol{\gamma}}$ are vectors of estimations estimated by the first- and second-part models, respectively. We empirically calculated the marginal effect of each observation. For observation i, information $\boldsymbol{x_i}$ comprised values from the database. $\widehat{\boldsymbol{\sigma}}$ and $\widehat{\boldsymbol{\gamma}}$ are fixed vectors that were estimated. Therefore, the marginal effect for observation i was

[8] If the independent variable j was s a dummy variable, its marginal or incremental effect was expressed as $E\big(y|x_j = 1, x_{-j}\big) - E\big(y|x_j = 0, x_{-j}\big)$

calculated given $\boldsymbol{x_i}$, $\boldsymbol{\hat{\sigma}}$, and $\boldsymbol{\hat{\gamma}}$. After obtaining the marginal effect of each observation, the average marginal effect is

$$E_x\left(\frac{\partial E(y|\boldsymbol{x})}{\partial x_j}\right) = \frac{1}{N}\sum_{i=1}^{N}\frac{\partial F(x_j, \boldsymbol{x_{-j}}, \widehat{\sigma}, \widehat{\gamma})_i}{\partial x_{ij}} \tag{3}$$

where N denotes the total number of observations. Averaging the marginal effects over all observations yielded the average marginal effect, which was a function of $\boldsymbol{\hat{\sigma}}$ and $\boldsymbol{\hat{\gamma}}$.

Online Appendix 3: Heterogenous effect

We modified the equation to discern the marginal effect on straw-burning numbers moderated by variable M, as follows:

$$Y_{itm} = \alpha + \gamma D_i + \mu M_{it} + \theta D_i M_{it} + \boldsymbol{x}_{itm}\boldsymbol{\delta} + A_i + B_t + C_m + \varepsilon_{imt} \qquad (4)$$

where M_{it} is a factor that influences Grid Management (GM) effectiveness, $D_i M_{it}$ is a cross-term between D_i and M_{it}, and $\frac{\partial Y}{\partial D} = \gamma + \theta M$ is the marginal effect of the GM on straw burning. The results indicated that the effects of the GM comprised two distinct components. One component is represented by γ, which reflects the influence of GM in counties with no assistance from M, where $M = 0$. The other component is represented by θM. The coefficient θ is the amplification factor, which can enlarge the influence of M. Thus, θ represents whether M improved the effectiveness of GM on straw-burning numbers.

Online Appendix 5：Tables and figures

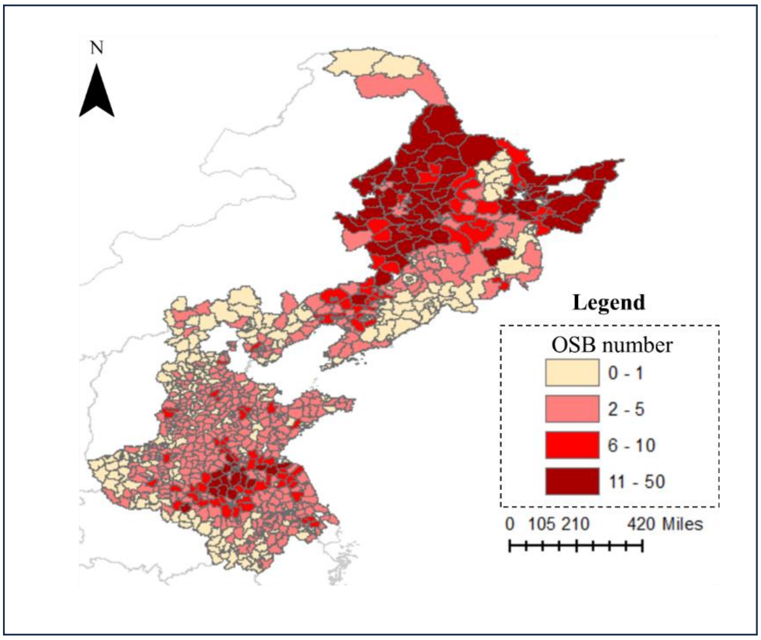


Figure A1. Spatial distribution of open-air straw-burning numbers

Note: Straw-burning numbers are at the month-county level, calculated by the monthly average value from our database.

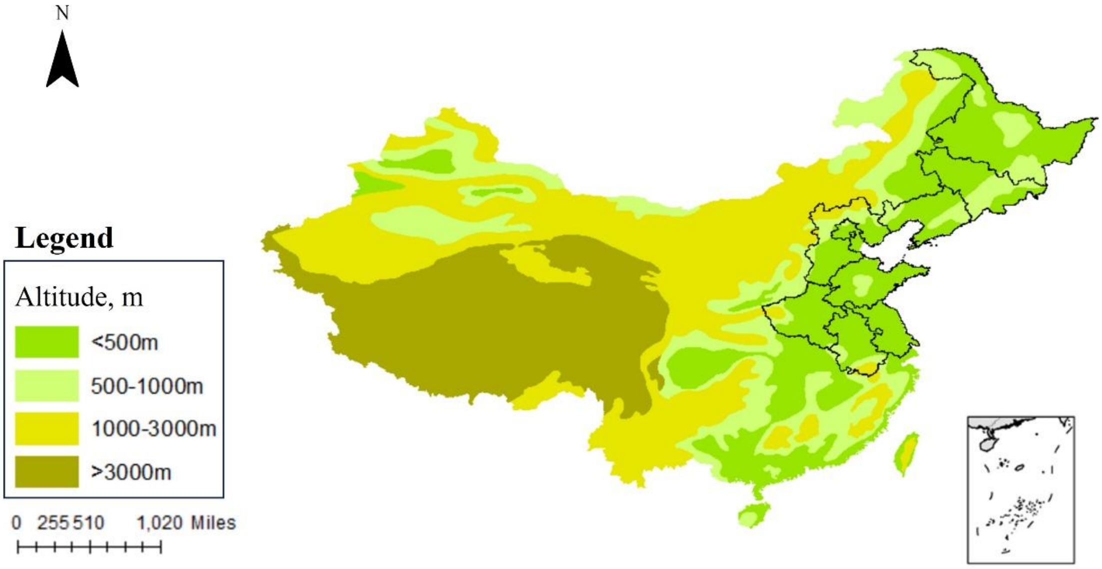


Figure A2. Research regions and their altitude

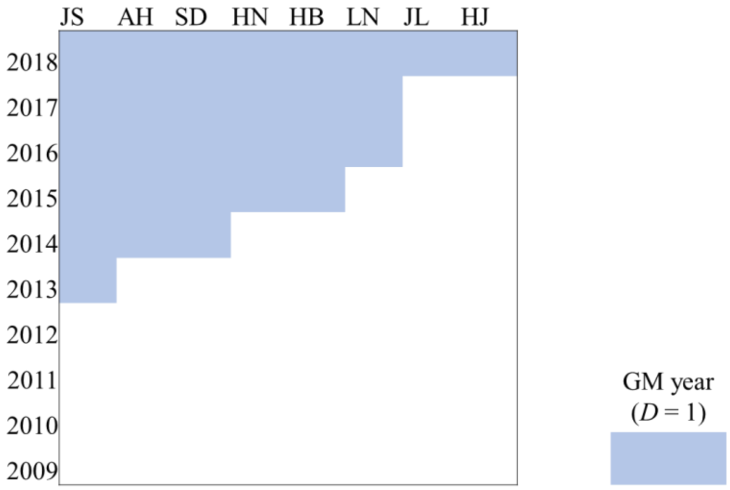
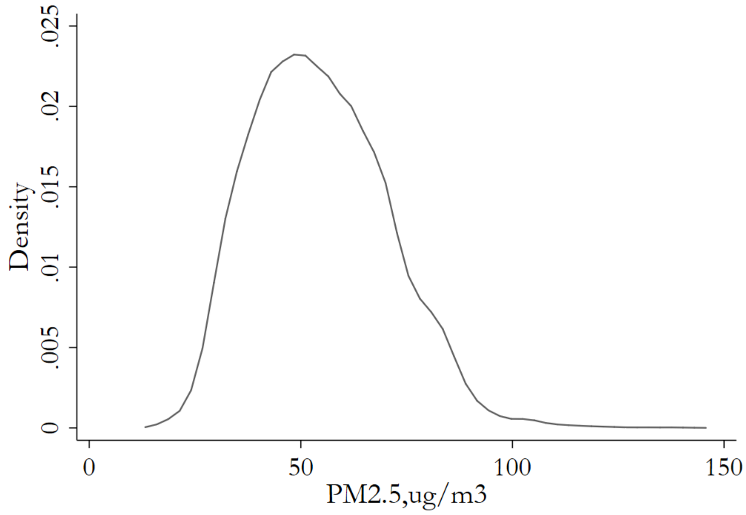


Figure A3. The introduction year of Grid Management (GM)

Note: JS=Jiangsu, AS=Anhui, SD=Shandong, HN=Henan, HB=Hebei, LN=Liaoning, JL=Jilin, HJ=Heilongjiang

a:



b:

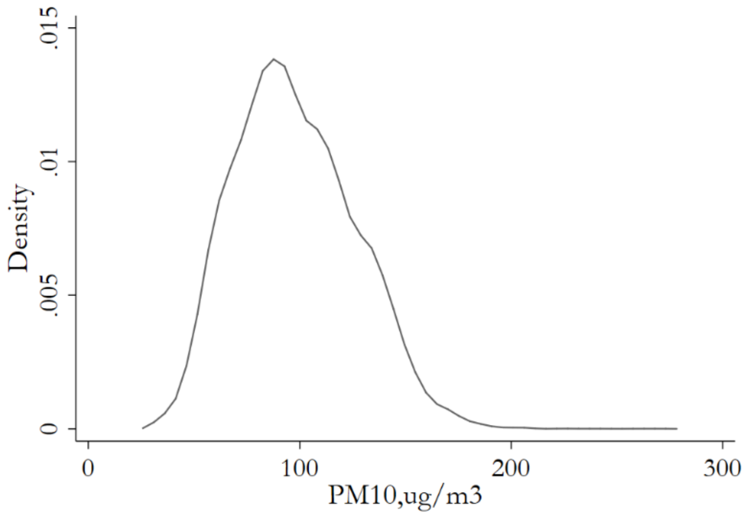


Figure A4. The density of $PM_{2.5}$ and PM_{10}

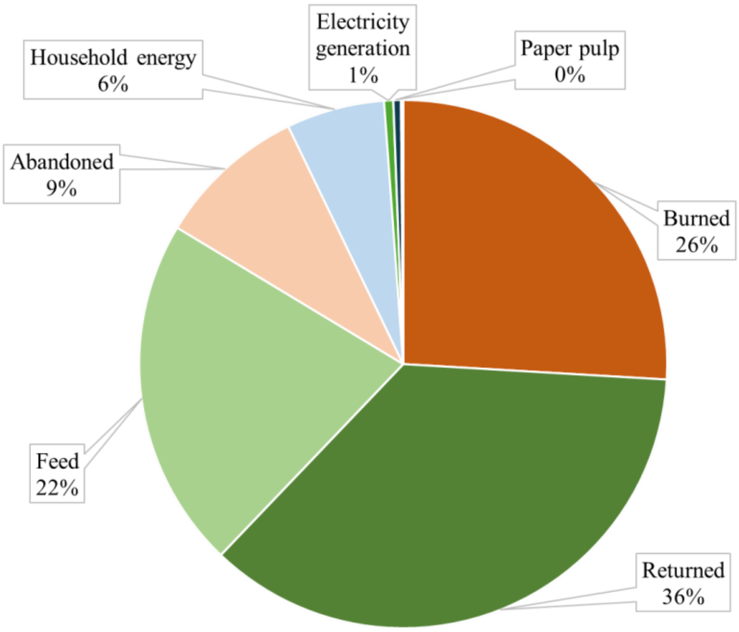


Figure A5. The proportion of straw utilization in 2016 in China

Note: (a) Data comes from Fang, Y.R., Wu, Y., Xie, G.H., 2019. Crop residue utilizations and potential for bioethanol production in China. Renewable and Sustainable Energy Reviews 113, 109288.

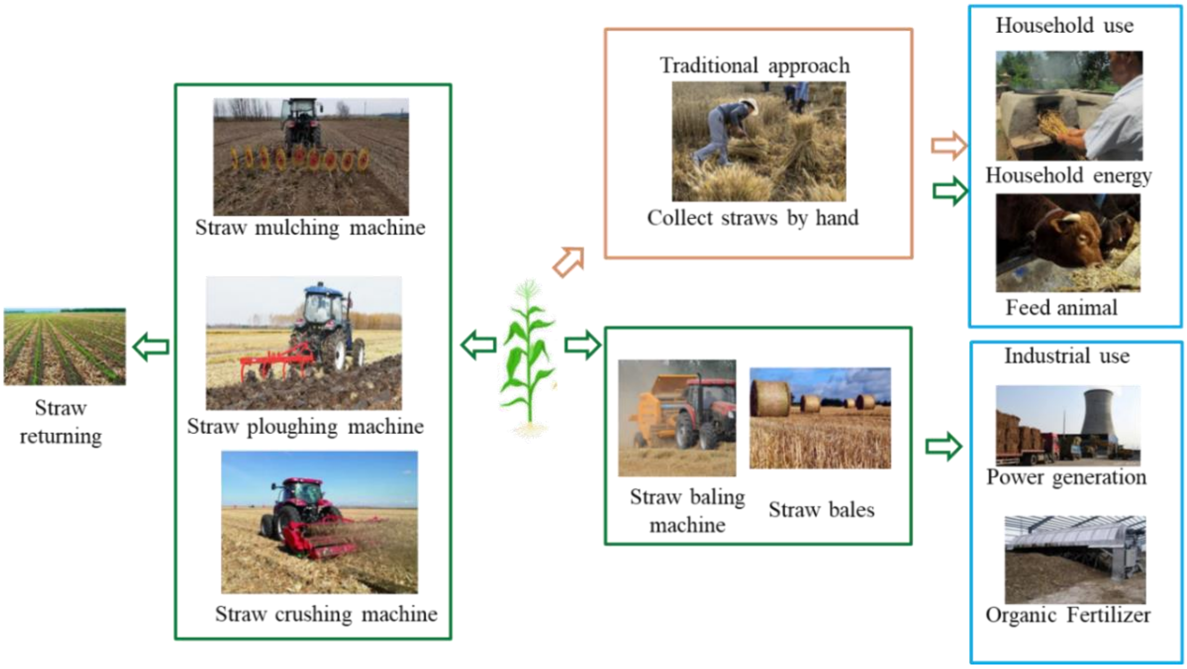


Figure A6 Straw sustainable utilization

Note: The pattern of straw sustainable use is summarized by the authors

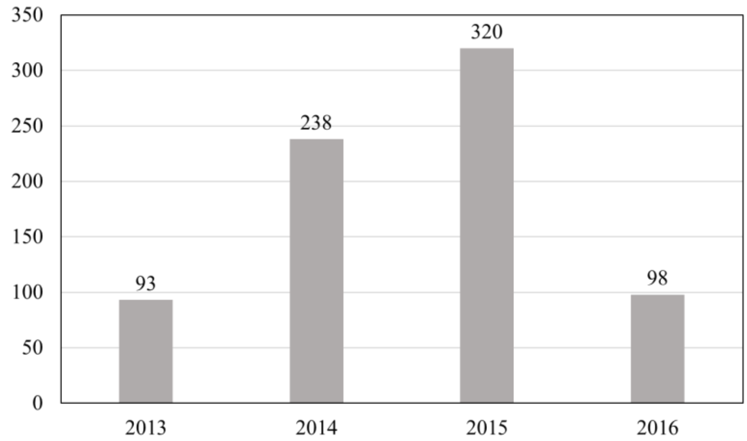


Figure A7. The yearly distribution of newly adopted Grid Management (GM) counties

Note: (a) The vertical axis depicts the count of counties that newly introduced GM. For instance, in 2014, 238 counties adopted GM, resulting in a total of 331 counties (238 + 93) implementing GM.

Table A1. Demonstration of Grid Management (GM) implementation

Province	Year	Policy title	Source	Principle: Geographical division	Principle: Performance evaluation	Principle: Penalty/reward rules
Jiangsu	2013.5	Measures for Assessment and Reward of Straw Burning Prohibition Work in Jiangsu Province	http://www.jintan.gov.cn/html/czjt/2013/JHIOAQHC_0517/3927.html	Establish a responsibility system of OSB regulation, sign responsibility certificates at all levels, and implement responsibilities for each person	A special inspection working group for the ban on OSB and comprehensive utilization of straw was established to supervise the ban on burning and comprehensive utilization of crop straw.	A one-time fine of RMB 10,000 will be deducted for each OSB spot in the county discovered by superior inspections or satellite remote sensing monitoring.
Anhui	2014.5	Notice from the General Office of the People's Government of Anhui Province on the issuance of the province-wide straw burning ban work plan in 2014	https://www.ah.gov.cn/public/1681/7946971.html	Each prefecture and county government has overall responsibility for the OSB regulation within its jurisdiction. The main responsible comrade of the government is the first person responsible, and the comrades in charge of the specific tasks are the specific responsible persons.	The assessment includes the intensity of OSB spots per million acres of crop planting area and the ban on burning in key areas.	For counties with more than 10 OSB numbers per million acres of crop planting area within their jurisdiction, the provincial government will interview the main persons in charge of the city and county governments.
Shandong	2014.9	Notice of Shandong Province on Strengthening the Burning Ban	https://www.pkulaw.com/lar/5e2819bc1c0eec4a5ff1310375c69bb4bdfb.html?keyword=%E7%A7%B8%E7%A7%86%20&way=listView	In accordance with the principle of localized management, each district and municipal government is responsible for banning straw burning within its jurisdiction.	Remote sensing monitoring of OSB spots is used to increase inspection and supervision of key areas.	The main leaders of the party and government must take charge personally, formulate practical implementation plans and internal assessment mechanisms for the ban on straw burning, and decompose target responsibilities at all levels.
Henan	2015.5	Notice of Henan Province on Strengthening the Banning of Straw Burning	https://www.henan.gov.cn/2015/06-29/247129.html	Work plans for banning straw burning and comprehensive utilization are formulated at each level, and grid management is implemented in which county cadres are responsible for townships, and township cadres are responsible for villages.	The assessment is based on the number of OSB spots and precise fire locations provided by the Provincial Environmental Protection Department.	For each OSB spot in the county, the provincial finance department directly deducts 500,000 yuan from the financial resources of the relevant county government.

Hebei	2015.5	Decision to Promote Comprehensive Utilization of Crop Straws and Ban Open Burning	http://hbepb.hebei.gov.cn/hbhjt/zwgk/zc/101645876394126.html	Incorporate the ban on straw burning into the grid-based management system, improve the working mechanism, make full use of scientific monitoring methods, and establish and improve fire disposal mechanisms	People's governments at all levels should establish and improve the assessment and evaluation mechanism and work reward and punishment system for the comprehensive utilization of straw and the prohibition of OSB.	For those who do not work well and cause open burning with serious consequences, the main responsible person should be held accountable.
Liaoning	2016.9	Interim Provisions on Accountability for the Prevention and Control of Straw Burning in Liaoning Province	https://www.ln.gov.cn/web/zwgkx/lnsrmzfgb/2016n/qk/2016n_desyq/szfbgtwj/25B4FE02B24245598C52DFD017F3CB35/index.shtml	Establish a three-level straw burning ban responsibility system of the county, town government, community, and village autonomous organization	According to the fire point information discovered by satellite remote sensing monitoring of OSB spots announced by the Ministry of Environmental Protection and provincial inspections, the government's responsibility shall be held	If three or more OSB spots are discovered in an administrative district at the county level within one day, the prefecture government will hold them accountable.
Jilin	2018.9	Measures for Quantitative Responsibility of Straw Burning Prohibition in Jilin Province	http://www.jl.gov.cn/szfzt/bhhjlxlg/zgdt_bhhj/201812/t20181226_5445989.html	Establish a grid-based supervision and guarantee responsibility system	According to the fire point information discovered by satellite remote sensing monitoring of OSB spots announced by the Ministry of Environmental Protection and provincial inspections, the government's responsibility shall be held	If four OSB spots are discovered in an administrative district at the county level within one day, the prefecture government will hold them accountable.
Heilongjiang	2018.9	Interim Provisions on Rewards and Punishments for Prohibiting Straw Burning in the Open Air in Heilongjiang	https://www.waizi.org.cn/policy/48454.html	Establish an interconnected grid management system. The first to fourth-level grid consists of the prefecture, county, town governments, and the village committee.	According to the fire point information discovered by satellite remote sensing monitoring of OSB spots announced by the Ministry of Environmental Protection and provincial inspections, the government's responsibility shall be held.	If eight OSB spots are discovered in an administrative district at the county level within one day, the prefecture government will hold them accountable.

Note: (a) As Jiangsu and Anhui implemented the policy early on, we were unable to locate the website source from the provincial government. Consequently, we opted to use websites from the prefectural government as substitutes. (b) OSB represents open-air straw burning. (C) Grid Management is expressed as different names such as "responsibility system", "localized management".

Table A2. Straw-returning costs

	Cost (Yuan/ha)	Occurrence probability	Expected cost
1. Visible cost			
1.1 Fixed cost			
Machine investment, yuan	164789.66	100%	64789.66
Maintenance, yuan/year	2298.01	100%	2298.01
1.2 Marginal cost			
Labor, yuan per ha, yuan/ha	50.87	100%	50.87
Fuel, yuan per ha, yuan/ha	152.21	100%	152.21
2. Invisible cost			
Pest damage	262.16	23.64%	61.98
Weed damage	301.94	29.30%	88.47
Seeds not germinating	2050.48	24.28%	497.88

Note: (a) The data comes from our farm survey. In 2021, we conducted surveys involving 80 cooperatives and 278 farmers in Lishu County, situated in Jilin Province. (b) The fixed and marginal costs are calculated using the cooperatives' survey. (c) The invisible cost is from the farmers' survey. (d) The occurrence probability is calculated by the proportion of farmers who reported damage.