frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 03 November 2022
DOI 10.3389/fenvs.2022.1008036

The impact of agricultural machinery services on cultivated land productivity and its mechanisms: A case study of Handan city in the North China plain

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SPECIALTY SECTION
This article was submitted to Land Use Dynamics,
a section of the journal
Frontiers in Environmental Science

RECEIVED 31 July 2022
ACCEPTED 17 October 2022
PUBLISHED 03 November 2022

CITATION
Liu Y, Shi X and Gao F (2022), The impact of agricultural machinery services on cultivated land productivity and its mechanisms: A case study of Handan city in the North China plain.
Front. Environ. Sci. 10:1008036.
doi: 10.3389/fenvs.2022.1008036

Studying the impact of agricultural machinery services (AMS) on cultivated land productivity is conducive to scientifically improving agricultural production and has far-reaching significance for ensuring food security. Taking Handan City in the North China Plain as the research context and using a surveyed sample of 1918 farming households, this paper examines the effect of AMS on the productivity of cultivated land using OLS estimation and estimates the average treatment effect on the treated (ATT) using the propensity score matching (PSM) method. The research findings are as follows. 1) AMS has a significantly positive impact on cultivated land productivity, and a heterogeneity analysis finds that the effects are larger for farmers with relatively less cultivated land and the marginal effects decrease as the adoption of AMS increases. 2) In various planting activities, AMS adoption in basic activities (e.g., ploughing, seeding, and harvesting) has positive effects on cultivated land productivity, while AMS adoption in management activities (e.g., fertilizing, irrigation, and pesticide spraying), has no obvious effect on cultivated land productivity. 3) According to the results of ATT, the conversion of non-adopting farmers to adopting AMS would increase cultivated land productivity by 7.6%–12.1%. 4) A mechanism analysis reveals that AMS adoption relieves financial constraints, improves technical efficiency, and increases smallholders' crop yields. These results suggest that AMS has a positive effect on cultivated land productivity and therefore have valuable policy implications for increasing smallholders' access to various types of AMS to improve the productivity of cultivated land in regions dominated by smallholders.

KEYWORDS

agricultural machinery services, cultivated land productivity, smallholders, mechanism identification, the North China plain

1 Introduction

Cultivated land productivity is an important indicator for facilitating agricultural production, ensuring food security, and alleviating poverty as well as improving the welfare of farmers (Desiere and Jolliffe 2018; Khan et al., 2019; Zhou and Ma, 2022). In developing countries that have undergone the green revolution and structural transformation (such as China, Thailand, and Myanmar), the rural population has been attracted by increasing wage rates in the urban sector (Belton et al., 2021). A trend towards a gradual shortage of agricultural labor has emerged. Mechanization is an effective labor-saving method, although smallholders have only a limited capacity to acquire and apply machinery as it carries a heavy financial burden and their farms are both small in scale and fragmented (Benin 2015; Adekunle et al., 2016; Qiao 2020; Wang et al., 2020; Mahasuweerachai and Suksawat 2022). In this context, increasing the availability of agricultural machinery may contribute to the viability of smallholder farming and therefore boost cultivated land productivity (Rigg et al., 2016; Takeshima, 2017; Zhang et al., 2017).

China, with 232.1 million farms occupying less than 10 mu (0.67 ha) of cultivated land, has experienced rapid agricultural mechanization during the last few decades (Yu and Zhao, 2009). This trend toward mechanization has relied on the growth of agricultural machinery services (AMS) (Yang et al., 2013; Wang et al., 2020; Qiu et al., 2021; Liu et al., 2022). Some of smallholders' planting activities can be undertaken by mechanized service providers on a much larger scale. For example, Zhang et al. (2017) described harvesting services, a typical AMS offering that utilizes the time lag between regional crop harvesting in China, which can last up to 8 months per year. By tapping into the national machinery services market, AMS may be able to overcome the constraints facing mechanization stemming from the small scale of farms and the fragmentation of cultivated land. This dynamic is not unique to China. Similar services have existed, for example, in Myanmar, Bangladesh, and Thailand in Southeast Asia (Mottaleb et al., 2017; Chaya et al., 2019; Belton et al., 2021), and in Ghana and South Africa in Africa (Benin, 2015; Emmanuel et al., 2016; Lyne et al., 2018).

The contemporary context of AMS gives rise to two major themes in the mechanization literature. First, the role of AMS in enhancing machine availability for smallholders and the determinants of AMS adoption (Yang et al., 2013; Lyne et al., 2018; Justice and Biggs 2020; Belton et al., 2021). Second, the impact of AMS on overcoming the shortage of family labor in agricultural production (Zhang et al., 2017), reducing the cost of agricultural production (Tang et al., 2018), and increasing crop income and household welfare (Wang et al., 2016; Mi et al., 2020). AMS adoption is also associated with the farm size adjustment and off-farm employment decisions of rural households (Ji et al., 2012; Qiu et al., 2021; Qian et al., 2022). Considering the effects of AMS on agricultural inputs and outputs, it follows that it may also affect cultivated land productivity. To date, although the potential impact of AMS adoption on cultivated land productivity has been mentioned in some studies (e.g., Justice S and Biggs S; Qiu et al., 2022), few studies examined how AMS may affect cultivated land productivity.

The objective of this paper is therefore to understand whether AMS improves cultivated land productivity and to examine its potential impact mechanisms, which have broader implications for farmers' welfare and national food security. The results of this study will help to reveal the impacts and obstacles to increasing cultivated land productivity in the presence of AMS. China is a new frontier for AMS research and the results may be of general relevance to other developing countries where AMS has emerged and agricultural systems are dominated by smallholders. The North China Plain is used as the research context in this paper considering that it is dominated by smallholders and its plain terrain is suitable for mechanization. In fact, AMS has been developed for decades in this area. This paper estimates the impact of AMS adoption on agricultural production in general and in different planting activities (e.g., ploughing, seeding, fertilizing, pesticide spraying, irrigation, and harvesting) in particular on arable land productivity, and estimates the average treatment effect on the treated (ATT). We collected our data through face-to-face interviews. The potential mechanisms of the impact of AMS on cultivated land productivity, such as the inputs of labor, capital, and technology, are further examined.

Our study extends the findings of previous studies and contributes to the literature on several fronts. First, our research focuses on the effect of AMS on cultivated land productivity at the micro-level by taking smallholders as the research sample. Despite evidence that mechanization affects cultivated land productivity (e.g., Ito, 2010; Zhou and Ma, 2022), the potential effects of AMS have been neglected in the existing literature. The adoption of AMS, as a market service purchase decision, represents neither an agricultural investment nor the acquisition of a household asset, but may allow smallholders to access mechanization that may have previously been held out of reach by financial constraints or small farm size. In addition, this paper provides implications for ensuring food security and promoting agricultural production, both of which remain serious challenges in many developing counties.

Second, this paper provides insights into AMS, including its adoption rate in general as well as that in various planting activities. Basic services include ploughing, seeding, and harvesting, and management services include fertilizing, spraying, and irrigation. As such, we follow the existing studies in measuring the overall adoption of AMS and adopt other, more detailed measures based on this. Meanwhile, this paper analyzes the heterogeneous impact of different types of AMS and estimates the ATT, which can provide a more targeted reference for policy-makers.

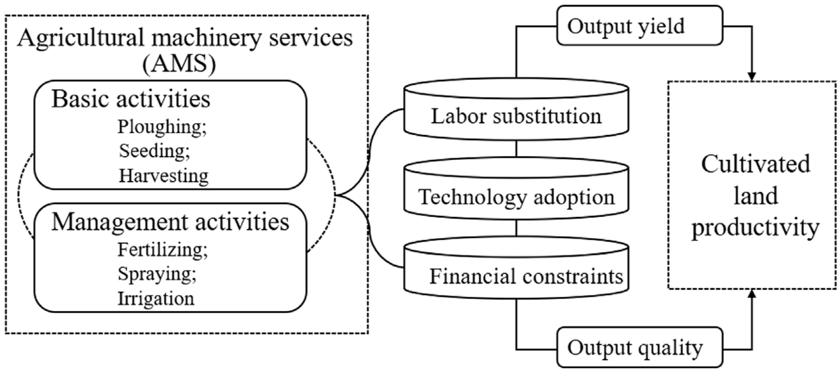

FIGURE 1
Conceptual framework of the impact of AMS on cultivated land productivity.

Finally, this study develops a conceptual framework for understanding the underlying mechanisms between AMS adoption and cultivated land productivity that includes factors such as agricultural labor substitution, financial constraints, technological improvements, and output quality and quantity enhancement and empirically tests these mechanisms. This extends upon the existing research and provides more detailed information with which to explain the pathways of the effects of AMS on agricultural production.

The rest of this paper proceeds as follows. Section 2 illustrates the conceptual framework. Section 3 introduces the data sources and describes the identification strategy. The results are presented and analyzed in Section 4. Section 5 concludes and suggests policy implications.

2 Conceptual framework

The essential elements of farming are land, labor, capital, and technology. For developing countries, the contributions of AMS are mainly reflected by its capacity to relieve the input constraints of agricultural labor, capital, and technology (Yang et al., 2013; Benin, 2015; Tang et al., 2018). In this study, we analyze the effect of AMS on cultivated land productivity through these mechanisms. Figure 1 depicts a simplified framework of potential mechanisms and illustrates how AMS adoption affects cultivated land productivity.

The first mechanism highlights the impact of AMS on cultivated land productivity by alleviating the constraints caused by agricultural labor shortages. The rising wage rate and the wage gap between rural and urban sectors have attracted increasingly rural labor migration, which has resulted in the agricultural labor pool shrinking and aging over time (Ji et al., 2012; Yamauchi, 2016; Min et al., 2017; Yu et al., 2021). Input constraints on the quantity and quality of agricultural labor may lead to extensive farming operations and lagging technology adoption, and ultimately reduce cultivated land productivity. AMS, as an available source of mechanization for smallholders, can reduce labor drudgery and alleviate agricultural labor shortages at a relatively lower cost than hired labor and/or purchased machinery (Tang et al., 2018; Daum and Birner, 2020; Qiao, 2020). As such, the adoption of AMS can reduce or compensate for the loss of cultivated land productivity due to agricultural labor shortages.

The second mechanism focuses on the impact of AMS on the application of agricultural technology. The adoption of specialized agricultural techniques, such as deep soil ploughing, straw returning, and soil formula fertilization, often requires specific types of machinery (Shikuku, 2019; Zhou et al., 2020; Yu et al., 2021). Smallholders are constrained by factors such as access to information and capital as well as the limited size of cultivated land, and their adoption of new technologies is often slow and/or limited as a result (Tan et al., 2006; Zhang et al., 2017). AMS provides mechanized operations and acts as a transmitter of agricultural technology (Mi et al., 2020; Yu et al., 2021). As such, AMS may lead to technological improvement *via* the substitution of agricultural labor by mechanization as well as through the use of specialized machinery. In this way, AMS can facilitate the adoption of agricultural technologies and improve the technical efficiency of smallholders and thus potentially increase cultivated land productivity (Pfeiffer et al., 2009; Kousar and Abdulai, 2016).

The third mechanism refers to the effect of AMS on financial constraints in agriculture. Various types of AMS can relieve the financial burden of purchasing machinery. Most agricultural machines have strong asset specificity; that is, they cannot easily be adapted for other purposes. Purchasing multiple complex and specified agricultural machines would require smallholders to assume a prohibitively heavy financial burden (Yu et al., 2021). Moreover, the mechanisms for labor-saving and adopting new technologies can separately reduce the cost per unit of cultivated land or the unit output yield. Therefore, the adoption of AMS may relieve smallholders' financial constraints and allow them to secure the capital inputs needed to increase their cultivated land productivity (Ma and Abdulai, 2016).

In light of the aforementioned mechanisms, AMS adoption may allow smallholders to secure essential inputs for agricultural production, reduce financial constraints and productivity loss due to agricultural labor shortages, and increase productivity through technology improvements. These effects manifest in terms of increased crop yield and/or quality. For example, the adoption of deep soil ploughing as a soil improvement measure may contribute to improving yield and/or output quality and thus improve cultivated land productivity (Pfeiffer et al., 2009; Kousar and Abdulai 2016). We therefore hypothesize that the adoption of AMS can increase cultivated land productivity.

Due to the unique characteristics of each planting activity, AMS adoption may have different effects in different activities. For example, a mechanized harvesting service allows farmers to reduce labor inputs as well as relieve financial constraints as they are not required to purchase the harvester. However, sprayers are relatively cheaper than harvesters, and AMS for pesticide spraying mainly substitutes labor rather than financial input. We divide planting activities into basic activities and crop management activities based on their characteristics. The former includes ploughing, seeding, and harvesting, all of which are essential and the mechanization of which relies on relatively expensive large machinery such as tractors and harvesters. The latter concerns fertilizing, spraying, and irrigation. Farmers may engage in these activities a variable number of times during planting, and their mechanization is largely based on the use of small machinery. As an example, the frequency of pesticide spraying depends on seasonal pest conditions, and the required sprayer is relatively inexpensive. In terms of the intensity of the labor input required for the different planting activities, basic activities often require intense physical input, while management can be done by older workers who are relatively less physically capable.

Considering the differential impact of AMS adoption in basic and management activities on capital constraints and labor input intensity, it follows that smallholder that predominantly use family labor are more likely to adopt AMS in basic activities and thus be more affected by it overall. Therefore, we hypothesize that AMS adoption in basic activities has a larger impact on cultivated land productivity than AMS adoption in management activities.

3 Materials and methods

3.1 Data source

The data used in this study were obtained from a rural household survey conducted in the North China Plain. This survey was conducted in February 2018 through face-to-face interviews in collaboration with Nanjing Agricultural University and China Agricultural University. With the assistance of computer-assisted personal interviewing techniques, we used an open-source software, ODK, to design the questionnaire and collect rich data (such as photos, GPS location and agricultural production data). It provides detailed information on the input and output of agricultural production in 2017 as well as the basic characteristics of rural households and villages.

Handan city, a prefecture-level city in Hebei Province, is set as a case study area in the North China Plain. The topography in Handan city is diverse, the west of which is the mountain and the hill (46%), while the east is the plain (54%). We selected four adjacent counties in the northeast, including Feixiang, Jize, Qiu, and Quzhou. The locations are shown in Figure 2. These four counties share some key characteristics which could help focus on our key research questions. First, they are all plain topography and are dominated by smallholders. Second, the majority of farmers grow double-season crops that consist of winter wheat and summer maize. Third, AMS has been developed for a few decades. (Liu et al., 2022). Moreover, these four counties differ in distance from Handan city center and then imply the variance in off-farm employment and AMS, which is necessary for the empirical identification. Therefore, the study area is representative of the North China Plain, which not only reduces the concerns about inconsistent results caused by agricultural production conditions, but also provides the necessary variation in key explanatory variables.

A multi-stage random sampling method was used in these four adjacent counties. Most townships in these four counties were selected as surveyed regions[1], and the townships were divided into three groups according to the number of villages in the township (i.e., 1–10, 11–20, and >20 villages). From each of these three groups, two, four, or six villages were randomly selected. In each of the selected villages, 16 households were randomly selected from a list of household heads. In total, 2080 households were randomly chosen from 130 villages. We used a sample of 1918 of those households that engaged in farming. The majority of the farmers in this area grow double crops, including winter wheat and summer maize. The composition of the sample is shown in Supplementary Appendix.

3.2 Variable definitions and descriptive analysis

The dependent variable for cultivated land productivity is measured as output per unit of cultivated land area. This is consistent with many existing studies (e.g., Martey et al., 2019; Zhou and Ma., 2022). In our study area, farmers usually grow more than one crop. To ensure consistent estimates of cultivated land productivity among the sampled households, we took the logarithm of the total value of maize and wheat per mu (15 mu = 1 ha).

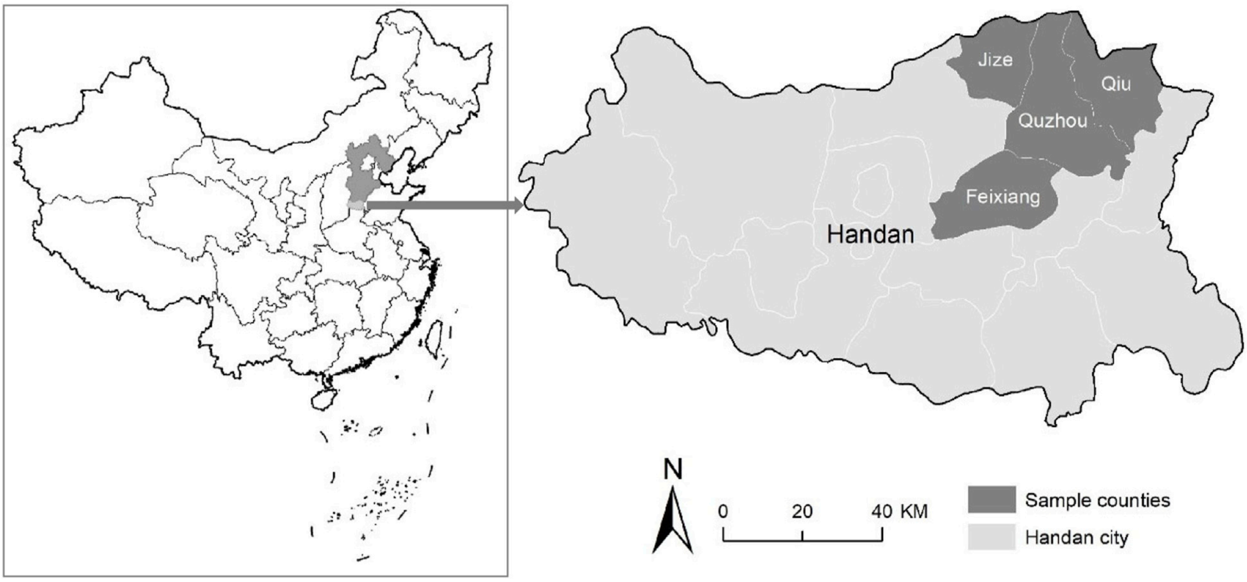

FIGURE 2
Geographical location of the study area.

In this study, the treatment variable refers to farmers' AMS adoption status. The treatment and non-treatment groups are classified as adopters and non-adopters based on their adoption of AMS. This is consistent with many studies that have focused on the impact of AMS on farm size adjustment, agricultural income, and the welfare of rural households (e.g., Chaya et al., 2019; Mi et al., 2020; Qian et al., 2022). Crop cultivation encompasses a variety of activities, such as ploughing, seeding, fertilizing, spraying, irrigation, and harvesting, which, in the study area, may require mechanization in the cultivation of wheat and maize. Thus, to identify the different effects of AMS in various planting activities, the treatment groups can be divided according to AMS adoption in general as well as that in each planting activity.

As described in Chapter 2, we divide planting activities into basic activities and crop management activities based on the characteristics of each. The overall proportion of AMS adoption in basic activities is relatively high (i.e., 86.9%–92.5%; see Table 1) and has been largely mechanized, while the average proportion of AMS adoption in crop management activities, which are generally performed manually or through the use of owned machines, is relatively low and ranges from 1.1% to 13.7% (also see Table 1). The obvious difference in the adoption rate between basic and management activities is consistent with the theoretical analysis in Section 2. As such, this study seeks to examine the impact of AMS adoption on cultivated land productivity, including overall adoption, adoption in different types of services, and adoption in each planting activity.

Drawing upon the work of Takeshima (2017), Baiyegunhi et al. (2019), Amoozad-Khalili et al. (2020), Zhou and Ma (2022), this study adds control variables in three categories that describe the characteristics of the household head, family, and village. The variables in the household head category include age, gender, education (in years), participation in agricultural training, off-farm experience, and membership in village cadres. Family-level variables include household size, contract land area, the net change in cultivated land area through land rental, main soil type of cultivated land, number of tractors owned, and the availability of loans. The variables in the village category include distance to the nearest township, the total number of households, and the total area of arable land. Detailed definitions and descriptive statistics for the above variables are presented in Table 1. To detect the collinearity, we tested for the degree of multicollinearity amongst the independent variables. The mean VIF (Variance inflation factors) for the independent variables was 2.42. Therefore, there was no significant multicollinearity amongst the independent variables.

3.3 Estimation strategy

As mentioned above, this study is interested in assessing the impact of AMS on cultivated land productivity. We begin by estimating the relationship between AMS adoption and cultivated land productivity at the household level. The specified equation is set as follows:

TABLE 1 Variable definitions and summary statistics.

Variable	Definition	Mean	S.D.
Dependent variables			
Land productivity	Total output value of cultivated land (RMB/mu), log	7.464	0.203
Independent variables			
AMS ratio	Percentage of planting activities adopted AMS (%)	42.07	14.67
Basic services	1, if any basic activities (ploughing, seeding, harvesting) adopted AMS	0.947	0.224
Ploughing	1, if AMS was adopted in ploughing activity; 0, otherwise	0.869	0.337
Seeding	1, if AMS was adopted in seeding activity; 0, otherwise	0.925	0.263
Harvesting	1, if AMS was adopted in harvesting activity; 0, otherwise	0.885	0.319
Management services	1, if any management activities (fertilizing, spraying, irrigation) used AMS	0.208	0.406
Fertilizing	1, if AMS was adopted in fertilizing activity; 0, otherwise	0.137	0.344
Spraying	1, if AMS was adopted in spraying activity; 0, otherwise	0.011	0.104
Irrigation	1, if AMS was adopted in irrigation activity; 0, otherwise	0.092	0.289
Control variables			
Household head			
Age	Age of the household head (years)	57.550	10.300
Gender	1, if the household head is male; 0, if female	0.943	0.232
Education	Number of years of education of the household head (years)	6.981	3.589
Village leader	1, if the household is a village cadre; 0, otherwise	0.314	0.464
Training	1, if the household participated in agricultural training; 0, otherwise	0.063	0.243
Off-farm	1, if the household has held an off-farm job; 0, otherwise	0.105	0.307
Family			
Household size	Number of household members	4.752	2.207
Contract land	Area of contracted land (mu)	7.224	4.117
Rented land	Area of rented-in land from land rental market (mu)	0.880	3.972
Soil type[a]	Main soil types of arable land cultivated by family	1.950	0.897
Tractor	Number of tractors owned by household	0.143	0.386
Credit	1, if a loan can be obtained from banks; 0, otherwise	0.198	0.399
Village			
Township distance	Village distance to the nearest township (km)	12.719	7.368
Household number	Total number of households in the village	306.070	191.319
Village cultivated land	Total size of village arable land (mu)	1840.884	955.747

Note: 6.18 RMB, 1 dollar (2018).[a] 1 = sandy soil; 2 = loamy soils; 3 = clay; 4 = others.
Data source: Authors' survey.

$$Y_i = \alpha_0 + \alpha_1 AMS_i + \alpha_2 \boldsymbol{X}_i + \sigma T_i + \mu_i \tag{1}$$

where Y_i represents the dependent variable for household i (i.e., cultivated land productivity) measured as the logarithm of output value per unit area of cultivated land. AMS_i is a set of variables on the AMS adoption of household i that includes the AMS adoption rate in total planting activities and that in different activities, including basic and management activities. $\boldsymbol{X}_i$ controls the characteristics of the household head, family, and village, which also affect land productivity. T_i is a series of dummy variables at the township level to control for differences across townships (e.g., agroclimate) . μ_i is the error term. Because the dependent variable in this paper (i.e., cultivated land productivity) is a continuous variable, the OLS estimator is suitable for Eq. 1.

Because farmers are not randomly assigned into the groups of those who adopt AMS and those who do not, the adoption of AMS by rural households may be self-selective and thus the OLS estimator in Eq. 1 may be biased (Takeshima, 2017; Khan et al., 2019). To achieve an unbiased estimation of the impact of AMS adoption on cultivated land productivity, we should first address the selection bias. Several solutions have been used in the existing studies to solve the self-selection problem, such as the Heckman selection model, Endogenous switching regression, and the instrumental variable method. However, all such approaches face challenges in identifying appropriate instrumental variables (Mendola, 2007; Zhang et al., 2020). In this study, AMS involves a range of adoption variables related to the total planting process and to different planting activities. It is challenging to find suitable instrumental variables that affect the AMS adoption in the ploughing, seeding, irrigation, fertilizing, pesticide spraying, and harvesting activities while not directly affecting cultivated land productivity.

Following Dehejia and Wahba (2002) and Zhang et al. (2020), this study uses a statistical matching approach to estimate the average treatment effect on the treated (ATT). In particular, the matching method matches AMS adopters and non-adopters that have similar observable attributes. The matching estimator will have a consistent treatment effect when the dependent variable is independent of AMS adoption (Mendola, 2007). To estimate the average treatment effect of AMS on land productivity, for each rural household i, Y_{io} and Y_{i1} represent the outcomes for treated and untreated groups (i.e., the cultivated land productivity of AMS adopters and non-adopters), respectively. For a rural household, the treatment effect of AMS adoption on cultivated land productivity can be derived from $E(Y_{i1} - Y_{i0})$. Because the treatment is exclusive, it is impossible to observe the cultivated land productivity of non-adoption for those who actually adopt AMS. Similarly, for non-adopters of AMS, we could not observe their cultivated land productivity if they adopt AMS. Using the counterfactual framework proposed by Rosenbaum and Rubin (1983) to randomize the non-random data, this study estimates the counterfactual probabilities for the treatment and control groups. To estimate the impact of AMS adoption on cultivated land productivity, we use a matching method to calculate the ATT, which we estimate by the following equation:

$$ATT = E[(Y_{i1} - Y_{i0})|T = 1] \tag{2}$$

where T represents a binary variable for treatment status and takes the value of 1 if household i in the treated group is an AMS adopter and 0 otherwise. Matching methods usually assume ignorability, common support selection on observables, or confoundedness (Dehejia and Wahba, 2002; Imbens and Wooldridge, 2008). This implies that the differences in land productivity between the treatment and control groups after matching are uniquely attributed to the treatment attributes and that the matched observations assigned to the treated group are random (Uematsu and Mishra, 2012).

Propensity score matching (PSM) is employed to match the AMS adopters to non-adopters with similar characteristics and to ensure that dissimilar households and outliers will have little or no influence on the treatment effects (Rosenbaum and Rubin, 1985). As a commonly used matching estimate in treatment effect analysis, PSM has been widely used in the agricultural economics literature (e.g., Mendola, 2007; Imbens and Wooldridge, 2008; Uematsu and Mishra, 2012; Mishra et al., 2017). It is popularly used as a non-experimental method to estimate ATT for specific program participation or technology adoption (Smith and Todd, 2005; Caliendo and Kopeinig, 2008; Mi et al., 2020). For example, Zhang et al. (2020) used PSM to estimate the effect of land rental market participation on the labor productivity of rural households. PSM is a non-parametric type of estimate without any specific functional forms or distribution assumptions (Imbens and Wooldridge, 2008). With the matched sample, ATT can be estimated directly by comparing outcomes between the treated and untreated groups (Austin, 2011). In this study, the control group is a sample of farm households that do not adopt AMS but have similar characteristics to those that do. We construct a near-random counterfactual dataset to compare the impact of AMS on cultivated land productivity.

The shortcoming of the PSM approach is that it cannot eliminate the selection bias caused by unobservable factors. If an unobservable factor simultaneously affects both the observations assigned to the treated group and the outcome variable, a hidden bias may arise to which matching estimation is not robust (Rosenbaum, 2002). For example, a farmer's agricultural ability is difficult to observe, although it may affect both AMS adoption and cultivated land productivity. In recognition of this, a sensitivity analysis of the robustness of the estimates is conducted to determine how strongly unobservable factors affect AMS adoption. We estimate a critical odds ratio as proposed by Rosenbaum and Rubin (1983) and Rosenbaum (2002) and followed by studies such as Khan et al. (2019) and Zhang et al. (2020).

4 Results

4.1 OLS estimation results

4.1.1 Main results

The estimated results of Eq. 1 are reported in Table 2. In column (1), the estimated coefficient of AMS is positive and statistically significant. The results show that the adoption rate of AMS increases cultivated land productivity when controlling for the characteristics of the household head, family, and village. A similar positive relationship between mechanization and land productivity was found by Paudel et al. (2019) in Nepal, and Zhou and Ma (2022) in China. This result is consistent with the hypothesis that the adoption of AMS has a positive impact on cultivated land productivity and implies that AMS can play an active role in promoting agricultural production and ensuring food security.

In addition to AMS, several control variables have a significant effect on cultivated land productivity. Specifically, the coefficients on the years of education and the membership in the village cadre of household heads are positive and significant. These are in line with existing studies that have found that the efficiency of household agricultural production is related to the capacity of the household head (Khan et al., 2019; Zhou et al., 2019; Zhang et al., 2020). Moreover, loan availability has a significant and positive impact on cultivated land productivity, thus indicating that the less financial

TABLE 2 OLS regression for the effect of AMS on cultivated land productivity.

	Full sample	Farm size		AMS ratio	
		[0,50]	(50,100]	[0,50]	(50,100]
	(1)	(2)	(3)	(4)	(5)
AMS ratio	0.002***	0.003***	0.002***	0.004***	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Age	0.000	0.000	0.000	0.000	-0.000
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Gender	0.005	−0.012	0.044	0.000	0.037
	(0.020)	(0.024)	(0.036)	(0.022)	(0.043)
Education	0.003*	0.004**	0.000	0.003*	0.003
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
Village leader	0.029**	0.008	0.047*	0.023	0.037
	(0.014)	(0.019)	(0.025)	(0.018)	(0.027)
Training	0.026*	0.034	0.025	0.034**	-0.047
	(0.015)	(0.023)	(0.021)	(0.017)	(0.042)
Off-farm	−0.002	−0.011	0.010	−0.006	0.015
	(0.010)	(0.016)	(0.016)	(0.013)	(0.020)
Household size	0.003*	0.004	0.003	0.004*	−0.003
	(0.002)	(0.003)	(0.003)	(0.002)	(0.005)
Contract land	0.002*	0.005	0.004**	0.001	0.006**
	(0.001)	(0.004)	(0.002)	(0.001)	(0.002)
Rented land	0.000	0.001	0.001	0.001	−0.001
	(0.001)	(0.009)	(0.001)	(0.002)	(0.002)
Soil type	0.008	0.003	0.017**	0.009	0.011
	(0.006)	(0.008)	(0.008)	(0.007)	(0.011)
Tractor	0.014	0.009	0.017	0.012	0.041
	(0.015)	(0.030)	(0.016)	(0.016)	(0.033)
Credit	0.047***	0.032*	0.064***	0.050***	0.014
	(0.010)	(0.017)	(0.014)	(0.012)	(0.024)
Township distance	−0.001	0.001	−0.003**	−0.002	−0.002
	(0.001)	(0.002)	(0.002)	(0.001)	(0.003)
Household number	−0.000	−0.000	−0.000	−0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Village cultivated land	0.000	0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Township FE	Yes	Yes	Yes	Yes	Yes
Constant	7.372***	7.266***	7.246***	7.251***	7.255***
	(0.052)	(0.064)	(0.079)	(0.055)	(0.126)
F test	8.74***	2.46***	3.48***	4.00***	2.20***
R^2	0.105	0.125	0.140	0.120	0.243
Observations	1918	967	951	1596	322

Note: The standard errors clustered at village level are shown in parentheses. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.
Data source: Authors' survey.

constraints, the higher possibility that farmers can increase land productivity. The village-level variables are not significant, most likely because the township fixed effect controls for most regional differences.

4.1.2 Heterogeneity analysis results

In columns (2) to (5) of Table 2, we explore the heterogeneity of the impact of AMS adoption on cultivated land productivity to deepen our understanding of this relationship. First, the sample is

TABLE 3 OLS regression for the effect of AMS on cultivated land productivity by planting activity.

Dependent variable: Cultivated land productivity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Basic services	0.109***							
	(0.038)							
Plaughing		0.076***						
		(0.019)						
Seeding			0.101***					
			(0.032)					
Harvesting				0.121***				
				(0.027)				
Management services					−0.016			
					(0.000)			
Spraying						−0.018		
						(0.012)		
Irrigation							−0.090	
							(0.060)	
Fertilizing								−0.005
								(0.014)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Township FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F test	9.02***	8.58***	9.34***	8.48***	7.81***	7.70***	7.53***	7.69***
R^2	0.091	0.092	0.093	0.111	0.078	0.079	0.080	0.078
Observations	1918	1918	1918	1918	1918	1918	1918	1918

Note: The standard errors clustered at the village level are shown in parentheses. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.
Data source: Authors' survey.

divided into two subsamples based on the median farm size, with columns (2) and (3) reporting the results of AMS adoption for farmers operating relatively smaller and larger farms. We find that AMS is more effective in increasing the cultivated land productivity among farmers with relatively small farms. Considering that smallholders usually operate fragmented plots and lack collateral, it is likely that they face financial constraints. As a result, it is more difficult for smallholders to access mechanization through machinery ownership, which is the standard method of mechanization (Tan et al., 2006; Wang et al., 2020). Furthermore, AMS can offer smallholders easier access to mechanization in various planting activities and thus has a greater effect on cultivated land productivity among farmers with relatively small farms. This finding is largely consistent with that of Zhou and Ma (2022) that small farms are more beneficial to land productivity through mechanization.

We separate the sample into observations with below-median and above-median AMS adoption rates for separate analyses. The estimated results are reported in columns (4) and (5). We find that households in the lower adoption rate group benefit more from AMS in terms of cultivated land productivity. In contrast, the coefficient for the higher adoption rate group is not significant. These results imply that the marginal effects of AMS adoption decrease as the rate of AMS adoption increases.

4.1.3 Effects of AMS adoption in different planting activities

Table 3 presents the estimated results of the adoption of AMS in different activities. The results in columns (1) to (4) reveal that the general adoption rate of AMS for basic activities and the specific adoption in the ploughing, seeding, and harvesting activities have significant and positive effects on land productivity at the 1% significance level. The effects of AMS adoption in basic activities on cultivated land productivity are between 7.6 and 12.1%. In contrast, columns (5) to (8) show that the adoption of AMS in management activities has no significant effect on cultivated land productivity. Combined with the reality that the rate of AMS adoption in management activities is very low compared to that in basic activities (see Table 1), the difference in the impact on cultivated land productivity between management and basic activities may be partly explained by the following two reasons. Machinery used in management activities (e.g., pumps) is less expensive than that used in basic activities (e.g., tractors), thus smallholders rely more on AMS in basic activities. And the agricultural labor force used

TABLE 4 Average treatment effect of AMS adoption on land productivity by PSM.

	Nearest neighbors	Mean outcome		Treatment effect	
		Treated	Controls	ATT	
AMS adoption	1	7.471	7.292	0.179**	(0.047)
	2	7.471	7.303	0.168***	(0.044)
	3	7.471	7.308	0.163***	(0.044)
Basic activities	1	7.468	7.296	0.172***	(0.047)
	2	7.468	7.296	0.172***	(0.045)
	3	7.468	7.303	0.164***	(0.044)
Plaughing	1	7.473	7.365	0.108***	(0.030)
	2	7.473	7.365	0.108***	(0.030)
	3	7.473	7.368	0.105***	(0.028)
Seeding	1	7.469	7.338	0.131***	(0.041)
	2	7.469	7.341	0.128***	(0.038)
	3	7.469	7.349	0.119***	(0.038)
Harvesting	1	7.476	7.335	0.141***	(0.036)
	2	7.476	7.354	0.122***	(0.033)
	3	7.476	7.355	0.121***	(0.032)
Management activities	1	7.456	7.466	−0.010	(0.017)
	2	7.456	7.470	−0.013	(0.015)
	3	7.456	7.475	−0.019	(0.014)
Fertilizing	1	7.446	7.471	−0.025	(0.020)
	2	7.446	7.473	−0.027	(0.018)
	3	7.446	7.473	−0.027	(0.017)
Spraying	1	7.377	7.392	−0.015	(0.087)
	2	7.377	7.422	−0.045	(0.073)
	3	7.377	7.451	−0.074	(0.070)
Irrigation	1	7.470	7.491	−0.021	(0.024)
	2	7.470	7.488	−0.018	(0.019)
	3	7.470	7.488	−0.018	(0.018)

Note: ATT, the average treatment effect on the treated; The standard errors are shown in parentheses. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.
Data source: Authors' survey.

by smallholders is often the residual family labor force after off-farm migration, which has a low opportunity cost and allows for the engagement in management activities that are relatively less physically demanding. The above results are therefore consistent with the hypothesis in the theoretical analysis that AMS adoption in basic activities has a larger impact on cultivated land productivity than AMS adoption in management activities.

4.2 Average treatment effects on the treated

Table 4 presents the results of the ATT of AMS on cultivated land productivity. We use the nearest neighbors matching method, and the radius matching method and kernel matching method are performed for comparison (see Supplementary Appendix). In particular, the households that adopt AMS in general, basic, and management activities are compared separately to the counterfactual households that do not adopt AMS. The results reveal a significant and positive impact of AMS adoption in general and basic activities as well as in each individual activity in basic services on cultivated land productivity. Since the dependent variable is in logarithmic form, the estimated results of ATT suggest that the overall adoption of AMS increases cultivated land productivity by between 16.3% and 17.9%. Furthermore, the AMS adoption in basic activities in general and in each individual activity increase land productivity by 10.3%–17.2%. However, the adopters of AMS in management activities are not significantly different from non-adopters in terms of cultivated land productivity.

Based on the results in Table 4, it can be concluded that in the absence of selection bias, cultivated land productivity for rural households who adopt AMS is significantly higher than that for non-adopters. This finding is similar to those of the studies that previously found a significant and positive effect of agricultural technology adoption on cultivated land productivity (e.g., Asfaw et al., 2012; Khonje et al., 2015; Zhou and Ma, 2022). In addition, the above results are also consistent with the results of the OLS estimation in Table 3 and support our first hypothesis. Given the consistency between the OLS and PSM results, it is convincing to use the ATT results of PSM to interpret the economic significance of the effect of AMS on cultivated land productivity, as well as to use the results of OLS regression to compare the effects among different groups mentioned above.

A Rosenbaum bounds sensitivity analysis is used to assess the presence of unobserved factors when the key assumption is relaxed by a quantifiable increase in uncertainty (Rosenbaum, 2002). The measurement of the critical value of hidden bias, Γ, is expressed in terms of the odds ratio of differential treatment. The magnitude of hidden bias, which would make the finding of a positive and significant effect of AMS adoption on cultivated land productivity questionable, should be higher than one[2]. At each Γ, we calculate the lower and upper hypothetical significance levels, which represent the bound on the significance level of the ATT in cases of endogenous self-selection into the treatment group. From the results of Rosenbaum's sensitivity in Supplementary Appendix, a hidden bias of Γ between 2.0 and 2.1 is required to declare that the finding of a positive effect of AMS adoption on cultivated land productivity is false. This small Γ suggests that the results of the ATT estimation can be trusted.

4.3 Mechanism test of the effect of AMS adoption on cultivated land productivity

Our analysis in the previous section demonstrates that AMS adoption increases cultivated land productivity both in general and in basic planting activities. This study also examines the heterogeneity in this effect across farm sizes and rates of AMS adoption. While limitations in the available data prevent us from revealing all possible mechanisms that link AMS adoption to cultivated land productivity, we consider the main mechanisms discussed in the conceptual framework (i.e., those shown in Figure 1), namely, labor substitution, technology improvement, financial constraints, and output yield and quality. The mechanism variables are defined and summarized in Supplementary Appendix.

The first mechanism is *via* the effect of AMS adoption on agricultural labor input. Column (1) of Table 5 shows that increasing the rate of AMS adoption has a negative effect on the amount of agricultural labor input needed by smallholders, although the coefficient is not significant.

2 Readers who are interested in the Rosenbaum sensitivity test are advised to read Rosenbaum (2002) and Diprete and Gangl (2004) for a detailed understanding of the method.

We speculate that the potential reasons for this insignificant result may be as follows. First, the labor force used by smallholders is usually the residual labor, that is, unable to obtain off-farm employment opportunities. In such a situation, even if AMS could reduce the input intensity of agricultural labor, this component of the household labor force may still engage in agriculture. Second, the adoption of AMS may result in the expansion of farm sizes, as found by Qian et al. (2022). Those households may then not be able to reduce the total amount of family labor needed for agriculture. Third, AMS adoption varies by planting activity, and activities for which AMS adoption is relatively weak generally rely on manual labor.

The second mechanism (i.e., technological improvement) is motivated by the idea of mechanization and has been cited in the literature as a mechanism for technological adoption. Because the adoption of AMS for different planting activities may involve different agricultural technologies that are not necessarily directly comparable with each other, we use technical efficiency as a more comparable measure of technological progress. We expect the adoption of AMS to improve the technical efficiency of adopters. As in previous studies (e.g., Villano and Fleming 2006; Michler and Shively 2015; Ma et al., 2017), we estimate technical efficiency using stochastic frontier analysis. In column (2) of Table 5, we find that AMS adoption has a significant and positive effect on technical efficiency. This is largely consistent with the existing studies that find that mechanization enhances technological improvement at the household level in Iran, Bangladesh, and parts of rural China (Hormozi et al., 2012; Zhou et al., 2019; Vorita et al., 2021).

The third mechanism is the effect of AMS on alleviating financial constraints. Financial constraints have been an important obstacle to smallholders purchasing agricultural machinery, adopting new technologies, and investing in agriculture. Given their lack of collateral, inter-farmer borrowing is the main method through which they alleviate financial constraints. In this paper, the number of times farmers borrowings from other villagers in the past 5 years is used to measure financial constraints. As the results in column (3) of Table 5 show, a rising adoption rate of AMS significantly reduces the frequency of borrowings from other villagers. This result is consistent with the theoretical analysis of Yu et al. (2021).

Increases in land productivity may be the result of quantity and/or quality improvements (i.e., increases in output yields and/or selling prices). Columns (4) and (5) show that the AMS adoption rate has a positive effect on crop yield, although there is no significant effect on selling price. Our results reveal that AMS adoption can increase the output yield per unit area of cultivated land. The insignificant coefficient on selling price can be partly explained by the low bargaining power of smallholders in agricultural markets, which makes selling prices relatively

TABLE 5 Mechanism analysis: the effect of AMS on potential mechanisms, OLS.

	Labor input	Technical efficiency	Financial constrains	Output yield	Selling price
	(1)	(2)	(3)	(4)	(5)
AMS ratio	−0.003	0.0004*	−0.016***	0.003***	−0.0004
	(0.002)	(0.0002)	(0.006)	(0.000)	(0.0003)
Controls	Yes	Yes	Yes	Yes	Yes
Township FE	Yes	Yes	Yes	Yes	Yes
F test	33.97***	8.89***	4.71***	9.37***	4.63***
R^2	0.321	0.086	0.056	0.116	0.102
Observations	1918	1888	1918	1918	1918

The standard errors clustered at village level are shown in parentheses. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.
Data source: Authors' survey.

exogenous to smallholders (Rutten, et al., 2017; Pingali et al., 2019).

5 Conclusions and policy implications

The importance of AMS for improving smallholders' access to mechanization and the need for mechanization to boost agricultural production and ensure food security have been greatly highlighted in the existing studies. However, few studies consider the effect of AMS, as a new mechanization source, on cultivated land productivity. In response to this gap, this study investigates the broad impact of AMS adoption and the adoption of AMS in various production activities on cultivated land productivity, and further identifies the mechanisms of those impacts. In the context of the North China Plain and based on the survey data of 1918 smallholders, this study uses OLS estimation as its basic results and PSM to address self-selection bias and estimate the average treatment effect on the treated (ATT).

The results of the OLS estimation show that AMS increases cultivated land productivity, especially for farmers with relatively small farms and relatively low AMS adoption rates. Moreover, we find that the adoption of AMS in basic activities (e.g., ploughing, seeding, and harvesting) significantly increases cultivated land productivity, while the adoption of AMS in management activities (e.g., spraying, irrigation, and fertilizing) has no obvious effect on land productivity. In addition, the results of PSM show that the adoption of AMS both in general and in basic activities increases cultivated land productivity by between 10.5% and 17.9%. Furthermore, we find that technological improvement, easing of financial constraints, and increasing yields are important mechanisms through which AMS affects cultivated land productivity.

Our findings have important implications for promoting agricultural modernization and ensuring food security. First, this study finds that AMS adoption can increase cultivated land productivity and suggests that improved adoption of AMS by smallholders can facilitate agricultural production. Second, the findings from the mechanism analysis suggest that AMS adoption can be an effective pathway for alleviating financial constraints, promoting technological improvement, and increasing crop yields. The existence of these mechanisms implies that there will be a complementary relationship between the extension of AMS and the support policies of the agricultural credit as well as the agricultural technology systems.

There are a few limitations that should be taken into account in interpreting and generalizing the results of this study. First, this study was conducted in a plain area dominated by smallholders with a similar crop structure, while for the other areas of rural China where the topography and crop structure are more diverse, the results may need some caveats. Future research should examine whether the effects of AMS on cultivated land productivity vary with topography and crop structure. Second, this study mainly examines the cultivated land productivity of smallholders. In recent years, however, the Chinese government has actively encouraged the development of farmer cooperatives and agricultural companies. These new actors in Chinese agriculture may also be providers of AMS. Taking these developments into account may provide a complete picture of the relationship between AMS and cultivated land productivity.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

YL: substantial contributions to conception and design, data collection, analysis data, drafting the paper; XS: project administration and revising the paper critically for important intellectual content; FG: contributions to conception and design and revising the draft.

Funding

This work was supported by National Natural Science Foundation of China (No. 72173065), 111 Project (No. B17024), Outstanding (Blue) Teaching Team Project of JiangSu Province, and the China Scholarship Council (No.201806850051).

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2022.1008036/full#supplementary-material

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