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Upscaling farming operations, agricultural mechanization and chemical pesticide usage: A macro-analysis of Jiangsu Province, China

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ABSTRACT

The upscaling of farming operations in China has been advancing rapidly in recent years. This trend is likely to increase the use of agricultural machinery inputs, and possibly also the use of chemical pesticides, which is already extremely high. The relationship between farm size and the intensity of chemical pesticide usage is a subject of debate, and little is known about the mechanisms that might underlie this relationship. In this paper, we apply an integrated framework of larger-scale farming, agricultural mechanization and the intensity of chemical pesticide usage to examine and quantify the mediating effect of agricultural mechanization on the relationship between larger-scale farming and the use of chemical pesticides. Results obtained by applying seemingly unrelated regression (SUR) considering two-way fixed-effects and mediation analysis to county-level data for Jiangsu Province (2002–2019) suggest that an increase of 1% in the ratio of scale of farming is related to a total decline of 0.070% in chemical pesticide usage per hectare of land. Mediation analysis subsequently identifies mechanical sowing/transplanting is the only mediating variable, through which an increase of 1% in the ratio of scale of farming reduces the unit consumption of chemical pesticides by 0.017%.

1. Introduction

In China, farming operations are being upscaled and landholding patterns are changing (Li et al., 2021). Although small-scale farming still dominates Chinese agriculture (Ji et al., 2016; Ren et al., 2019; Rogers et al., 2021), rural farmland transfers have accelerated sharply since 2008 (from 8.84% in 2008 to 35.90% in 2019), thereby creating favourable conditions for larger-scale farming. In 2019, the total area of rural farmland transfers (about 555 million mu[1]) was 5.09 times that of 2008 (around 109 million mu), with an average annual expansion of 41 million mu (MOA/MARA,[2] 2009–2020). By 2016, rural land transfers accounted for more than 30% of the total area of rural contracted land in China, and the number of larger-scale farmers with an area of more than 50 mu exceeded 3.5 million.[3]

One potential benefit of larger-scale farming is that it helps to achieve economies of scale, while reducing the average cost per unit of production (Duffy, 2009; Benin, 2015; Lu et al., 2018b). Several empirical studies have investigated the relationship between farm size and agricultural production inputs, particularly agrochemicals (Rahman, 2003; Wu et al., 2018; Ren et al., 2019; Gao et al., 2021; Zhu and Wang, 2021), which could potentially pollute the environment and influence human health (Jin et al., 2015; Su et al., 2021). The findings on impacts on chemical pesticide usage reported in this literature are mixed. For example, as reported in studies by Rahman (2003), Gong et al. (2016), Wagner et al. (2016) and Qin and Lv (2020), farm size tends to increase the likelihood and/or intensity of chemical pesticide usage. In contrast, empirical studies by Heerink et al. (2007), Liu and Huang (2013), Schreinemachers et al. (2017), Wu et al. (2018), Ren et al. (2019), Salazar and Rand (2020), Schreinemachers et al. (2020), Hou et al. (2020), Su et al. (2021), Zhu and Wang (2021), Gao et al.

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[1] 1 ha = 15 mu.

[2] Since the institutional reform in 2018, the Ministry of Agriculture (MOA) has been known as the Ministry of Agriculture and Rural Affairs (MARA).

[3] These data are available at https://www.sohu.com/a/119282755_114731 (in Chinese).

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(2021) and other authors suggest a negative relationship between farm size and chemical pesticide usage per unit of land.

Mechanization of ploughing, sowing, inputs application, harvesting and other agricultural operations plays an important role in the ongoing transformation of landholding patterns in China (Takeshima et al., 2013; Kienzle et al., 2013; Liu et al., 2014). There is ample evidence that larger-scale farming increases the use of agricultural machinery (Wang et al., 2016a, 2020; Ji et al., 2017; Yamauchi, 2016), and that mechanization can either increase pesticide usage by eliminating human physical constraints on spraying (Ma et al., 2018; Zhang et al., 2019) or reduce pesticide usage by enabling application of improved technology and higher efficiency (Li et al., 2017; Zhang et al., 2019). It is important to note, however, that the focus of these studies is limited to either the impact of larger-scale farming on agricultural mechanization or the impact of agricultural mechanization on the use of chemical pesticides. They do not consider larger-scale farming, agricultural mechanization and chemical pesticide usage within an integrated framework. In other words, the current literature has largely ignored the possibility that agricultural mechanization might play a mediating role in the relationship between larger-scale farming and chemical pesticide usage.

The purpose of this study is to examine and quantify the mediating effect of agricultural mechanization on the relationship between larger-scale farming and the use of chemical pesticides. The mixed results reported in the available literature on the relationship between farm size and the use of chemical pesticides are based predominantly on cross-sectional household data. It is highly desirable to supplement the existing empirical evidence with macro-level analysis based on panel data and to consider the possible mediating role of mechanization underlying this relationship. The potential sample-selection bias that often plagues the aforementioned household-level studies can be avoided by using aggregated panel data on all farms within a given region (Xie et al., 2020).

This study is based on official county-level panel data from Jiangsu Province. Jiangsu was selected as the focus of this case study for three reasons. First, it was one of the first provinces in mainland China to promote larger-scale farming, and it has the highest rate of farmland transfers (Li et al., 2021; Ministry of Agriculture and Rural Affairs, 2009-2020). At the end of 2019, 54% of all farm households in Jiangsu Province were engaged in farmland transfers. Moreover, 59.07% of the total area of farmland in the province (around 2.1 million hectares) operating under the household responsibility system (HRS) was under transfer (Management and Administration Station of Rural Cooperative Economy of Jiangsu MASJS, 2002)—a share far exceeding the Chinese average of 35.90% (MARA, 2019). A second reason for selecting Jiangsu Province is that it was one of the earliest and fastest transforming provinces with regard to the development of agricultural mechanization. As early as 1996, many farmers in Jiangsu's main grain-producing area had bought tractors and combines and had started to provide local and cross-regional mechanization services to other farm operators (Yang et al., 2013). In 2020, more than 50,000 sets of machines from these machine-owning farmers were used to provide cross-regional mechanization services to other farmers in more than 20 provinces, with a total income of more than four billion yuan.[4] Third, Jiangsu is one of the largest pesticide consumers in mainland China.[5] From 2002 to 2019, its unit chemical pesticide consumption averaged 112.07 tons per hectare of land, far more than the Chinese average of 100.98 (NBS, 2003–2020). In 2019, Jiangsu consumed 6.74 million tons of chemical pesticides and was the third largest consumer among ten eastern coastal provinces (National Bureau of Statistics, 2003-2020). Jiangsu has the most severe overuse of agrochemicals in all provinces in China (Li et al., 2017).

Our study makes two contributions to the available literature. First, it expands the literature on the relationship between farm size and chemical pesticide usage (e.g. Heerink et al., 2007; Wu et al., 2018; Ren et al., 2019; Gao et al., 2021) by taking into account the potential mediating effect of agricultural mechanization. Second, it distinguishes four stages of machinery use (i.e. mechanical ploughing, mechanical sowing/transplanting, mechanical crop management and mechanical harvesting/post-harvesting) that may affect the application of chemical pesticides in different ways. In contrast to recent studies, which use the total agricultural machinery power (e.g. Li et al., 2021; Qiao, 2017) or a dummy variable for the adoption/non-adoption of mechanization service (e.g. Ma et al., 2018; Zhang et al., 2019; Gao et al., 2021), this study uses the share of the land area operated by machines in each stage as a proxy for agricultural mechanization.

The rest of the paper is structured as follows. Section 2 outlines the conceptual framework and develop six testable hypotheses, after which we introduce the empirical strategy and data in Section 3. The estimation results are presented in Section 4, followed by the discussion in Section 5. Conclusion are drawn in Section 6.

2. Impact mechanisms of larger-scale farming on chemical pesticide usage, and hypotheses

The impact of larger-scale farming on chemical pesticide usage can be subdivided into direct and indirect effects. Direct effects relate to economies of scale (Duffy, 2009; Benin, 2015) and land rights (Nkamleu and Adesina, 2000; Migheli, 2017). Indirect effects are associated with the adoption of modern agricultural technologies and management practices, including the adoption of machinery, which could further affect the use of chemical pesticides (Wu et al., 2018; Duan et al., 2021; Yu et al., 2022). These two pathways of impact are addressed in the following theoretical analysis.

2.1. Direct effect of larger-scale farming on chemical pesticide usage

Larger-scale farming may directly either reduce or increase the unit input of chemical pesticides. On the one hand, large-scale farming brings economies of scale that directly reduce the average unit consumption of chemical pesticides (Duffy, 2009; Benin, 2015; Lu et al., 2018b). More specialized production capabilities and lower (transaction) costs that accompany larger-scale farming are generally regarded as the two primary determinants of such economies of scale (Klasen et al., 2016). First, larger-scale farms are relatively more specialized in pesticide application. For example, small farms often apply pesticides based on a practice of avoiding leftovers in pesticide packages/bottles rather than on the amounts that are actually needed (Brauns et al., 2018). Larger-scale farms are able to use pesticides more efficiently (Zhu and Wang, 2021). Second, larger-scale farming helps to lower average (transaction) costs. For example, larger-scale farms generally have greater bargaining power and therefore can benefit from purchasing pesticides at lower prices. In addition, they are likely to be able to obtain pest-management advice directly from extension stations, thereby decreasing transaction costs and information distortion (Jin et al., 2015). Larger-scale farms are therefore expected to reduce[6] the use of chemical pesticides directly.

On the other hand, large-scale farmers in China hold only temporary land rights to a large share, or all of, the land they cultivate. Arable land is allocated by village collectives to households living in the village on the basis of household size. Farmers retain long-term contract rights over their allotted land, and are allowed to transfer the management right if they choose to lease the land to others, mortgage it to banks or invest it in a cooperative in exchange of shares (Zhou et al., 2020). For the large-scale farms in Jiangsu Province (farm operations above 2 ha), most or all of the cultivated farmland must come from others, either by

[4] These data are available at https://baijiahao.baidu.com/s?id=1682759552315776921&wfr=spider&for=pc (in Chinese).

[5] https://data.stats.gov.cn/easyquery.htm?cn=E0103 (in Chinese).

[6] Following the meta-analysis results of Böcker and Finger (2017), we assume that the own-price response of pesticides consumption is strongly inelastic.

leasing, cooperative sharing, or other forms. Given that pesticides increase land productivity in the short run and decrease it in the long run, farmers trade-off immediate and future profits (Migheli, 2017). Farmers holding short-term land management rights, such as large-scale farmers in China, are therefore expected to use larger quantities of chemical pesticides. Nkamleu and Adesina (2000) present empirical evidence of a positive relationship between temporary land rights and use of chemical pesticides by farmers in Cameroon.

2.2. Indirect effects of larger-scale farming on chemical pesticide usage

2.2.1. Effects of larger-scale farming on agricultural machinery usage

Larger-scale farming might increase the likelihood of using machines or mechanization services in crop production for two reasons. First, due to the high monitoring cost of hired labour, larger-scale farms may adopt more labour-saving production methods, including the use of machinery (Otsuka et al., 2016). Particularly given the rapid increase in real agricultural wages over time in Asia (Tian et al., 2020; Wang et al., 2020), emerging larger-scale farms are likely to face higher labour costs if they continue to use traditional labour-intensive technology (Wang et al., 2016b; Qing et al., 2018; Lu et al., 2018b). Mechanization will thus result in savings for relatively labour-intensive processes, such as ploughing, sowing/transplanting, crop management and harvesting/post-harvesting (Liu et al., 2014; Wang et al., 2016a; Ji et al., 2017; Ma et al., 2018). Second, given the complementarity between machines and land, it is economical for larger farms to introduce machinery (Otsuka et al., 2016). Fragmented farms with a large number of small plots tend to have relatively high transaction costs of machinery usage (Wang et al., 2020). The boundaries and ridges between small and dispersed plots contribute to increased working time when machines have to turn, thus decreasing the speed and efficiency of machinery on these plots (Lu et al., 2018b). For this reason, machinery cannot be used efficiently on small farms (Otsuka et al., 2016; Li et al., 2017; Wang et al., 2017).

2.2.2. Effects of agricultural mechanization on chemical pesticide usage

Agricultural mechanization entails several distinct stages of crop production: ploughing, sowing/transplanting, crop management and harvesting/post-harvesting (Cheng, 2017; Li et al., 2017). Each of these mechanical stages involves the control of weeds and/or pests and therefore affect the use of pesticides.

1. Mechanical ploughing. This stage is defined as the mechanical manipulation of soil and plant residues for the preparation of seedbeds (Reicosky and Allmaras, 2003). The rotary tillers or tractor-mounted ploughs used in this process can turn over the soil more deeply than is possible when ploughing with draught animals. This helps to control weeds by destroying more weed seeds and propagules and exposing the root systems of weeds to upper soil, thereby causing desiccation (Varsa et al., 1997). Deep ploughing could also depose weed seeds into deep layers of soil, thus decreasing the density of weeds (Duary et al., 2016). Deeper ploughing reduces the presence of weeds species and the annual infestation of weeds (Carter and Ivany, 2006; Gronle et al., 2015; Zhang et al., 2019). Mechanical ploughing is therefore expected to reduce the use of chemical herbicides per unit of land.
2. Mechanical sowing/transplanting. First, mechanical sowing/transplanting may ensure more uniform spacing and optimum plant density than is possible with manual sowing/transplanting, thereby reducing the likelihood or relative severity of pests in the later growing period (Dosdall et al., 1996; Juroszek and Tiedemann, 2011). Second, compared to broadcasting (manual sowing), mechanical transplanting makes it possible to foster young rice seedlings separately on small parcels of land, thus reducing the need for pesticide for two reasons (Reidsma et al., 2011). One reason is that crop management is easier on small plots than it is on large paddy plots, thereby increasing the efficiency of pesticide usage (Heerink et al., 2007). A second reason is that physical insect-control techniques (e.g. non-woven fabrics) are more easily applied over small areas than they are over large areas (paddies). Mechanical sowing/transplanting is therefore expected to reduce the use of chemical pesticides per unit of land.
3. Mechanical crop management. In China, small-scale farms most commonly use backpack pesticide sprayers, while larger-scale farms are able to use spraying machines, uncrewed aerial vehicles or spraying aircraft (Zhu and Wang, 2021). Mechanical spraying may help to reduce pesticide loss and waste, as compared to backpack sprayers (Li et al., 2017; Zhang et al., 2019; Gao et al., 2021). As evidenced by some empirical studies (e.g. Ma et al., 2018), however, machines might also increase pesticide usage, due to less mature or less accurate techniques. Hence, mechanical crop management may either reduce or increase the use of chemical pesticides per unit of land.
4. Mechanical harvesting/post-harvesting. Combine harvesters are widely used to harvest grain crops, while simultaneously returning straw[7] to the soil, due to the official Chinese ban on the burning of straw in the field (Shan et al., 2021). Straw is regarded an effective organic fertilizer, and the nutrients released by straw decomposition improve soil fertility (Jin et al., 2020). The practice of returning straw to the soil may also affect the growth and development of crops (Jin et al., 2020; Shan et al., 2021). Several micro-organisms that affect the leaves, stems and heads of plants may survive on crop straw (Kerdraon et al., 2019). Various pathogens and the eggs, larvae and pupae of any pests remaining in the returned straw increase the extent to which the next season's crops will be exposed to diseases and pests (Jin et al., 2020; Shan et al., 2021). This is particularly likely to increase the risk of epidemics of various foliar diseases for cereal crops (Kerdraon et al., 2019). Mechanical harvesting/post-harvesting is therefore expected to increase the use of chemical pesticides per unit of land.

The impact mechanisms presented above are depicted schematically in Fig. 1. The total effect of larger-scale farming on chemical pesticide usage per unit of land is displayed in Panel A, and the decomposition of the total effect is displayed in Panel B, with the ovals indicating the mediating effects of the four stages of agricultural mechanization. The total effect (c) of larger-scale farming on chemical pesticide usage per unit of land is expressed as the aggregate of the direct effect (c') and the four indirect effects (i.e. $a1 * b1$; $a2 * b2$; $a3 * b3$; $a4 * b4$). Based on the theoretical considerations presented above, the following hypotheses are formulated:

Hypothesis 1. The total effect of larger-scale farming on chemical pesticide usage per unit of land (c) is significant.

Hypothesis 2. The direct effect of larger-scale farming on chemical pesticide usage per unit of land (c') is significant.

Hypothesis 3. The indirect effect going through mechanical ploughing ($a1 * b1$) is negative.

Hypothesis 4. The indirect effect going through mechanical sowing/transplanting ($a2 * b2$) is negative.

Hypothesis 5. The indirect effect going through mechanical crop management ($a3 * b3$) is significant.

Hypothesis 6. The indirect effect going through mechanical harvesting/post-harvesting ($a4 * b4$) is positive.

[7] In Jiangsu, the return of straw to the soil is the primary way to use straw, accounting for more than 80% of all straw usage in 2019. Source: http://www.jiangsu.gov.cn/art/2019/6/21/art_60095_8367656.html (in Chinese).

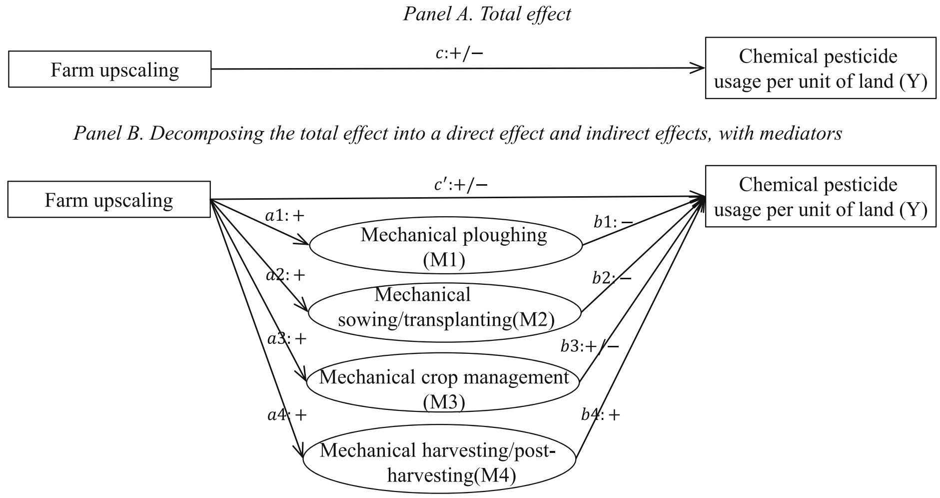

Fig. 1. Direct and indirect effects of farm upscaling on chemical pesticide usage.

3. Empirical strategy and data

3.1. Model specification

To examine the direct, indirect and total effects of larger-scale farming on the use of chemical pesticides per unit of land, this study performed a causal mediation analysis (Baron and Kenny, 1986; Hicks and Tingley, 2012) and constructed the following model to be estimated:

$$Y_{it} = cLSF_{it} + dX_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

$$M_{jit} = a_j LSF_{it} + d^{'}X_{it} + \mu_i^{'} + \lambda_t^{'} + \varepsilon_{jit}^{'} \text{ for } j = 1,2,3,4 \tag{2}$$

$$Y_{it} = c^{'}LSF_{it} + \sum_j b_j M_{jit} + d''X_{it} + \mu_i'' + \lambda_t'' + \varepsilon_{it}'' \tag{3}$$

where Y is the quantity of chemical pesticide usage per hectare of land, with i and t representing county and year, respectively. LSF represents larger-scale farming and is defined as the ratio of land area cultivated by so-called 'large-scale farms' (farms with cultivated land areas exceeding 2 ha)[8] in the total area of rural contracted land. The four mediation variables are as follows: mechanical ploughing (*M1*), mechanical sowing/transplanting (*M2*), mechanical crop management (*M3*) and mechanical harvesting/post-harvesting (*M4*).[9] They are defined respectively as dependent variables in Eq. (2) and, in Eq. (3), as independent variables affecting Y. Previous studies commonly measure these mediation variables using a dummy variable for the adoption of mechanization services at the household level (Ma et al., 2018; Zhang et al., 2019; Gao et al., 2021). To measure agricultural mechanization at the macro level, Qiao (2017) and Li et al. (2021) suggest using total agricultural machinery power. In this paper, we respectively use the share of land covered by each of the four stages of mechanization at the county level as a proxy, thereby obtaining a more precise description of the development of agricultural mechanization.

In the model, X is a set of exogenous factors that may affect the use of agricultural machinery and chemical pesticides. These factors include non-farm employment, share of rice crops, share of vegetables, GDP per capita and its squared term, sunshine, temperature, and precipitation. Given that non-farm employment reduces the amount of labour available for farm production, it is likely to increase the use of machinery and decrease the use of chemical pesticides (Feng et al., 2010; Ma et al., 2018). At the same time, however, income earned from non-farm work activities relaxes budget constraints, thereby enabling farm households to use more machinery and chemical pesticides (Ji et al., 2012; Zhang et al., 2019). In China, the profitability of using machines differs between crops and between cultivation stages (Li et al., 2017; Lu et al., 2018a; Ren et al., 2021). Rice and vegetables have been found to demand the most chemical pesticides (Rahman, 2003), and vegetable production has been identified as one of the main drivers of the overuse of agrochemicals (Duan et al., 2021). For this reason, greater shares of rice crops and vegetables are expected to increase the use of chemical pesticides while they may also affect the usage of machinery. GDP per capita and its squared term have been included to reflect the environmental Kuznets curve, assuming that the consumption of chemical pesticides increases in the early stages of economic growth and declines in later stages (Wu et al., 2018). In addition, GDP per capita might also have a positive effect on machinery usage, as an increasing standard of living is likely to increase demand for leisure. Weather conditions, including sunshine, temperature and precipitation, are considered, as they may influence the machinery costs and then affect the use of machinery (Kolberg et al., 2019). Furthermore, they are important factors affecting pests populations and disease occurrence and thus impact the use of pesticides (Chen and Maccarl, 2001; Juroszek and Tiedemann, 2011).

To control for potential endogeneity issues, this study takes the following measures. First, the use of panel data can reduce the omitted variables bias (Qiu et al., 2021). Applying the two-way fixed-effects model, which includes both county dummies and year dummies in the specification, helps to control for potential endogeneity problems relating to unobserved time-invariant county-specific effects and unobserved county-invariant time-specific effects. This method has previously been applied in studies by Qiao (2017), Su et al. (2021), Zhu and Wang (2021) and Gao et al. (2021) to explore the driving force of agricultural mechanization or chemical pesticide usage in China.

[8] Given the absence of a nationwide farm size threshold set by China's central government to define larger-scale farming, provinces determine their own standards according to local economic and social development levels, production technology conditions and labour-transfer situations (Li et al., 2021). Farms exceeding 2 ha (= 30 mu) are defined as larger-scale farms in Jiangsu Province.

[9] In the current case study, we ignore the lagged effect of mechanical harvesting/post-harvesting for the following reasons: according to the Jiangsu rural yearbook, rice, maize, soybeans and cotton are planted in the summer and harvested in the autumn of the same year. Wheat and rapeseed are planted in the autumn and harvested in the following summer. The lagged impact of straw-returning in harvesting/post-harvesting is related only to wheat. In Jiangsu, however, wheat grows in the winter and consumes fewer pesticides. In addition, a review of the literature indicates that the positive impact of straw-returning during harvesting/post-harvesting on the use of pesticides is realized primarily in rice crops.

Second, the treatment variable (*LSF*) and all variables included in *X* except three weather conditions are measured at the prefecture level, while the outcome variable (*Y*), four mediators (*M1*, *M2*, *M3* and *M4*) and three weather conditions are measured at the county level. It helps to minimize the potential effects of reverse causality.

The coefficient *c* reflects the total effect of farm upscaling on chemical pesticide usage per hectare of land, whereas the coefficient c' reflects the direct effect of farm upscaling on chemical pesticide usage per hectare of land after controlling for the mediators and other control variables. Further, a_1, a_2, a_3, a_4, b_1, b_2, b_3, b_4, d, d' and d'' are the estimated coefficients of the relevant independent variables, with μ_i, μ_i', and μ_i'' representing the county fixed effects, λ_t, λ_t' and λ_t'' representing the year fixed effects, and ε_{it}, $\varepsilon_{1,it}'$, $\varepsilon_{2,it}'$, $\varepsilon_{3,it}'$, $\varepsilon_{4,it}'$ and ε_{it}'' being error terms with standard properties.

Given that the effect of the treatment variable on the outcome variable is affected by mediators (Mackinnon, 2008), the size of the direct effect of the treatment variable with mediating variables may be unequal to (i.e. either less than or greater than) the total effect of the treatment variable without mediating variables. In case only one mediator exists, the mediating effect occurs when the direct effect differs significantly from the total effect or when the indirect effect is significantly different from 0. In our case, agricultural mechanization is expected to mediate the effect of farm upscaling on chemical pesticide usage per unit of land, and this is supported when each indirect effect ($a1 * b1$, $a2 * b2$, $a3 * b3$ or $a4 * b4$) differs significantly from 0.

Note that, if we run single-equation models using ordinary least squares (OLS) for *M1*, *M2*, *M3* and *M4* individually in Eq. (2) or for Eqs. (2) and (3) individually, we will encounter seemingly unrelated biases (Zellner, 1962). The assumption of independence for these four or five equations is invalid, as factors that affect *M1* might also affect *M2*, *M3*, *M4* or *Y*. The single-equation approach might thus be inefficient (Qiao, 2017). To solve this problem, the multiple mediating effects captured by Eqs. (2) and (3) are estimated in one step by using seemingly unrelated regression (SUR) combined with bootstrapping, as suggested by Preacher and Hayes (2008). The SUR method accounts for contemporaneous correlations and estimates the parameters of all equations simultaneously, such that the parameters of each single equation also take into account the information provided by the other equations (Zellner, 1962). The bootstrapping method is used to obtain correct standard errors for the mediating effects and reliable *z*-test and *p*-values for the indirect effects (Preacher and Hayes, 2008).

3.2. Data

Official statistics for Jiangsu Province were used to provide county-level information for this study. The Jiangsu Rural Statistical Yearbook (2003–2020) provides information on agricultural mechanization, chemical pesticide usage, share of rice crops, share of vegetable crops and non-farm employment.[10] The Jiangsu Statistical Yearbook (2003–2020) provides information on GDP per capita.[11] The Compilation of Jiangsu Rural Collective Finance, Assets and Agricultural Economic Statistical Annual Report (2002–2019) provides information on larger-scale farming.[12] National Meteorological Science Data Sharing provides information on three weather conditions, i.e., sunshine, temperature and precipitation.[13]

Jiangsu Province comprised 13 prefecture-level cities, which were further subdivided into 99 county-level cities: 55 city-governed districts, 23 county-level cities and 21 counties (Li et al., 2021). Following Li et al. (2021), we confine the analysis to 44 county-level districts and exclude the 55 city-governed districts, as they are predominantly urban or suburban, with very little farmland.[14] Jiangsu has six traditional crop rotation schedules—wheat-rice, wheat-maize, wheat-cotton, wheat-soybeans, rapeseed-rice and rapeseed-cotton, with wheat-rice double cropping being the most popular planting system (Li et al., 2017).

Table 1 presents the precise definitions of the variables, and Table 2 provides an overview of the mean values of all variables used in the empirical analysis. From 2002 to 2007, the average share of land cultivated by larger-scale farming (over 2 ha) in Jiangsu Province increased slowly from 4% to 9%. The average level of chemical pesticide usage increased steadily from 11 kg/ha to 15 kg/ha during the same period. After 2007, however, average chemical pesticide usage decreased gradually to less than 10 kg/ha, coinciding with the rapid increase in the average share of larger-scale farming to 34% before 2014

Table 1
Definition of variables used in empirical analysis.

Variable	Definition (unit of measurement)	Measurement level
Outcome variable		
Pesticide usage (*Y*)	Total physical quantity of chemical pesticides divided by total planting area (kg/ha)	County
Treatment variable		
Larger-scale farming (*LSF*)	Land area cultivated under large-scale farming (over 2 ha) divided by total area of rural contracted land (ratio)	Prefecture
Mediation variables		
Mechanical ploughing (*M1*)	Land area covered under mechanical ploughing divided by total planting area (ratio)	County
Mechanical sowing/ transplanting (*M2*)	Land area covered under mechanical sowing/transplanting divided by total planting area (ratio)	County
Mechanical crop management (*M3*)	Land area covered under mechanical crop management divided by total planting area (ratio)	County
Mechanical harvesting/ post-harvesting (*M4*)	Land area covered under mechanical harvesting/post-harvesting divided by total planting area (ratio)	County
Control variables (X)		
Non-farm employment	Share of workers involved in non-agricultural sectors (ratio)	Prefecture
GDP per capita	Gross domestic product per capita (yuan/person)	Prefecture
Share of rice crops	Sown-area of rice crops divided by total planting area (ratio)	Prefecture
Share of vegetable crops	Sown-area of vegetable crops divided by total planting area (ratio)	Prefecture
Sunshine	Sunshine hours in the county capital (hours)	County
Temperature	Average temperature in the county capital (degrees Celsius)	County
Precipitation	Precipitation in the county capital (millimetre)	County

Note: Pesticide usage refers to physical quantities, as no information was available on the active ingredient in the pesticides.

[10] The Jiangsu Rural Statistical Yearbook for Year *t* provides information on Year *t*-1.

[11] The Jiangsu Statistical Yearbook for Year *t* provides information on Year *t*-1.

[12] The Compilation of Jiangsu Rural Collective Finance, Assets and Agricultural Economic Statistical Annual Report for Year *t* provides information on Year *t*. This volume was not compiled for 2004, 2005 or 2009, and it compiled information at the prefecture level only for 2010 and 2011.

[13] Source: http://www.nmic.cn/(in Chinese).

[14] In 2019, one county-level city and two counties were designated as city-governed districts, with the rest remaining unchanged; see http://xzqh.org/html/show/js/38062.html (in Chinese). In accordance with Li et al. (2021), we do not expect that the adjustment in administrative division had any immediate impact on the local economic structure.

Table 2
Mean values of variables used in empirical analysis between 2002 and 2019.

Year	Outcome variable	Treatment variable	Mediation variables				Control variables						
	Pesticide usage (kg/ha)	Larger-scale farming (ratio)	Mechanical ploughing (ratio)	Mechanical sowing/ transplanting (ratio)	Mechanical crop management (ratio)	Mechanical harvesting/post-harvesting (ratio)	Non-farm employment (ratio)	GDP per capita (yuan/ person)	Share of rice crops (ratio)	Share of vegetable crops (ratio)	Sunshine (hours)	Temperature (degrees Celsius)	Precipitation (millimetre)
2002	11.142	0.039	0.521	0.251	0.580	0.427	0.483	13,756	0.270	0.158	1,990	15.718	993
2003	12.221	0.105	0.512	0.243	0.628	0.440	0.529	15,993	0.256	0.169	1,889	15.068	1,204
2006	13.967	0.076	0.490	0.340	0.674	0.612	0.627	23,421	0.315	0.150	1,924	15.954	1,015
2007	14.568	0.094	0.522	0.403	0.741	0.687	0.647	26,691	0.316	0.141	1,930	16.101	1,110
2008	13.418	0.141	0.695	0.409	0.695	0.605	0.588	29,795	0.306	0.144	1,943	15.288	1,034
2012	10.668	0.289	0.749	0.518	0.716	0.636	0.695	45,678	0.296	0.168	1,935	15.021	1,052
2013	10.367	0.336	0.754	0.571	0.740	0.660	0.703	48,824	0.296	0.173	2,171	15.693	881
2014	10.210	0.343	0.769	0.581	0.749	0.741	0.707	52,446	0.296	0.175	1,903	15.562	1,126
2015	10.134	0.338	0.771	0.601	0.735	0.665	0.712	54,812	0.294	0.182	1,838	15.533	1,280
2016	10.088	0.329	0.765	0.614	0.738	0.673	0.716	58,419	0.294	0.185	1,878	15.935	1,442
2017	10.010	0.335	0.763	0.616	0.747	0.676	0.721	63,162	0.296	0.189	2,072	16.189	1,065
2018	9.919	0.322	0.815	0.613	0.732	0.686	0.726	65,974	0.302	0.193	2,005	15.994	1,136
2019	9.783	0.307	0.772	0.622	0.723	0.679	0.732	71,033	0.303	0.195	1,867	15.989	914

Note: MASJS provides 'land area cultivated by large-scale farming' for 2002–2008 and only provides 'total area of farmland transfer' and 'land area that transfers to small farmers' for 2012–2019. Following Li et al. (2021), the variable 'Larger-scale farming' is calculated as 'land area cultivated by large-scale farming/total area of rural contracted land' for 2002–2008 and is calculated as '(total area of farmland transfer - land area that transfers to small farmers)/total area of rural contracted land' for 2012–2019. The variable 'GDP per capita' has been deflated to 2002 prices, using national consumer price index data.

and its subsequent slight decreased to 31%. The decreasing trend in chemical pesticide usage is consistent with official information from Jiangsu Province, which indicates that the use of chemical pesticides has exhibited negative growth for 10 consecutive years.[15] The average shares of mechanical ploughing, mechanical sowing/transplanting, mechanical crop management and mechanical harvesting/post-harvesting have exhibited fluctuating but increasing trends over time. These trends suggest that a decrease in the consumption of chemical pesticides has been accompanied by higher levels of larger-scale farming and more intensive agricultural mechanization. Interestingly, the average share of vegetable crops in the total planting area decreased from 16.9% in 2003 to 14.1% in 2007, while it increased steadily to 19.5% in 2019 since then. The share of rice crops increased rapidly from 25.6% in 2003 to 31.6% in 2007, and remained at a level around 30% with small fluctuations since then.

4. Results

Table 3 presents the two-way fixed-effects regression results of Eqs. (1)–(3). Column 1 is the result of Eq. (1), which captures the total effect of larger-scale farming on chemical pesticide usage without the four mechanization variables. Columns 2–5 contain the results of Eq. (2), which captures the effect of larger-scale farming on machinery usage in the four stages of mechanization, respectively. Column 6 is the result of Eq. (3), which captures the direct effect of larger-scale farming on chemical pesticide usage with the four mechanization variables. The Breusch-Pagan test, presented in the last row of the table, indicates the assumption of independence for Eqs. (2) and (3) is not supported, thereby indicating that the level of agricultural mechanization is related to the unit consumption of chemical pesticides, through unobserved effects captured by the model's error terms. It is therefore more efficient to use SUR to estimate Eqs. (2) and (3) simultaneously than using a single-equation estimation approach. Table 4 further presents the results of decomposing the effects of larger-scale farming on the use of chemical pesticides, based on SUR combined with the bootstrapping method.

The most notable finding is that larger-scale farming is negatively related to chemical pesticide usage per hectare of land. Without the four mechanization variables (Column 1, Table 3), the coefficient estimate for larger-scale farming indicates that a 1% increase in larger-scale farming is related to a decline of 0.070% (total effect, *c*) in the use of chemical pesticides. This finding provides support for Hypothesis 1, which postulates that larger-scale farming has a significant impact on chemical pesticide usage per unit of land. Similar significant, negative relationships have been reported by Wu et al. (2018), Zhu and Wang (2021), Su et al. (2021) and Gao et al. (2021) for China, by Schreinemachers et al. (2017) and Schreinemachers et al. (2020) for Southeast Asia and by Salazar and Rand (2020) for Vietnam. After controlling for the mechanization variables (Column 6, Table 3), the coefficient estimate for larger-scale farming remains significant but decreases to 0.055% (direct effect, *c'*). This finding supports Hypothesis 2, which states that the direct effect of larger-scale farming is significant. The absolute size of the direct effect (*c'*) is smaller than the total effect (*c*), providing preliminary evidence that the effect of larger-scale farming on chemical pesticide usage per hectare operates partly through the mediator of mechanization (Mackinnon, 2008).

We further find that mechanical sowing/transplanting (*M2*) is the only mediator for the effects of larger-scale farming on the use of chemical pesticides. Larger-scale farming has a significant positive effect on mechanical sowing/transplanting (*a2* in Column 3, Table 3), and use of mechanical sowing/transplanting has a significant negative effect on chemical pesticides per hectare of land (*b2* in Column 6, Table 3). Both estimators (*a2* and *b2*) are significant at the 0.01 level, providing

[15] These data are available at http://news.jschina.com.cn/scroll/guonei/201808/t20180804_1812814.shtml (in Chinese).

Table 3
Two-way fixed-effects results.

Variables	Pesticides usage (ln)	Mechanical ploughing (*M1*, ln)	Mechanical sowing/ transplanting (*M2*, ln)	Mechanical crop management (*M3*, ln)	Mechanical harvesting/ post-harvesting (*M4*, ln)	Pesticides usage (ln)
	(1)	(2)	(3)	(4)	(5)	(6)
Larger-scale farming (*LSF*, ln)	−0.070** (0.027)	0.004(0.019)	0.105***(0.036)	−0.008(0.029)	0.028(0.029)	−0.055** (0.026)
Mechanical ploughing (*M1*, ln)	–	–	–	–	–	−0.013(0.057)
Mechanical sowing/ transplanting (*M2*, ln)	–	–	–	–	–	−0.166*** (0.045)
Mechanical crop management (*M3*, ln)	–	–	–	–	–	0.005(0.037)
Mechanical harvesting/post-harvesting (*M4*, ln)	–	–	–	–	–	0.105*(0.056)
Non-farm employment (ln)	0.241(0.282)	0.058(0.132)	0.201(0.243)	0.144(0.197)	0.056(0.196)	0.202(0.174)
GDP per capita (ln)	2.516** (0.999)	0.006(0.645)	0.995(1.190)	−0.064(0.962)	−2.915***(0.959)	2.658*** (0.874)
GDP per capita * GDP per capita (ln)	−0.128** (0.053)	0.008(0.033)	0.002(0.061)	0.012(0.049)	0.161***(0.049)	−0.146*** (0.044)
Share of rice crops (ln)	0.465** (0.234)	−0.004(0.162)	0.629**(0.299)	0.318(0.241)	0.661***(0.241)	0.498** (0.223)
Share of vegetable crops (ln)	0.599*** (0.183)	0.321**(0.129)	−0.011(0.238)	0.175(0.192)	0.062(0.191)	0.598*** (0.171)
Sunshine (ln)	1.534** (0.614)	−1.218*** (0.407)	0.900(0.752)	0.599(0.608)	0.647(0.606)	1.298** (0.544)
Temperature (ln)	−9.464*** (2.662)	2.216(1.803)	−1.240(3.327)	−1.954(2.690)	2.020(2.681)	−9.432*** (2.390)
Precipitation (ln)	0.134(0.152)	−0.136(0.108)	0.614***(0.200)	0.205(0.161)	0.257(0.161)	0.003(0.145)
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	572	572	572	572	572	572
R^2	0.692	0.614	0.643	0.318	0.646	0.722
Breusch-Pagan test of independence	–	Chi2(10) = 383.465, Pr = 0.000				

Note: *,**and *** indicate significance at the 0.10, 0.05 and 0.01 levels, respectively; standard errors are presented in parentheses.

Table 4
Decomposition of mediation effects of larger-scale farming on pesticide usage (Two-way fixed-effects, N = 572).

Decomposition	Pesticide usage (ln)		
	Bias-corrected bootstrap		
	Coefficient	SE	Significance
Total effect (*c*)	−0.070	0.029	**
Direct effect (*c'*)	−0.055	0.029	*
Total indirect effect (*a1*b1* + *a2*b2* + *a3*b3* + *a4*b4*)	−0.015	0.011	
Mediation pathway through each of four mediators			
Pathway 1: Mechanical ploughing (*a1*b1*)	−0.000	0.001	
Pathway 2: Mechanical sowing/ transplanting (*a2*b2*)	−0.017	0.009	**
Pathway 3: Mechanical crop management (*a3*b3*)	−0.000	0.002	
Pathway 4: Mechanical harvesting/post-harvesting (*a4*b4*)	0.003	0.004	

Note: *,** and *** indicate significance at the 0.10, 0.05 and 0.01 levels, respectively; SE represent 1000 re-sampling bootstrapped standard errors.

preliminary evidence of a significant indirect effect of larger-scale farming on using chemical pesticides through mechanical sowing/transplanting (Baron and Kenny, 1986). However, no significant impact of larger-scale farming on any of other three mechanization variables, i.e., mechanical ploughing (*M1*), mechanical crop management (*M3*) and mechanical harvesting/post-harvesting (*M4*) (*a1*, *a3* and *a4* in Columns 2, 4, 5, Table 3, respectively) is found. Neither do we find a significant impact of two of these three mechanization variables on pesticide usage (*b1* and *b3* in Column 6, Table 3); the only exception is a significant positive impact (at the 0.10 level) of mechanical harvesting/post-harvesting (*M4*) on chemical pesticides per hectare of land (*b4* in Column 6, Table 3). To identify whether the four mechanization variables are mediators or not and the size of their indirect effects, the key coefficients (*a1*–*a4*, *b1*–*b4*) estimated by seemingly unrelated regression combined with the bootstrapping method are applied (Preacher and Hayes, 2008). Results reported in Table 4 demonstrate that only the mechanical sowing/transplanting pathway (*a2*b2*) is significant at the 0.05 level with a value of −0.017%. In contrast, the effects of the other three mechanization pathways (*a1*b1*, *a3*b3* and *a4*b4*) are insignificant. It provides empirical support for Hypothesis 4: 'The indirect effect going through mechanical sowing/-transplanting (*a2*b2*) is negative'. The other three hypotheses on indirect effects, hypothesis 3, 5 and 6, are not supported. The reason for these different findings remains unclear and calls for further research.

The coefficient estimate for larger-scale farming (*a2*) indicates that an increase of 1% in larger-scale farming leads to an increase of 0.105% in mechanical sowing/transplanting (Column 3 of Table 3). This is consistent with the finding that larger farm size induces greater use of farm machinery reported by Ma et al. (2018) and Zhang et al. (2019) for the provinces of Gansu, Henan and Shandong. Due to the advantages of contiguous land plots and cost savings in terms of labour, larger-scale farmers appear more willing to increase the adoption of machinery in sowing and/or transplanting on their land by either purchasing machines or hiring mechanization services (Wang et al., 2016a; Qiu and Luo, 2021). The estimated coefficient for mechanical sowing/-transplanting (*b2*) indicates that a 1% increase in mechanical sowing/-transplanting is related to a decline of 0.166% in the use of chemical pesticides per hectare of land (Column 6 of Table 3). A possible explanation is that mechanical sowing/transplanting brings more uniform spacing and optimal plant density, which can reduce the risk and/or severity of pests, and thus the need for applying chemical pesticides (Dosdall et al., 1996; Juroszek and Tiedemann, 2011). Moreover, in rice cultivation, mechanical transplanting instead of broadcasting makes it possible to foster young rice seedlings separately on small parcels of land, thus reducing the need for pesticides (Heerink et al., 2007;

Reidsma et al., 2011). Due to data limitations, we cannot further identify whether the negative effect is the result of mechanical sowing, mechanical transplanting or both. Reidsma et al. (2011) report that mechanical transplanting helps to reduce the use of pesticides. Additional research is needed in order to examine this negative relationship.

With regard to the impacts of control variables on chemical pesticide usage, it is worth noting that both the share of rice crops and the share of vegetable crops in the total planting area are positively related to chemical pesticide usage per hectare of land, respectively at the 0.05 level and the 0.01 level (Columns 1 and 6, Table 3). For rice, an increase of 1% in the share of rice crops is related to an increase ranging between 0.465% and 0.498% in chemical pesticide usage per hectare of land. Similar results have been reported by Rahman (2003) for Bangladesh, by Hou et al. (2020) and by Su et al. (2021) for China. A possible explanation is that intensive rice production influences the composition of the local ecosystem and reduces landscape diversity, thereby increasing the need for pesticide usage (Hou et al., 2020). The share of vegetable crops has a relatively strong, positive impact on the use of chemical pesticides (Columns 1 and 6, Table 3). The estimated coefficients indicate that an increase of 1% in the share of vegetable crops is related to an increase of 0.598% or 0.599% in chemical pesticide usage per hectare of land. This positive effect is consistent with the findings reported by Rahman (2003) for Bangladesh and by Duan et al. (2021) for China. The effect of GDP per capita on the use of chemical pesticides is significant and follows an inverted U-shaped relationship (Columns 1 and 6, Table 3). The turning point for GDP per capita ranges between 8,980 Yuan (Column 6, Table 3) and 1,8548 Yuan (Column 1, Table 3). Below these points, increases in GDP per capita positively affect chemical pesticide usage, while the effect becomes negative after these points. These findings provide support for the existence of an environmental Kuznets curve for chemical pesticide usage, and they are consistent with the findings reported by Wu et al. (2018). Weather conditions also have an impact on the use of chemical pesticides. Sunshine has a significant positive effect (at 0.05 level) on chemical pesticide usage per hectare of land. In contrast, a higher temperature has a significant negative effect (at 0.01 level) on chemical pesticide usage per hectare of land, which is consistent with the findings from the study of Chen and Maccarl (2001) for U.S..

Also noteworthy is the effect of control variables on the use of machinery. As expected, the share of rice crops has a positive impact, at the 0.05 level, on mechanical sowing/transplanting, and at the 0.01 level, on mechanical harvesting/post-harvesting (Columns 3 and 5, Table 3). This result is consistent with the finding of Li et al. (2017), Lu et al. (2018a) and Ren et al. (2021) that machines are widely used in grain production in China. The share of vegetables in the total planting area does not significantly affect machinery usage, except for mechanical ploughing. Perhaps mechanical ploughing involves only manipulating soil and plant residues for seedbed preparation (Reicosky and Allmaras, 2003), thus making it suitable for vegetables before they are planted as well. GDP per capita impacts mechanical harvesting/post-harvesting in a U-shape relationship (Column 5, Table 3), with a turning point when GDP per capita equals 8,542 yuan. This result implies that for about 6% of the sample, higher GDP per capita has a negative effect on the use of combined harvesters.

5. Discussion

Our results provide empirical evidence of a negative relationship between farm size and chemical pesticide usage per unit of land. In our case, a 1% increase in the ratio of large-scale farms is related to a decline of 0.070% in the use of chemical pesticides. It suggests that chemical pesticides can be reduced in rural China by promoting the upscaling of farm operations. Our results also indicate that mechanical sowing/transplanting is mediating the relationship between larger-scale farming and chemical pesticide usage. The negative effect of larger-scale farming on chemical pesticide usage through mechanical sowing/transplanting was estimated at 0.017%. It suggests that along with upscaling farm operations, agricultural mechanization also contributes to reducing chemical pesticides.

An earlier study on China found that a 1% increase in farm size is associated with a 0.5% decrease in the use of chemical pesticides per hectare (Wu et al., 2018). More recent studies estimated negative responses that equal around 0.2% (Gao et al., 2021; Zhu and Wang, 2021). The estimate reported in our paper (0.07%) is even smaller in absolute size than those reported in the latter studies. The differences may be due to differences in the main independent variables and the data sets used. The main independent variable in our study is the ratio of the land area cultivated under large-scale farming (over 2 ha) to the total area of rural contracted land in a prefecture. This variable is insensitive to changes in farm sizes below 2 ha and highly sensitive to changes in farm sizes of farms just below or above the 2 ha's cut-off point. Since the majority of farms in Jiangsu and other parts of China is smaller than 2 ha, the larger elasticities found in studies using farm size as independent variable suggest that the use of chemical pesticides is most responsive to changes in farm sizes at the lower end of the distribution. Wu et al. (2018) used national farm-level cross-sectional data. Due to the cross-sectional nature of the data, omitted variables bias could not be addressed in that study. Gao et al. (2021) and Zhu and Wang (2021) used panel data sets to reduce omitted variable bias, like was done in this study. The data sets in those two studies cover China as a whole and, in Zhu and Wang (2021), Henan Province, while the data set used in this study covers Jiangsu Province. As mentioned in the Introduction, Jiangsu Province actively promoted larger-scale farming, has the highest rate of farmland transfers, experienced a rapid development of agricultural mechanization, and is one of the largest pesticide consumers in mainland China. Hence, much caution should be exercised when comparing estimates obtained for Jiangsu Province with those for other parts of China or China as a whole.

An interesting additional result is that the share of land planted with vegetables has a significant positive effect on pesticides use. The average share of vegetable crops in the total planting area increased steadily from 14.1% to 19.5% from 2007 to 2019. Combining this trend with the estimated value of 0.598 for the elasticity of vegetables share (see Table 3) suggests that pesticide usage would have gone up by more than 20 percent since 2007; but in reality it declined by 33% in Jiangsu Province (see Table 2) as a result of other factors, such as the upscaling of farms. Given that continued urbanization is expected to stimulate meat and fruit consumption at the expense of vegetables consumption (Hovhannisyan and Devadoss, 2018), while farm scale enlargement will continue to be stimulated by the Chinese government, pesticide usage is expected to decline even faster in the years to come.

Although the results of our study cannot easily be compared with those obtained from previous studies on farm scale enlargement and pesticide usage in China, we do believe that the results may be relevant for other regions in China and perhaps even regions with similar land tenure systems outside China. The insights gained from this study are expected to hold in regions facing similar agro-climatic conditions that would affect options for farm scale enlargement and the usage of pesticides and machinery in agricultural production, provided observed values in those regions for the core variables falls within the range of variation observed in our sample. Table A1 in the Appendix presents detailed information about the variation over time in large-scale farming ratio, mechanization and pesticide usage for the 44 counties in Jiangsu Province that were examined for this study.

The findings of this study have several policy implications. First, they suggest that upscaling farm operations in rural China has positive environmental effects as it reduces the use of chemical pesticides per unit land. Given that China is a land-scarce country, larger-scale farming is not associated with conversion of land to agricultural uses that could increase total pesticide usage. Yet, farm scale enlargement may have important negative environmental impacts, such as landscape diversity reduction, biodiversity and habitat loss, and greenhouse gas emissions, that could outweigh the benefits. Policies aimed at promoting sustainable agricultural development should take those negative effects into account as well. Second, it is important to note that modern agricultural machines, particularly those used for sowing and/or transplanting, contribute to the development of sustainable agriculture by encouraging lower levels of chemical pesticide usage. Given the recent increases in the price of agricultural mechanization services (Qiu et al., 2021), it is important to promote effective agricultural mechanization service systems and improve access to agricultural mechanization and technical services to counterbalance the negative impact of rising prices.

Two limitations should be taken into account when interpreting our results. First, the empirical analysis performed in this study is at the county level. We acknowledge that more detailed insights may be obtained from micro level data, as such data would allow the consideration of potentially important factors at the level of households and plots, especially land tenure security (see Section 2.1). Second, our measurement of chemical pesticides is not perfect, as it is not based on active ingredients, due to the unavailability of such data. We have attempted to address this problem by following the strategy proposed by Su et al. (2021), Gao et al. (2021) and Zhu and Wang (2021) which involves using the year dummy to control for technical advancement in the development of chemical pesticides affecting the relative content of active ingredients.

6. Conclusion

Farm size and agricultural mechanization are potentially important factors that influence the use of chemical pesticides. This paper extends the scientific literature on this subject by exploring the relationship between larger-scale farming and chemical pesticide usage, especially the potential mediating effect of agricultural mechanization in China. Based on official statistics covering the period 2002–2019 in Jiangsu Province, we used seemingly unrelated regression considering two-way fixed-effects to examine the relationship between larger-scale farming and chemical pesticide usage per hectare of land. Mediation analysis was used to explore the mechanisms underlying this relationship, focusing on four mediation variables: mechanical ploughing, mechanical sowing/transplanting, mechanical crop management and mechanical harvesting/post-harvesting. The analysis revealed two major findings. First, larger-scale farming is related to a decline in the use of chemical pesticides per hectare of land. Second, mechanical sowing/transplanting is the only mediator among the four mechanization variables for the effects of larger-scale farming on the use of chemical pesticides.

We recommend that further research in this field focuses on micro-level data and on active ingredients of pesticides. In addition, more complex mediating relationships among farm upscaling, agricultural mechanization, crop structure adjustment and agrochemicals use may be estimated, when relevant data are available, to examine the extent to which the main findings of our research are confirmed.

CRediT authorship contribution statement

Min Su: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Nico Heerink:** Conceptualization, Methodology, Validation, Writing – review & editing, Supervision, Funding acquisition. **Peter Oosterveer:** Conceptualization, Validation, Writing – review & editing, Supervision. **Shuyi Feng:** Conceptualization, Methodology, Validation, Resources, Data curation, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A

Table A1
Descriptive statistics of key variables: 10th, 25th, 50th, 75th and 90th percentiles

Variable	Year	p10	p25	p50	p75	p90
Pesticide usage (kg/ha)	2002	5.932	6.740	10.548	14.677	18.224
	2008	6.002	8.978	12.376	17.572	22.626
	2014	4.673	7.533	9.773	12.462	14.815
	2019	4.545	6.857	8.465	11.629	15.982
Larger-scale farming (ratio)	2002	0.001	0.010	0.019	0.036	0.125
	2008	0.037	0.072	0.103	0.157	0.337
	2014	0.208	0.220	0.305	0.391	0.476
	2019	0.156	0.220	0.274	0.342	0.428
Mechanical ploughing (ratio)	2002	0.387	0.462	0.522	0.579	0.649
	2008	0.455	0.603	0.740	0.825	0.885
	2014	0.567	0.678	0.791	0.857	0.928
	2019	0.578	0.666	0.792	0.854	0.962
Mechanical sowing/transplanting (ratio)	2002	0.097	0.171	0.252	0.298	0.395
	2008	0.242	0.337	0.394	0.489	0.637
	2014	0.409	0.516	0.588	0.691	0.736
	2019	0.438	0.510	0.675	0.723	0.744
Mechanical crop management (ratio)	2002	0.352	0.486	0.575	0.692	0.769
	2008	0.481	0.603	0.674	0.838	0.894

(*continued on next page*)

Table A1 (*continued*)

Variable	Year	p10	p25	p50	p75	p90
	2014	0.578	0.631	0.760	0.815	0.865
	2019	0.509	0.600	0.723	0.829	0.944
Mechanical harvesting/post-harvesting (ratio)	2002	0.268	0.347	0.433	0.530	0.601
	2008	0.399	0.539	0.626	0.716	0.798
	2014	0.465	0.564	0.690	0.791	0.885
	2019	0.509	0.561	0.723	0.791	0.841

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