The adoption of agricultural machinery and its economic impacts in China

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Abbreviations	**Definitions**
ATT	Average treatment effects on the treated
ATU	Average treatment effect on the untreated
CFD	Chinese Family Database
CHFS	China Household Finance Survey
ESR	Endogenous switching regression
FIML	Full information maximum likelihood
FMIS	Farm Management Information Systems
GPS	Generalized propensity score
LR	Likelihood ratio
MVN	Multivariate normal distribution
MVP	Multivariate probit
OLS	Ordinary least squares
PMC	Pattern Management China
PSM	Propensity score matching
SWOT	Strengths, weaknesses, opportunities, and threats
UAVs	Unmanned aerial vehicles

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Doctoral study was an extraordinary experience in my life. There were many ups and downs during this period. In the beginning, I felt lost and did not know how to carry out my doctoral research. Meanwhile, I encountered many difficulties and learned how to think critically and how to solve problems by myself. Now, I am calm and confident to overcome most of the challenges in the field of my expertise. Even for issues outside the area of my expertise, I can handle them without panic. Doctoral study has sharpened my self-learning abilities, analytical skills, problem-solving skills, and willpower.

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Summary

In modern agriculture, machinery plays an important role to substitute manual labor and to improve productivity and economic performance of farm households. Conventional agricultural machinery in crop production includes tractors, cultivators, tillers, combine harvesters, pumps, threshers, planters, fertilizer spreaders, seeders, etc. In recent years, as an innovative agricultural machinery, unmanned aerial vehicles (UAVs) have been adopted in precision agriculture for crop monitoring and crop spraying. However, factors influencing Chinese farmers' adoption of agricultural machinery and the economic impacts of the adoption have not been adequately studied, especially regarding farm machinery in maize production and UAVs in precision agriculture. In addition, there is limited literature that systematically summarizes the use of UAVs in maize production. The development of UAV-based pattern management in Chinese agriculture and the prerequisites for adopting and implementing this approach remain unclear.

By utilizing farm household data, qualitative methods, and econometric quantitative methods, this dissertation aims to (i) identify the factors influencing the adoption of farm machinery and UAVs by Chinese farmers; (ii) estimate the economic impacts of adopting farm machinery and UAVs; (iii) provide an overview of UAV applications in maize production; (iv) study the prerequisites for adopting and implementing UAV-based pattern management in Chinese agriculture; (v) outline and recommend policy instruments to promote the use of farm machinery and UAVs in China.

The empirical results indicate that the determinants of farm machinery adoption and UAV adoption can be attributed by three major aspects: farmer characteristics (e.g., age, education level, and perceptions about agricultural machinery), farm characteristics (e.g., farm size, land fragmentation, and cooperative membership), and other external socio-economic factors (e.g., subsidies, technical assistance, and labor shortages). The adoption of farm machinery and UAVs has shown significantly positive economic effects. However, the effects vary among farm household types due to the heterogeneous farm characteristics and socio-economic conditions. Farm machinery use significantly increased maize yield by 0.216 tons/ha and improved labor productivity by 18.65%. Young, male, and better-educated farmers benefit more from adopting farm machinery, and farms located in plain regions with cooperative membership and rented land can gain higher economic benefits from machinery use. In addition, the impacts of farm machinery adoption on maize yield and labor productivity slightly

decrease with farm size. The adoption of UAVs in pesticide application significantly increased revenue and reduced the time spent on pesticide application by approximately 434-488 USD/ha and 14.4-15.8 hours/ha, respectively. In terms of marginal revenue and marginal time spent on pesticide application, the optimal area for using UAVs in pesticide spraying is estimated to be 20 hectares of arable land, suggesting that small and medium-scale farmers are the main beneficiaries of UAV adoption. For the wide application of UAV-based pattern management in precision agriculture, certain socio-economic and technical prerequisites are necessary. These include farmers possessing adequate UAV-related capabilities, relatively large farm sizes, availability of UAV-related subsidies, and superior UAV performance.

Balancing the pros and cons, the effective promotion of farm machinery in maize production and UAVs in precision agriculture requires the establishment of a comprehensive socio-economic institution. This institution should integrate strategies from both the public and private sectors such as the implementation of land consolidation, the establishment of agricultural machinery cooperatives for benefit-risk sharing, the provision of practical training and education on agricultural machinery, and subsidies for the purchase of agricultural machinery. Due to the heterogeneous effects of farm machinery adoption and UAV adoption, it is necessary to develop customized extension services tailored to various types of farm households to prevent inequity among farmers.

Zusammenfassung

In der modernen Landwirtschaft spielen Maschinen eine wichtige Rolle, indem sie manuelle Arbeit ersetzen, sowie Produktivität und wirtschaftliche Leistungsfähigkeit verbessern. Konventionelle Landmaschinen umfassen Traktoren, Kultivatoren, Pflüge, Mähdrescher, Pumpen, Dreschmaschinen, Pflanzmaschinen, Düngerstreuer, Sämaschinen usw. In den letzten Jahren wurden unbemannte Luftfahrzeuge (Unmanned Aerial Vehicles, UAVs) als innovative landwirtschaftliche Maschinen in der Präzisionslandwirtschaft eingesetzt, sowohl zur Überwachung von Pflanzen als auch zur Schädlingsbekämpfung. Jedoch wurden die Faktoren, die die Akzeptanz landwirtschaftlicher Maschinen durch chinesische Landwirte und die ökonomischen Auswirkungen ihrer Übernahme, nicht ausreichend untersucht, insbesondere im Hinblick auf Landmaschinen in der Maisproduktion und unbemannte Luftfahrzeuge in der Präzisionslandwirtschaft. Darüber hinaus gibt es nur wenig Literatur, die den Einsatz von UAVs in der Maisproduktion systematisch zusammenfasst. Die Entwicklung eines auf UAVs basierenden Managements in der chinesischen Landwirtschaft und die Voraussetzungen für die Übernahme und Umsetzung dieses Ansatzes bleiben unklar.

Unter Verwendung von Daten zu landwirtschaftlichen Haushalten, von qualitativen Methoden und ökonometrischen quantitativen Methoden zielt diese Dissertation darauf ab, (i) die Faktoren zu identifizieren, die die Akzeptanz von landwirtschaftlichen Maschinen und UAVs durch chinesische Landwirte beeinflussen; (ii) die wirtschaftlichen Auswirkungen der Einführung von landwirtschaftlichen Maschinen und UAVs zu schätzen; (iii) einen Überblick über die Anwendungen von UAVs in der Maisproduktion geben; (iv) die Voraussetzungen für die Implementierung eines UAV-basierten Managements in der chinesischen Landwirtschaft zu untersuchen; (v) Politikinstrumente zur Förderung des Einsatzes von landwirtschaftlichen Maschinen und UAVs in China zu formulieren.

Die empirischen Ergebnisse deuten darauf hin, dass die Determinanten der Akzeptanz von landwirtschaftlichen Maschinen und UAVs auf drei Hauptaspekte zurückzuführen sind: die Eigenschaften der Landwirte (z. B. Alter, Bildungsniveau und Wahrnehmung von Landmaschinen), die Merkmale des landwirtschaftlichen Betriebs (z. B. Betriebsgröße, Landfragmentierung und Mitgliedschaft in einer Genossenschaft) sowie andere externe sozioökonomische Faktoren (z. B. Subventionen, technische Unterstützung und Arbeitskräftemangel). Der Einsatz von landwirtschaftlichen Maschinen und UAVs hat deutlich positive wirtschaftliche Auswirkungen gezeigt. Allerdings variieren die Effekte

aufgrund der unterschiedlichen Merkmale der landwirtschaftlichen Betriebe und der sozioökonomischen Bedingungen von Haushalt zu Haushalt. Der Einsatz landwirtschaftlicher Maschinen hat den Maisertrag und die Arbeitsproduktivität signifikant erhöht. Der Maisertrag hat sich um 0,216 Tonnen pro Hektar erhöht und die Arbeitsproduktivität um 18.65%. Junge, männliche und besser gebildete Landwirte profitieren mehr von der Akzeptanz von Landmaschinen, und Betriebe in ebenen Regionen mit Genossenschaftsmitgliedschaft und höherem Pachtanteil können höhere wirtschaftliche Vorteile durch den Maschineneinsatz erzielen. Darüber hinaus nehmen die Auswirkungen der Akzeptanz von landwirtschaftlichen Maschinen auf den Maisertrag und die Arbeitsproduktivität leicht mit der Betriebsgröße ab. Die Akzeptanz von UAVs bei der Pestizidanwendung hat den Ertrag signifikant um etwa 434-488 USD pro Hektar erhöht und die für die Pestizidanwendung aufgewendete Zeit um 14,4-15,8 Stunden pro Hektar reduziert. In Bezug auf den marginalen Ertrag und die marginale Zeit für die Pestizidanwendung wird der optimale Bereich für den Einsatz von UAVs bei der Pestizidapplikation auf 20 Hektar Ackerland geschätzt, was darauf hinweist, dass kleine und mittelgroße Betriebe die Hauptnutznießer der Akzeptanz von UAVs sind. Für den breiten Einsatz des auf UAVs basierenden Muster-Managements in der Präzisionslandwirtschaft sind bestimmte sozioökonomische und technische Voraussetzungen erforderlich. Dazu gehören Betriebe, die über ausreichende Fähigkeiten im Umgang mit UAVs verfügen, relativ große Flächenausstattung aufweisen, die Verfügbarkeit von UAV-bezogenen Subventionen und eine ausreichende Leistung der UAVs.

Bei der Abwägung der Vor- und Nachteile, erfordert die wirksame Förderung des Einsatzes von Landmaschinen in der Maisproduktion und UAVs in der Präzisionslandwirtschaft die Einrichtung einer umfassenden sozioökonomischen Institution. Diese Institution sollte Strategien aus beiden Sektoren, dem öffentlichen und privaten Sektor, wie die Umsetzung der Flurbereinigung, die Gründung von landwirtschaftlichen Maschinenkooperativen zur Vorteils- und Risikoteilung, die Bereitstellung von praktischer Schulung und Ausbildung im Umgang mit landwirtschaftlichen Maschinen sowie Subventionen für den Kauf von landwirtschaftlichen Maschinen integrieren. Aufgrund der unterschiedlichen Ergebnisse bei der Übernahme von landwirtschaftlichen Maschinen und UAVs in den Betrieben, ist es notwendig, maßgeschneiderte Beratungsdienste zu entwickeln, die auf die verschiedenen Arten von landwirtschaftlichen Haushalten zugeschnitten sind, um Ungleichheiten unter den Landwirten zu vermeiden.

Chapter 1 General introduction

1.1 Introduction

1.1.1 Agricultural machinery and agricultural production

In modern agriculture, machines play an important role to substitute hand labor and to improve productivity because they increase labor productivity and efficiency (Zhou et al., 2020). Nowadays, in the context of resource scarcity and rural labor shortages, agricultural mechanization is vital to enhance productivity and to ensure food security (Kienzle et al., 2013). Agricultural machinery has been using in many agricultural processes such as land preparation, seeding, fertilizer application, pesticide application, weeding, harvesting, threshing, transportation, and pumping (Barrett and Just, 2021). Conventional agricultural machinery in crop production includes tractors, cultivators, tillers, combine harvesters, pumps, threshers, planters, fertilizer spreaders, seeders, etc. (Kienzle et al., 2013). In recent years, integrated with artificial intelligence, internet of things, global positioning system, variable rate application systems, and varied sensors etc., agricultural machinery has become more intelligent and more precise. For example, unmanned aerial vehicles and agricultural robots have been partly adopted in precision agriculture for crop monitoring, crop spraying, and harvesting, etc. (Rejeb et al., 2022; Tsouros et al., 2019a; Yang et al., 2023). As technological progress, agricultural machinery has shifted from conventional roughly undifferentiated operations to precise site-specific operations.

1.1.2 Economic impacts of adopting agricultural machinery

Many studies have shown positive economic impacts of adopting agricultural machinery (Barrett and Just, 2021). Wang et al. (2016) found that machines can significantly reduce labor input in agricultural production in rural China because farm machinery has a strong substitution effect on labor. Zhang et al. (2019) reported that farm machinery use improved pesticide application efficiency and reduced pesticide expenditure in Chinese maize farming by 58.87%. According to Pan et al. (2017), deep placement of nitrogen fertilizer through specialized machines can enhance nitrogen use efficiency and decrease nitrogen fertilizer use in direct-seeded rice production. Ma et al. (2018) and Zhou et al. (2020) found that farm machinery use significantly increased maize yield by 15% and 13%, respectively. Paudel et al. (2023) reported that farm mechanization can increase productivity and profit in Nepal's maize production by 14% and 11%, respectively. Wang et al. (2020) showed that unmanned aerial vehicle-based pesticide application increased the effect of pest and disease control in citrus production by 20.3% and saved cost by 266 USD/ha.

1.1.3 Agricultural mechanization and maize production in China

In 2020, maize is the most cultivated cereal crop in China in terms of 42.12% sown area and 42.26% harvested yield (National Bureau of Statistics of China, 2022). From 2008 to 2021, the comprehensive mechanization level in China's maize production increased from 51.78% to 90.00% (Figure 1.1). However, China's average maize yield in 2020 was 6.31 tons/ha, which was relatively low compared to 10.79 tons/ha in the United States (FAO, 2019). One of the main reasons is that the USA has higher mechanization level in maize production compared to China (Qian et al., 2016). Yang and Jiang (2023) emphasized that facilitating sustainable mechanization in Chinese maize production to achieve higher productivity is an important task for China in the future. Reflecting on this increasing importance of maize in Chinese crop production and agricultural mechanization, the relationship between maize production and agricultural mechanization in China will be thoroughly explore in this dissertation.

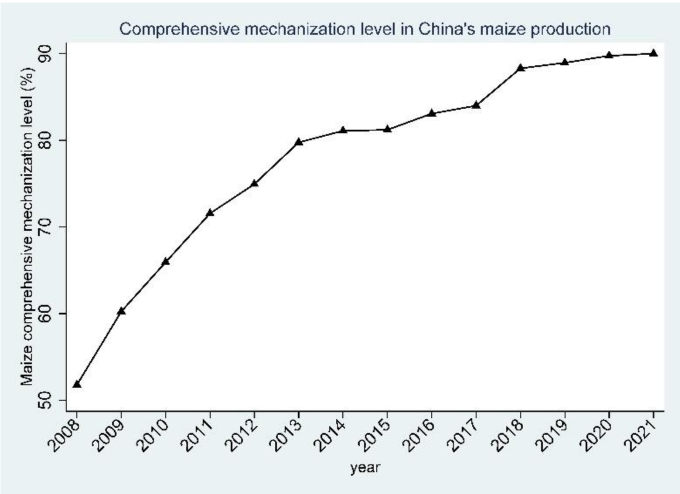

Figure 1.1 Comprehensive mechanization level in China's maize production.
Comprehensive mechanization level = mechanical tillage rate*0.4 + mechanical seeding rate*0.3 + mechanical harvesting rate*0.3. Data source: National Bureau of Statistics of China (2022).

1.1.4 Unmanned aerial vehicles (UAVs) in China's precision agriculture

As one of the most recent advanced agricultural machinery, UAVs are best known for the ability to overcome terrain obstacles to perform field tasks rapidly and precisely. UAVs attached with sensors or tanks can be used in many agricultural processes such as pesticide spraying, fertilizer spraying, seeding, and crop monitoring (Figure 1.2) (Kim et al., 2019; Radoglou-Grammatikis et al., 2020; Tsouros et al., 2019a). China started to use UAVs in agricultural production in

2010 (Zheng et al., 2019). Over a decade of development in China, agricultural UAVs are cheaper, smarter, and better than before (Chung, 2019). So far, China's agricultural UAV industry has become the first in the world in terms of the number of UAVs, flight control technology, and cumulative areas of operation per year (Ministry of Agriculture and Rural Affairs of People's Republic of China, 2019).

In worldwide, the most common use of UAVs in agriculture is remote sensing, while aerial application of agricultural chemicals is an emerging use of UAVs (Tsouros et al., 2019a; Van Der Merwe et al., 2020). However, in China, pesticide spraying is the most common UAV application in agriculture (Yang et al., 2018); other UAV applications such as seeding, fertilizer spraying, and crop monitoring are not widespread, but are gradually growing (Chung, 2019). In 2020, 70,344 UAVs were being used in China for plant protection purposes and they were treating 14.48 million hectares of cropland (China Agricultural Machinery Industry Association, 2021). Considering the increasing importance of UAVs in Chinese agriculture, UAVs have been chosen for in-depth research in this dissertation.

Figure 1.2 An UAV used for crop monitoring in Pattern Management China (PMC) project. Source: own picture.

In addition, UAVs can be used in precision agriculture for precision spraying, crop monitoring, and field management (Radoglou-Grammatikis et al., 2020; Sylvester et al., 2018; Tsouros et al., 2019a). UAV-based pattern management is an innovative and holistic approach proposed by Spohrer (2019) for sustainable and site-specific precision agriculture in respect of fertilization, plant protection, and irrigation. Pattern management includes three pillars: structured land management, UAV-based image acquisition, and data management. Structured land management divides fields into different spatiotemporal patterns. UAVs attached with sensors (e.g., infrared and hyperspectral) fly over fields to capture images and spatiotemporal data of these patterns. Images and field spatiotemporal data are processed by modified algorithms (Zhang and Kovacs, 2012) and stored in the database. Fertilizer, pesticide, and water variable-rate prescription maps are derived from the processed data to instruct fertilization, plant protection, and irrigation (Tsouros et al., 2019b). Data management is responsible for data storage, data retrieval, data processing, data mapping, and UAV flight control, etc. The processed spatiotemporal data are shown on terminal devices (e.g., tablets, smartphones, and laptops) in a straightforward way, and farmers can manage and monitor different patterns on the field through user-friendly interfaces.

1.2 Problem statement

Many studies have analyzed the factors that influence the adoption of farm machinery or the impacts of farm machinery use on agricultural performance, specifically in Chinese maize farming. Zhou et al. (2020) used an unconditional quantile regression model to estimate the heterogeneous impacts of farm machinery use across different quantiles of maize yield, while addressing the selection bias of farm machinery use by the control function approach. They found that farm machinery use has higher positive impacts on low productivity farmers than on high productivity farmers. Their results also suggest that education and household size have significant negative effects on farm machinery adoption, while farm size and the expenditures of pesticide and fertilizer have significant positive effects on farm machinery adoption. A study by Ma et al. (2018) found that farm machinery use has a significantly positive effect on maize yield and averaged in a 15% increase in yield. They also found that large farm size and fertile soil can boost the adoption of farm machinery, while large household size would discourage the adoption of farm machinery by farmers. Jetté-Nantel et al. (2020) used production function to estimate the impact of farm machinery use on maize yield, and the results imply that the efficiency gains from farm machinery use is limited. Zhang et al. (2019) performed the endogenous switching regression model to examine the factors that influence the adoption of farm machinery in pesticide application and the effects of adoption on pesticide expenditure among 493 Chinese maize farmers. Their findings suggest that off-farm work and farm size have significantly positive impacts on the adoption of farm machinery in pesticide application, and the adoption significantly reduced the total pesticide expenditure by 58.87%. However, farmers may adopt different types of farm machinery at the same time, and these articles did not study the interrelation among different adoption decisions. In addition, the impacts of farm machinery use on labor productivity and the heterogeneous impacts of farm machinery use across farm households have not been sufficiently investigated.

On the other hand, some studies have investigated the adoption of UAVs in agriculture. Zheng et al. (2019) used a probit model involving 897 farmers in Jilin province of China to estimate the factors influencing the adoption of UAVs for plant protection. Their results suggest that perceived usefulness, perceived ease-of-use, UAV-related knowledge level, and agricultural income ratio have a positive influence on UAV adoption. Caffaro et al. (2020) used a technology acceptance model to find that perceived usefulness positively influences Italian farmers' adoption intention of agricultural drones, and farmers are more willing to adopt agricultural drones if this technology can improve productivity on the farm. Chen et al., (2020) reported that farmers' intention to adopt UAVs in pesticide application would increase by 18% after explaining the benefits of using UAVs to farmers. Wachenheim et al. (2021) used a probit model to estimate the effects of social networks, resource endowment, and perceptions on Chinese farmers' intention to adopt UAVs for pesticide application. The results indicate that arable land area, agricultural income share, within-family village leadership, perceived usefulness, and credit availability have positive effects on UAV adoption. However, these articles only focused on UAV adoption intention research and only analyzed the use of UAVs from farmers' perspective but did not from the view of other UAV stakeholders such as agricultural UAV manufacturers, UAV service providers, agricultural extension staff from government, and researchers focusing on UAVs. In addition, there are limited studies to quantitatively estimate the economic effects of the adoption of UAVs in China. Thus, it is necessary to find empirical evidence to show the positive benefits of using UAVs, thereby promoting the adoption of UAVs. Furthermore, maize is one of the most important cereal crops around the world, but there is limited literature that systematically summarizes the use of UAVs in maize production. In addition, as an innovative and holistic approach, the status quo of UAV-based pattern management in Chinese agriculture and the prerequisites for adopting and implementing this approach remain unclear. Closing these research gaps will help to better understand the use of UAVs in maize farming, the determinants and economic impacts of UAV adoption, and the prerequisites for implementing UAV-based pattern management in China.

1.3 Research questions and objectives

This dissertation chooses traditional farm machinery in maize production and recent advanced agricultural machinery, specifically UAVs, in precision agriculture as case studies to explore the adoption of agricultural machinery and its economic impacts, to provide an overview of UAV applications in maize production, and to study the prerequisites for implementing UAV-based pattern management in Chinese agriculture. An interdisciplinarity approach which includes qualitative and econometric quantitative methods will be performed to address these issues.

This dissertation mainly addresses four research questions.

- Which factors can affect the adoption of farm machinery and UAVs in Chinese agriculture?
- What are the economic effects of adopting farm machinery and UAVs in Chinese agriculture?
- How UAVs are being used for maize production?
- How is the status quo of UAV-based pattern management in Chinese agriculture? What are the prerequisites for adopting and implementing this approach?

The major objectives of this dissertation are to:

- identify the factors influencing the adoption of farm machinery and UAVs by Chinese farmers;
- estimate the economic effects of adopting farm machinery and UAVs;
- provide an overview of UAV applications in maize production;
- study the prerequisites for adopting and implementing UAV-based pattern management in Chinese agriculture;
- outline and recommend policy instruments to promote the use of farm machinery and UAVs in China.

1.4 Methodology

To address the research questions proposed in this dissertation, an interdisciplinarity approach which includes qualitative and econometric quantitative methods was used.

- Firstly, farmers may adopt different agricultural machinery at the same time, and the adoption decisions of different agricultural machinery might be interrelated. Univariate probit or logit models estimate the adoption decisions independently and fail to capture the interrelations among different adoption decisions, and it may lead to biased results (Kassie et al., 2009; Rodríguez-Entrena and Arriaza, 2013). The multivariate probit model can individually estimate farmers' agricultural machinery adoption decisions and simultaneously account for the interdependence among these adoption decisions (Rodríguez-Entrena and Arriaza, 2013). Thus, multivariate probit models were performed to identify the factors that affect Chinese maize farmers' adoption of four machinery technologies as well as the interrelation among these adoption decisions.

- Secondly, the adoption of farm machinery and the impacts of adoption on outcome variables (e.g., maize yield and labor productivity) can be estimated by probit models (or logit models) and ordinary least squares regressions, respectively. However, depending on farm characteristics and other factors, farmers may self-select as farm machinery adopters and non-adopters other than randomly assigned, and this causes the selection bias (Di Falco et al., 2011). In addition, some unobserved variables (e.g., farmers' motivation, managerial ability, and experience) may influence farm machinery adoption and outcome variables at the same time, and this will cause endogeneity and will lead to biased estimates in ordinary least squares regressions (Huang et al., 2015). The endogenous switching regression (ESR) model addresses selection bias and endogeneity by constructing a two-stage estimation (Lokshin and Sajaia, 2004). In the first stage, farm machinery adoption equation was used to explore the determinants of adoption and to compute the inverse Mills ratios (Diiro et al., 2021). In the second stage, inverse Mills ratios were added into outcome equations to correct the selection bias (Abdulai and Huffman, 2014). Hence, the ESR model was adopted to explore the factors influencing the adoption of farm machinery and to estimate the impacts of adoption on maize yield and labor productivity.
- Thirdly, most previous studies only analyzed the use of UAVs from farmers' perspective but did not from the view of other UAV stakeholders. In addition, there is limited data about UAV-based pattern management in China. Expert interviews primarily focus on qualitative analysis and do not need too much statistical data and are able to provide fresh first-hand information, specialized knowledge, and professional opinions from specialists on specific topics (Von Soest, 2023). In order to get a holistic view of UAV usage in Chinese agriculture, especially UAV-based pattern management, a series of structured in-depth expert interviews were conducted with agricultural UAV manufacturers, UAV service providers, agricultural extension staff from government, and researchers focusing on UAVs to study the status quo of UAV use, determinants of UAV adoption, and development of UAV-based pattern management in China.
- Lastly, the effects of using UAVs in pesticide application can be estimated by adding UAV adoption as a dummy variable into a simple regression model, but this approach cannot yield consistent estimates if selection bias exists (Schreinemachers et al., 2016). Although the ESR model can solve selection bias, the estimation results may be

sensitive to model specification and the validity of instrumental variables (Khonje et al., 2015). The direct comparison of outcome variables of UAV adopters and non-adopters can lead to biased results because confounding factors are not controlled (Gitonga et al., 2013). Propensity score matching (PSM) is a non-parametric method and does not require the assumption of functional forms between UAV adoption and outcome variables (El-Shater et al., 2016). PSM addresses the selection bias by matching UAV adopters and non-adopters conditioning on the propensity score of a set of observed covariates (Khandker et al., 2009). The average treatment effects of UAV adoption are the mean difference of outcome variables of matched pairs (Caliendo and Kopeinig, 2008). Thus, PSM was chosen to estimate the economic effects of adopting UAVs in pesticide application.

1.5 Dissertation structure

This cumulative doctoral dissertation includes seven chapters and addresses the research questions raised previously one by one.

Chapter 1 is a general introduction of this dissertation, including introduction, problem statement, research questions and objectives, methodology, and dissertation structure.

Chapter 2, entitled “Factors influencing the adoption of agricultural machinery by Chinese maize farmers”, uses multivariate probit models to identify the factors that affect Chinese maize farmers’ adoption of four machinery technologies as well as the interrelation among these adoption decisions. The empirical results indicate that maize sowing area, arable land area, crop diversity, family labor, subsidy, technical assistance, and economies of scale have positive effects on machinery adoption, while the number of discrete fields on the farm has a negative impact. The adoption of these four machinery technologies are interrelated and complementary.

Chapter 3, entitled “Farm machinery adoption and its impacts on maize yield and labor productivity: insights from China”, uses farm household survey data from Chinese maize farmers to explore the factors that influence the adoption of farm machinery and to estimate the impacts of adoption on maize yield and labor productivity by using the endogenous switching regression (ESR) model. In addition, the heterogeneous effects of farm machinery adoption were analyzed across farm households. The empirical results show that rented land and cooperative membership are main drivers of farm machinery adoption, while land fragmentation is a barrier of adoption. Farm machinery use has significantly positive impacts on maize yield and labor productivity, but the impacts differ across farm households.

Chapter 4, entitled “Unmanned aerial vehicle (UAV) technical applications, standard workflow, and future developments in maize production – water stress detection, weed mapping, nutritional status monitoring and yield prediction”, is a literature review regarding four major applications of UAVs in maize production: (i) water stress detection, (ii) weed mapping, (iii) nutrient status monitoring and (iv) yield prediction. This review summarizes UAV data management methods, explains how expert systems work in UAV systems, and provides standardized workflow data for farmers in maize production. In addition, strengths, weaknesses, opportunities, and threats of UAV use in maize production were analyzed. This study points out key issues of UAV usage in maize farming and research gaps that need to be filled, along with a number of recommendations for the development of UAVs in maize production in the future.

Chapter 5, entitled “The determinants of unmanned aerial vehicle (UAV) adoption and status quo of UAV-based pattern management in Chinese agriculture: insights from expert interviews”, is a qualitative research which includes a series of structured in-depth expert interviews with 18 experts from various backgrounds related to UAVs and agriculture in China to study the status quo of UAV use, determinants of UAV adoption, and development of UAV-based pattern management in China. This research shows that the adoption of UAVs in China is influenced by farmers’ production characteristics, farmers’ perceptions about UAVs, and social factors. UAV-based pattern management is at the initial stage in China. For the widespread implementation of this approach, certain socio-economic and technical prerequisites are necessary.

Chapter 6, entitled “The economic effects of unmanned aerial vehicles in pesticide application: evidence from Chinese grain farmers”, uses propensity score matching to evaluate the economic effects of UAV adoption on outcome variables including revenue, pesticide costs, time spent on pesticide application, and pesticide application frequency based on a dataset covering over 2,000 grain farmers across 11 provinces of China. The empirical results show that adoption of UAV increased revenue by approximately 434-488 USD/ha and reduced the time spent on pesticide application in the range of 14.4-15.8 hours per hectare. In addition, generalized propensity score matching was performed to estimate the heterogeneous effects of outcome variables arising from differing UAV adoption intensities. In terms of marginal revenue and marginal time spent on pesticide application, the optimal area with use of UAVs for pesticide spraying is estimated to be 20 hectares of arable land.

Chapter 7 gives a general discussion on the key findings of research questions in this dissertation and concludes with some recommendations for the promotion of farm machinery in maize production and UAVs in precision agriculture in China.

Chapter 2 Factors influencing the adoption of agricultural machinery by Chinese maize farmers

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Abstract: As the major labor force has shifted from rural areas to cities, labor shortages in agricultural production have resulted. In the context of technical progress impact, and depending on farm resource endowments, farmers will choose effective labor saving technology such as machinery to substitute for the missing manual labor. The reasons behind farmers' adoption of machinery technology are worth exploring. Therefore, this study uses 4165 Chinese maize farmers as the target group. Multivariate probit models were performed to identify the factors that affect maize farmers' adoption of four machinery technologies as well as the interrelation between these adoption decisions. The empirical results indicate that maize sowing area, arable land area, crop diversity, family labor, subsidy, technical assistance, and economies of scale have positive effects on machinery adoption, while the number of discrete fields in the farm has a negative impact. Maize farmers in the Northeast and North have higher machinery adoption odds than other regions. The adoption of these four machinery technologies are interrelated and complementary. Finally, moderate scale production, crop diversification, subsidizing agricultural machinery and its extension education, and land consolidation, are given as recommendations for promoting the adoption of agricultural machinery by Chinese maize farmers.

Keywords: agricultural machinery; China; maize production; technology adoption.

2.1 Introduction

As agricultural mechanization develops, farm machinery is gradually playing an important role in replacing manual labor and draft animals (e.g., horses, oxen, mules) and improving agricultural productivity. The economic benefits of machinery use, however, depend highly on economies of scale (Duffy, 2009; Li et al., 2018; Wang et al., 2016b). Farmers can use agricultural machinery by purchasing, renting, or buying machinery services (Ma et al., 2018). China, known as the second largest maize producer in the world (FAO, 2019), has adopted agricultural machinery in plowing, seeding, and harvesting for a long time. Figure 2.1 indicates the growth trend of mechanization in China's maize production at the national level. Mechanical plowing and mechanical seeding are well developed, while mechanical harvesting lags a little behind compared with them. In 2018, the average maize comprehensive mechanization rate was 88.31% in all production regions of China (Mechanical Industry Press, 2018).

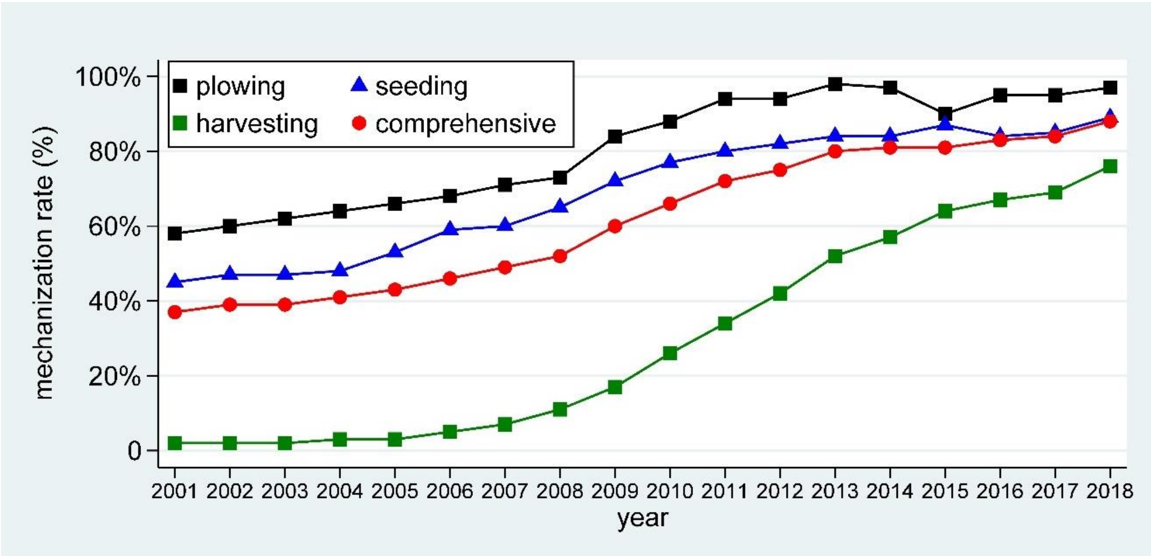

Figure 2.1 Mechanization rate of maize production in China, 2001–2018.
Data source: China Agricultural Machinery Industry Yearbook (Mechanical Industry Press, 2018). Note: mechanical plowing rate— areas of mechanical plowing (hm^2)/areas that are supposed to be plowed (hm^2); mechanical seeding rate—areas of mechanical seeding (hm^2)/total areas of sowing (hm^2); mechanical harvesting rate—areas of mechanical harvesting (hm^2)/total areas of sowing (hm^2); comprehensive mechanization rate—0.4×mechanical plowing rate + 0.3×mechanical seeding rate + 0.3×mechanical harvesting rate.

Several studies have analyzed the factors influencing the adoption of agricultural machinery by Chinese maize farmers (Lai et al., 2015; Ma et al., 2018; Wang et al., 2016a; Yi and Min, 2018; Zhang et al., 2019; Zhou et al., 2020) (Table 2.1). These factors mainly include three aspects: farmer features (e.g., age, gender, education level, farming experience, off-farm employment, etc.), farm characteristics (e.g., farm size, location, soil fertility, etc.), and social facilitating conditions (e.g., subsidies, extension services, farmer organizations, etc.). Probit models, multivariable probit models, and other econometric models were performed to analyze the quantitative relations between these factors and farmers' adoption decisions.

Table 2.1 The research of agricultural technology adoption: a review

Agricultural technology	Country	Target group	Method of analysis	Factors affect the adoption	References
Rotary cultivator for plowing	China	Maize farmers	A control function approach with an instrumental variable	Education (−), Household size (−), Extension contact (+), Transportation condition (+), Access to credit (+), Irrigation (+), Farm size (+), Pesticide costs (+), Fertilizer costs (+), Seed costs (−)	Zhou et al. (2020)
Several farm machines which can be used in maize production and postharvest management	China	Maize farmers	Bivariate ordered probit model and endogeneity-corrected ordinary least square regression model	Gender (−), Household size (−), Farm size (+), Soil fertility (+), Subsidy (+)	Ma et al. (2018)
Mechanization services	China	Maize farmers	Multivariable probit model	Number of family members, Number of parcels, The distance to township, Off-farm employment (+), Age (+)	Yi and Min (2018)
Total machinery horsepower used in plowing, sowing, and harvesting	China	Wheat farmers and maize farmers.	Ordinary least squares (OLS) with instrumental variables (IV)	Land fragmentation (−), Total operating area (+), Machinery price (−),	Lai et al. (2015)
Agricultural machines for pesticide application	China	Maize farmers	Endogenous switching regression model	Gender (−), Risk preference (−), Transportation condition (+), Subsidy (+), Extension contact (+)	Zhang et al. (2019)
Three soil conservation practices	Spain	Olive farmers	Multivariate probit model	Olive grove area (+), Family labor force (−), Belong to an irrigation district (+), Farm profitability (+)	Rodríguez-Entrena and Arriaza (2013)
Conservation tillage, compost, and chemical fertilizer	Ethiopia	Wheat farmers, barley farmers, and teff farmers	Trivariate probit model	Male (+), Age (−), Labor (+), Extension (+), Farmer organizations (+), Farm size (+), Plot ownership (+), Plot slope (−)	Kassie et al. (2009)

Note: In column 5, the effects of factors are shown in the brackets. “+” means a positive effect and “−” means a negative effect.

Specifically, Zhou et al. (2020) estimated the impacts of farm machinery use on maize yields by using a control function approach. In the first stage, smartphone use was employed as an instrumental variable in the farm machinery adoption equation; in the second stage, the inverse mills ratio estimated from the first stage was added to the maize production function as an extra regressor to correct the endogeneity issue caused by selection bias in farm machinery adoption. The results indicated that farmers' educational level, household size, extension service, transportation convenience of farm, farm size, and production inputs (e.g., pesticides, fertilizers, and seeds) are the main factors that affect farmers' adoption of machinery in maize production. Ma et al. (2018) used a bivariate ordered probit model with an instrumental variable (whether or not receiving a machinery purchasing subsidy) to estimate farmers' adoption of farm machinery in the first step. In the second step, endogeneity-corrected ordinary least square regression models were performed to test the effect of machinery use on maize yields and agricultural expenses. The empirical results indicate that off-farm employment, farm size, and subsidy had positive impacts on machinery adoption. Yi and Min (2018) estimated 600 maize farmers' adoption of agricultural mechanization services in seven regions of China with a multivariable probit model. To overcome the endogeneity of off-farm employment on the adoption of agricultural mechanization services, the average wage of off-farm work was used as an instrumental variable in the adoption equation. The results showed that both population aging and off-farm employment contributed positively to farmers' adoption of agricultural mechanization services. Zhang et al. (2019) used an endogenous switching regression model to simultaneously identify the factors influencing the adoption of farm machines in pesticide application and the impact of this adoption on pesticide expenditures. The mechanical pesticide spraying rate in each village was used as an instrumental variable in the farm machine selection equation to overcome the endogeneity of adoption decision caused by observed and unobserved factors. This study shows off-farm employment and farm size would positively affect farmers' decision to use farm machines in pesticide application. Similarly, these abovementioned studies solved model endogeneity issues by using instrumental variables. However, it is tricky sometimes to find appropriate instrumental variables.

In addition to research on machinery technology adoption among Chinese farmers, there are also some papers addressing the adoption of other agricultural technologies such as conservation and sustainable agriculture practices around the world (Kassie et al., 2009; Rodríguez-Entrena and Arriaza, 2013) (Table 2.1). Rodríguez-Entrena and Arriaza (2013) used a trivariate probit model to identify the determinants in the adoption of three soil conservation practices in Spanish olive production. Their results suggest that the farmers' decision to adopt a practice is correlated with other practices and that the adoption of one practice could promote the adoption of others.

A number of papers only study farmers' adoption of one particular technology or a set of technologies and thus have biased results caused by ignoring the interrelation from the adoption of different technologies (Lai et al., 2015; Ma et al., 2018; Zhang et al., 2019; Zhou et al., 2020). Zhou et al. (2020) only studied the adoption of the rotary cultivator for plowing in maize production among 493 farmers in Gansu, Henan, and Shandong provinces. Ma et al. (2018) investigated the adoption of machinery in 12 maize production stages among 493 farmers in three provinces of China by using a bivariate ordered probit model, but failed to consider the potential interrelation from the adoption of different technologies. Moreover, most of the existing research on Chinese maize farmers' machinery adoption is only focused on some specific regions with limited samples (Lai et al., 2015; Ma et al., 2018; Yi and Min, 2018; Zhou et al., 2020). Nationwide maize farmers' machinery adoption research is still missing in China.

The contributions of this paper are threefold: firstly, this is the first research to use nationwide data to study Chinese maize farmers' machinery adoption. The databases include 4165 maize farmers across six agroecological maize regions of China: Southwest, Northeast, North, Yellow-Huai River Valley, Northwest, and South. These samples are comprehensive and sufficient to represent most of the maize farmers in China. And the regional differences in machinery adoption were compared in six agroecological maize regions. Secondly, in order to obtain a good understanding of maize farmers' machinery adoption decisions, we investigated their adoption of machinery technologies in four key production processes: seeding, plowing, harvesting, and pesticide spraying. Thirdly, given the potential interrelation among these adoption decisions, multivariate models were performed to study the factors that influence the adoption of these machinery technologies. The aims of this paper are: (i) to identify the factors that influence the adoption of four machinery technologies by Chinese maize farmers; (ii) to explore the correlations among the adoption decisions of these four machinery technologies; and (iii) to provide some policy implications based on these conclusions to promote the use of agricultural machinery by Chinese maize farmers.

2.2 Materials and methods

2.2.1 Data source

This study uses data from the 2017 Chinese Family Database (CFD) of Zhejiang University, and from the 2017 China Household Finance Survey (CHFS) conducted by the Survey and Research Center for China Household Finance at the Southwestern University of Finance and Economics (China). These databases contain 5979 households who produced maize as one of the main crops on their farm. After data cleaning, 669 outliers were removed if they had have zero agricultural output values or where the areas of mechanical operation in their farm were larger than the farm size itself. After 1145 observations with missing values were removed, only 4165 valid maize farmers across 24 provinces were left.

2.2.2 Research study design

The 2017 CFD and 2017 CHFS are national representative surveys conducted in 2016, including more than 40,000 households across 29 provinces in the mainland of China. The survey adopted stratified three-stage sampling: county level, village level, and household level. Samples were selected randomly in each stage.

The questionnaire includes household demographic characteristics, family assets, agricultural production, family incomes and expenditures, etc. Since this study wants to explore the factors that influence the adoption of four machinery technologies in maize production, some explanatory variables and four dependent variables were selected from the databases (Table 2.2).

Table 2.2 Descriptive statistics of variables

Variables	Definitions	Mean	Std. Dev.
Dependent variables			
Mechanical plowing	1 if the farm used machines for plowing in maize production; 0 otherwise	0.580	0.494
Mechanical seeding	1 if the farm used machines for seeding in maize production; 0 otherwise	0.439	0.496
Mechanical harvesting	1 if the farm used machines for harvesting in maize production; 0 otherwise	0.467	0.499
Mechanical spraying	1 if the farm used machines for pesticide spraying in maize production; 0 otherwise	0.178	0.383
Explanatory variables			
Maize sowing area	Total areas of maize growing in the farm (mu)	6.487	12.650
Number of discrete fields in the farm	Number of discrete fields in the farm used for agricultural production	5.754	6.157
Arable land area	Total areas of arable land in the farm (mu)	10.001	19.446
Crop diversity	Number of crops produced on the farm	2.727	1.648
Family labor	Number of people participating in agricultural production in the family	1.961	0.822
Subsidy	1 if the farm received a subsidy to support agricultural production; 0 otherwise	0.763	0.425
Technical assistance	1 if the farm received technical assistance for agricultural production; 0 otherwise	0.100	0.300
Economies of scale	Total value of agricultural output by the farm (unit: 1000 yuan)	12.907	36.084
Southwest	1 if the farm is located in Sichuan, Chongqing, Guizhou, or Yunnan; 0 otherwise	0.248	0.432
Northeast	1 if the farm is located in Liaoning, Jilin, or Heilongjiang; 0 otherwise	0.181	0.385
North	1 if the farm is located in Beijing, Tianjin, Hebei, or Inner Mongolia; 0 otherwise	0.128	0.334
Yellow-Huai River Valley	1 if the farm is located in Shanxi, Shandong, Henan, Shaanxi, Anhui, or Jiangsu; 0 otherwise	0.299	0.458
Northwest	1 if the farm is located in Gansu or Ningxia; 0 otherwise	0.055	0.228
South	1 if the farm is located in Guangxi, Hainan, Hunan, Hubei, or Zhejiang; 0 otherwise	0.089	0.285
Number of observations	4165		

To compare regional heterogeneity, farm households were grouped together based on agroecological maize regions in China (Meng et al., 2006) (Figure 2.2): 1032 farms (24.78%), 754 farms (18.10%), 533 farms (12.80%), 1247 farms (29.94%), 229 farms (5.50%), and 370 farms (8.88%) are located in the Southwest, Northeast, North, Yellow-Huai River Valley, Northwest, and South respectively.

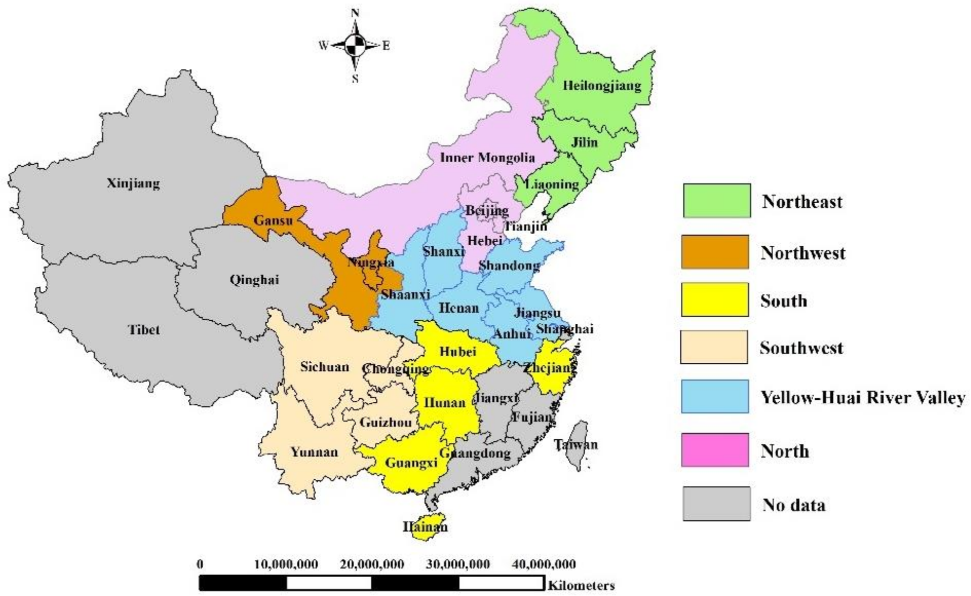

Figure 2.2 The division of six agroecological maize regions in this study

2.2.3 Theoretical framework

Given that the adoption of the four machinery technologies in this study is not mutually exclusive, the adoption of one technology could affect the adoption of others. Failure to consider the correlation among adoption decisions regarding different technologies will cause biased results (Kassie et al., 2009; Rodríguez-Entrena and Arriaza, 2013). Therefore, univariate probit or logit models are not sufficient for use in modeling the adoption of several interrelated technologies because they estimate the adoption of each technology independently, which ignores the correlations among these adoption decisions. The multivariate probit (MVP) model could overcome this problem. MVP models not only estimate the influence of a set of independent variables on the adoption of each of the different technologies but also account for the interdependence among these simultaneous adoption decisions (Kassie et al., 2009; Rodríguez-Entrena and Arriaza, 2013). Hence, the MVP model was chosen for this study.

The MVP model is specified as follows (Greene, 2003):

$$Y_{ij}^{*} = \beta_j X_{ij} + \varepsilon_{ij}\,, \qquad (j = 1, 2, 3, 4) \tag{1}$$

$$Y_{ij} = \begin{cases} 1, & if\ Y_{ij}^{*} > 0 \\ 0, & if\ Y_{ij}^{*} \leq 0 \end{cases} \tag{2}$$

where j = 1, 2, 3, 4 denotes mechanical plowing, mechanical seeding, mechanical harvesting, and mechanical spraying. Y_{ij}^{*} is a latent variable of the rational i^{th} farmer, which captures the unobserved preferences or demand associated with the j^{th} choice of machinery technologies. β_j is the coefficient to be estimated by a simulated maximum likelihood procedure. X_{ij} is the vector which represents the factors that affect the adoption of machinery. Given the nature of the latent variable, Y_{ij}^* is estimated by the observable dichotomous variable Y_{ij}. ε_{ij} is the stochastic error term following a multivariate normal distribution (MVN):

$$(\varepsilon_{i1}, \varepsilon_{i2}, \varepsilon_{i3}, \varepsilon_{i4})' \sim \text{MVN}\left(0, \begin{bmatrix} 1 & \rho_{12} & \rho_{13} & \rho_{14} \\ \rho_{12} & 1 & \rho_{23} & \rho_{24} \\ \rho_{13} & \rho_{23} & 1 & \rho_{34} \\ \rho_{14} & \rho_{24} & \rho_{34} & 1 \end{bmatrix}\right) \quad (3)$$

where ρ_{jk} is the correlation coefficient of ε_j and ε_k ($j \neq k$). This assumption with non-zero off-diagonal allows the correlation of error terms among these four adoption equations. If $\rho_{jk} > 0$, the adoptions of these two technologies are complementary; if $\rho_{jk} < 0$, the adoptions of these two technologies are substitutable (Rodríguez-Entrena and Arriaza, 2013).

2.3 Results and discussion

2.3.1 Descriptive statistics

Table 2.2 presents the description of variables used in the empirical analysis. The average maize sowing area of each farm is 6.49 mu. On average, each farm has five discrete fields and arable land areas of 10 mu. Most of the farmers produce 2 to 3 crops on the farm, while an average of only 1 to 2 family members participated in agricultural production. A total of 76.3% of farmers had received subsidy from the government to support agricultural production. Only 10% of farmers received technical assistance in agricultural production. Economies of scale averaged 12,907.27 yuan, from a minimum of 60 yuan to a maximum of 1567,400 yuan.

Table 2.3 shows the adoption rates of four agricultural machinery technologies in six agroecological maize regions. The adoption rates are differentiated by technology and region. Compared with other regions, the Northeast has the highest average adoption rate while the South has the lowest. The overall mechanical plowing adoption rate is 58.01% across six regions, while mechanical spraying is only 17.82%.

Table 2.3 Adoption rates of four agricultural machinery technologies in six agroecological maize regions and the overall adoption rates (%)

	Adoption Rates of Machinery Technologies in Six Agroecological Maize Regions						Overall
	Southwest	Northeast	North	Yellow-Huai River Valley	Northwest	South	
Mechanical plowing	13.74%	22.43%	16.80%	35.10%	6.66%	5.26%	58.01%
Mechanical seeding	2.13%	25.45%	21.46%	42.42%	7.17%	1.37%	43.87%
Mechanical harvesting	10.84%	20.85%	18.13%	38.42%	5.75%	6.01%	46.75%
Mechanical spraying	6.74%	48.92%	13.21%	24.53%	4.45%	2.16%	17.82%

2.3.2 Empirical results

Table 2.4 shows the correlation coefficients of the machinery technology adoption equations. The likelihood ratio (LR) test is significant (χ^2 (6) = 1772.26***, H_0 is rejected), which suggests the joint significance of the error correlations. This supports the idea that using MVP models is more efficient than univariate models. All the error correlation coefficients are positive and significantly different from zero. This result indicates the interdependence among the adoption decisions of different machinery technologies. More specifically, the adoptions of these four machinery technologies are complementary. The adoption of one machinery technology could promote the adoption of other machinery technologies.

Table 2.4 Correlation coefficients of machinery technology adoption equations

		ρ	Std. Err.
Mechanical seeding vs. Mechanical plowing	ρ_{21}	0.621 ***	0.021
Mechanical harvesting vs. Mechanical plowing	ρ_{31}	0.524 ***	0.022
Mechanical spraying vs. Mechanical plowing	ρ_{41}	0.483 ***	0.030
Mechanical harvesting vs. Mechanical seeding	ρ_{32}	0.725 ***	0.017
Mechanical spraying vs. Mechanical seeding	ρ_{42}	0.448 ***	0.030
Mechanical spraying vs. Mechanical harvesting	ρ_{43}	0.337 ***	0.030
Likelihood ratio test	$\rho_{21} = \rho_{31} = \rho_{41} = \rho_{32} = \rho_{42} = \rho_{43} = 0$ (H_0); χ^2 (6) = 1772.26 ***		

Note: *** indicates significant at the 1% level.

The coefficients of independent variables in multivariate probit models are presented in Table 2.5. The Wald test indicates the model is significant (χ^2 (52) = 2090.25 ***). This justifies that the model fits well. Considering the possibility of multicollinearity, a collinearity diagnostic test was performed. The variance inflation factors of all explanatory variables are less than 3.13, suggesting that multicollinearity is not an issue (Curto and Pinto, 2011). Most of the explanatory variables we considered in this study show statistical significance and their signs are as expected.

Table 2.5 Results of multivariate probit models of adoption of four machinery technologies

Variables	Mechanical Plowing		Mechanical Seeding		Mechanical Harvesting		Mechanical Spraying	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Maize sowing area	0.003	(0.005)	0.019 ***	(0.004)	0.021 ***	(0.004)	0.025 ***	(0.003)
Number of discrete fields in the farm	−0.003	(0.004)	−0.020 ***	(0.005)	−0.012 ***	(0.004)	−0.016 ***	(0.006)
Arable land area	0.016 ***	(0.004)	0.004	(0.003)	0.002	(0.002)	0.000	(0.002)
Crop diversity	0.031 **	(0.015)	0.002	(0.018)	0.078 ***	(0.015)	0.069 ***	(0.020)
Family labor	0.107***	(0.026)	0.084 ***	(0.028)	0.074 ***	(0.026)	0.000	(0.031)
Subsidy	0.478 ***	(0.050)	0.397 ***	(0.057)	0.546 ***	(0.052)	0.119 *	(0.066)
Technical assistance	0.245 ***	(0.072)	0.067	(0.076)	0.108	(0.069)	0.193 **	(0.079)
Economies of scale	0.001 *	(0.001)	0.002 ***	(0.001)	0.001 **	(0.001)	0.000	(0.001)
Northeast	0.775 ***	(0.080)	1.450 ***	(0.096)	0.589 ***	(0.081)	1.300 ***	(0.102)
North	1.141 ***	(0.081)	2.039 ***	(0.097)	1.186 ***	(0.081)	0.669 ***	(0.104)
Yellow-Huai River Valley	0.876 ***	(0.061)	1.760 ***	(0.080)	1.014 ***	(0.064)	0.539 ***	(0.088)
Northwest	0.907 ***	(0.102)	1.671 ***	(0.108)	0.722 ***	(0.097)	0.531 ***	(0.124)
South	0.038	(0.080)	0.138	(0.112)	0.325 ***	(0.082)	−0.073	(0.131)
Constant	−1.215 ***	(0.093)	−1.983 ***	(0.117)	−1.614 ***	(0.097)	−1.940 ***	(0.128)
Wald χ^2 (52)	2090.25 ***							
Log pseudo-likelihood	−7506.263							
Replications	200							
Number of observations	4165							

Note: * indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level. The Southwest is set as the base level in the regressions.

The maize sowing area has a positive effect on machinery technology adoption except for mechanical plowing. This result is consistent with Zhou et al. (2020), Ma et al. (2018), and Zhang et al. (2019). A greater maize sowing area promotes the adoption of agricultural machinery because machines are even more necessary to substitute for manual labor in this case. The number of discrete fields in the farm shows a negative impact on the adoption of mechanical seeding, mechanical harvesting, and mechanical spraying, because scattered fields increase the difficulty of machinery operation. Lai et al. (2015) and Wang et al. (2020) also found that land fragmentation decreases machinery use. The total areas of arable land on the farm indicate a positive effect on the adoption of mechanical plowing in maize production. Plowing is a labor intensive form of agricultural production. The larger the arable land on the farm, the more likely the farmer is to use machines for plowing.

Crop diversity exerts a positive impact on machinery technology adoption except for mechanical seeding. Higher crop diversity on their farms could motivate farmers to adopt more agricultural machinery technologies and use them on different crops to improve machinery use efficiency. Similarly, Mishra and Park (2005) revealed that farm diversification could promote the adoption of more internet applications by U.S. farmers. More family labor participating in agricultural production increases the likelihood of machinery adoption in plowing, seeding, and harvesting. It could be that these farms are specializing in agricultural production. A number of machines are used on these farms to increase productivity and profitability. On the contrary, Zhang et al. (2019) and Ma et al. (2018) found that larger households would reduce the use of agricultural machinery because the farms have a sufficient labor supply. Subsidy increases the likelihood of using agricultural machinery. This result is in line with the findings from Ma et al. (2018). Government subsidies lower the initial machinery purchase prices indirectly and boost agricultural mechanization (Huang et al., 2013).

Technical assistance contributes positively to the adoption of mechanical plowing and spraying. This result is parallel to the study of Carrer et al. (2017) about the adoption of computers in citrus farming in Brazil. This is because technical assistance from agricultural professionals gives farmers a chance to learn the application of agricultural innovations, somehow promoting the adoption of new practices. Economies of scale affect machinery adoption positively. This finding is in accordance with the results for the adoption of computers by Brazilian citrus farmers (Carrer et al., 2017). Three reasons can explain this phenomenon. Firstly, China' s agriculture sector is predominantly small household farms whose typical size is estimated around 7.5 mu (Wu et al., 2018). Small household farms are more willing to manage their agricultural activities with household labor and they have less incentive to invest in agricultural machinery than large farms. Secondly, due to the scale of production, the economic benefit that small household farmers could obtain from using agricultural machinery is less than their larger counterparts (Qing et al., 2019). Thirdly, large economies of scale grant farmers the financial ability to invest in agricultural machinery.

Finally, machinery adoption also indicates regional differences in the six maize growing regions. Farmers located in the Northeast, North, Yellow-Huai River Valley, and Northwest are more likely to be machinery adopters than farmers in the Southwest. Farms in Southwest China have the lowest machinery adoption probability because of the hilly or mountainous terrain, which constrains large-scale machinery operation. Maize farmers in the Northeast and North may have higher machinery adoption odds than other regions because of the regions' plain topography and relatively large farm size. The regional differences in machinery adoption are due to uneven resource endowments such as topography, soil fertility, farm size, labor price, and off-farm employment among these regions.

2.4 Conclusions

In this study, household-level data on 4165 cases in six agroecological maize regions of China were used in multivariate probit models to identify the factors that influence maize farmers' decisions to adopt machinery technologies, with a specific focus on mechanical plowing, mechanical seeding, mechanical harvesting, and mechanical spraying. The findings support that the adoption of these four machinery technologies is interrelated and complementary. The results of multivariate probit models imply that maize sowing area, arable land area, crop diversity, family labor, subsidy, technical assistance, and economies of scale have positive effects on machinery adoption, while the number of discrete fields in the farm has a negative impact. Maize farmers in the Northeast and North have higher machinery adoption odds than other regions.

Based on these empirical results, the following recommendations are given to promote the adoption of agricultural machinery by Chinese maize farmers:

(I) Moderate scale production

Since maize sowing area, total areas of arable land in the farm, and economies of scale have positive effects on machinery adoption, moderately increasing the scale of agricultural production is a possible approach to reduce machinery operation costs and to facilitate machinery adoption. Especially in large-scale agricultural production, machinery is increasingly needed as a substitute for manual labor. We must be aware that scale production can increase the total agricultural output, but that the output per unit area is not always increased as the scale expands. Therefore, finding the moderate scale of production which facilitates machinery adoption and maximizes agricultural productivity is the key.

(II) Crop diversification

Crop diversity has a positive effect on machinery adoption. To an extent, an increase in crop varieties produced on the farm could promote the adoption of agricultural machinery and guarantee an overall income under price volatility in some agricultural products.

(III) Subsidizing agricultural machinery and its extension education

The adoption of machinery is influenced positively by subsidy. Obtaining subsidies from the government could boost the adoption of machinery by Chinese maize farmers, but it is only a temporary solution, and it also increases government administrative burdens. Farmers' intrinsic motivation is an important factor influencing agricultural machinery adoption. On the one hand, government can provide subsidies to support the purchase of agricultural machinery. In addition, agricultural machinery extension education is also necessary to make farmers realize the importance and benefits of agricultural mechanization.

(IV) Land consolidation

The number of discrete fields on the farm has a negative effect on machinery adoption. Land fragmentation is a barrier for machinery adoption because it increases the difficulty of mechanical operations. Considering the farm size growth, decreasing family labor, and land fragmentation in rural China, land consolidation might be an approach to promote machinery use. Merging scattered fields through land consolidation not only builds a convenient environment for large-scale agricultural mechanization but also improves agricultural productivity. However, small farms are more efficient in resource utilization than large farms. It is important to consolidate scattered fields into a size appropriate for machinery application but also optimal for resource utilization.

The proposals discussed above are just a general framework to promote the adoption of agricultural machinery by maize farmers in China. As indicated by the results in this study, the adoption of agricultural machinery shows regional differences. When it comes to a specific region, these proposals should be adjusted correspondingly to fit well with regional resource endowments.

There are also some shortcomings of this study. Due to data availability, this research could not add some explanatory variables regarding farmers' sociodemographic characteristics into the models. This study only considers whether farmers use machinery technologies or not, but the intensity of adoption of machinery technologies is not clear. Future work can focus on the intensity of adoption of machinery technologies in maize production. The economic and social impacts of using machinery in maize production compared with those who are not using it would be an interesting direction in the future as well.

Author Contributions

Conceptualization, X.Q. and R.D.; methodology, X.Q.; software, X.Q.; validation, X.Q. and R.D.; formal analysis, X.Q.; investigation, X.Q.; resources, R.D.; data curation, X.Q.; writing—original draft preparation, X.Q.; writing—review and editing, X.Q. and RD; visualization, X.Q.; supervision, R.D.; project administration, R.D.; funding acquisition, R.D. All authors have read and agreed to the published version of the manuscript.

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Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

Data Availability Statement

The data that support the findings of this study are available from Zhejiang University. After registration on the website http://ssec.zju.edu.cn/dataset/CRHPS/CRHPS.asp, accessed on 1 November 2021, you will get a personal account which allows full access to the database. However, the raw data cannot be downloaded. Only data analysis results and graphs are allowed for download with the permission of administers from Zhejiang University.

Acknowledgments

This research uses data from the 2017 Chinese Family Database (CFD) of Zhejiang University, and 2017 China Household Finance Survey (CHFS) conducted by the Survey and Research Center for China Household Finance at the Southwestern University of Finance and Economics (China).

Conflicts of Interest

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Chapter 3 Farm machinery adoption and its impacts on maize yield and labor productivity: insights from China

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Abstract

Farm machinery plays an important role in Chinese maize farming by replacing manual labor and increasing productivity. However, it remains unclear how the impacts of farm machinery use differ across farm households. Thus, this study used farm household survey data from Chinese maize farmers to identify the factors that influence the adoption of farm machinery and to estimate the impacts of adoption on maize yield and labor productivity by using the endogenous switching regression (ESR) models. In addition, the heterogeneous effects of farm machinery adoption were analyzed across farm households. The empirical results show that rented land and cooperative membership are main drivers of farm machinery adoption, while land fragmentation is a barrier of adoption. Farm machinery use has significantly positive impacts on maize yield and labor productivity, but the impacts differ across farm households. Finally, some policy implications were proposed to promote the adoption of farm machinery and to optimize its economic effects.

Keywords: China**,** farm machinery, adoption, maize yield, labor productivity, endogenous switching regression models, heterogeneous impacts, policy implications

3.1 Introduction

In modern agriculture, farm machinery is important for farmers to improve efficiency and profitability in agricultural production (Benin, 2015). Farm machinery can substitute manual labor and draught animals in agricultural production and reduce the need to hire workers and increase labor productivity of each worker (Hamilton et al., 2021). With the assistance of farm machinery, economies of scale and intensification of production are easier to realize (Benin, 2015; Ma et al., 2018; Mrema et al., 2008).

In 2020, maize is the most cultivated cereal crop in China in terms of 42.12% sown area and 42.26% harvested yield (National Bureau of Statistics of China, 2022). However, China's average maize yield in 2020 was 6.31 tons/ha, which was relatively low compared to the 10.79

tons/ha in the United States (FAO, 2019). One of the main reasons is that the USA has higher mechanization level in maize production compared to China (Qian et al., 2016). Thus, agricultural mechanization is one of the most important approaches to achieve high productivity of maize production in China.

In 2004, the “Law of the People's Republic of China on Promotion of Agricultural Mechanization” was launched in China as a policy and financial framework to encourage farmers to use agricultural machinery and to promote agricultural mechanization. The agricultural machinery purchase subsidies provided by the Chinese government increased from 70 million yuan in 2004 to 19 billion yuan in 2021 (National Bureau of Statistics of China, 2022). From 2008 to 2021, the comprehensive mechanization level in China’s maize production increased from 51.78% to 90.00%, and maize yield increased from 5.56 tons/ha to 6.29 tons/ha (Figure 3.1). In addition to mechanization, other factors such as improved seeds, fertilizers, and pesticides also contributed to the increased maize yield in China (Meng et al., 2006).

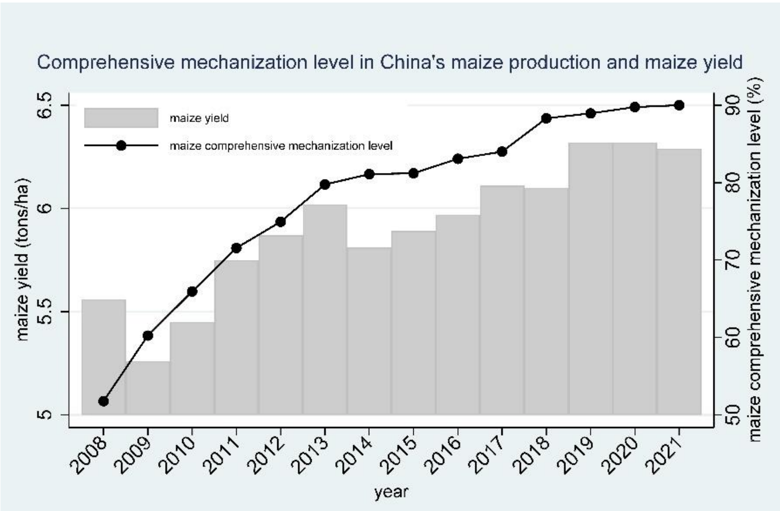

Figure 3.1 Comprehensive mechanization level in China’s maize production and maize yield.
Comprehensive mechanization level = mechanical tillage rate*0.4 + mechanical seeding rate*0.3 + mechanical harvesting rate*0.3. Data source: National Bureau of Statistics of China (2022).

Many studies have analyzed the factors that influence the adoption of farm machinery or the impacts of farm machinery use on agricultural performance in China’s maize production. Zhou et al. (2020) used an unconditional quantile regression model to estimate the heterogeneous impacts of farm machinery use across different quantiles of maize yield, while addressing the selection bias of farm machinery use by the control function approach. They found that farm machinery use has higher positive impacts on low productivity farmers than on high productivity farmers. Their results also suggest that education and household size have significant negative effects on farm machinery adoption, while farm size and the expenditures of pesticide and fertilizer have significant positive effects on farm machinery adoption. A study by Ma et al. (2018) found that farm machinery use has a significantly positive effect on maize yield and averaged in a 15% increase in yield. They also found that large farm size and fertile soil can boost the adoption of farm machinery, while large household size would discourage the adoption of farm machinery by farmers. Wang et al. (2016) reveled that farm machinery showed a strong substitution effect to labor in China's maize production by using provincial level panel data from 1984 to 2012. Jetté-Nantel et al. (2020) used production function to estimate the impact of farm machinery use on maize yield, and the results imply that the efficiency gains from farm machinery use is limited. Zhang et al. (2019) performed the endogenous switching regression (ESR) model to examine the factors that influence the adoption of farm machinery in pesticide application and the effects of adoption on pesticide expenditure among 493 Chinese maize farmers. Their findings suggest that off-farm work and farm size have significantly positive impacts on the adoption of farm machinery in pesticide application, and the adoption can significantly reduce pesticide expenditure by increasing the efficiency of pesticide application.

However, limited studies have been found to estimate the impacts of farm machinery use on labor productivity in Chinese maize production, and most existing articles that estimate the effects of farm machinery use on maize yield only showed the average treatment effects of farm machinery adoption on maize yield but not the heterogeneous treatment effects of adoption across farm households. This article contributes to literature in two ways. Firstly, this paper used ESR models to identify the factors that influence the adoption of farm machinery and to estimate the impacts of farm machinery adoption on maize yield and labor productivity in Chinese maize production. Secondly, majority studies only estimate the homogenous impacts of farm machinery adoption on outcome variables (e.g., maize yield and agrochemical expenses). Nevertheless, the impacts of farm machinery adoption on outcome variables may not be the same for all adopters, and it remains unclear how the impacts differ across farm households. This study used the average treatment effects of farm machinery adoption on maize yield and labor productivity, generated from the ESR model, as dependent variables in two ordinary least squares (OLS) regressions respectively to explore the heterogeneous treatment effects of farm machinery adoption across farm and farmer characteristics.

3.2 Materials and methods

3.2.1 Data source

The data used in this study is based on the “National Scientific Fertilizer Application Research Project 2019” headed by the Ministry of Agriculture and Rural Affairs of China. This national survey focused mainly on evaluating the farm-level impact of a scientific fertilizer application project. The survey was carried out in 2019 by the National Academy of Agriculture Green Development, China Agricultural University and was based on face-to-face interviews with farmers from 11 of the country’s main grain producing provinces: Heilongjiang, Jilin, Hebei, Henan, Shandong, Shaanxi, Gansu, Anhui, Jiangsu, Hunan, and Guangxi. This survey applied stratified multi-stage sampling and random sampling. Firstly, within each province, counties were classified according to the cultivated area, and 4 counties were randomly selected. Secondly, within the selected counties, townships were classified according to per capita income, and 3 townships were randomly selected. Thirdly, within the selected townships, villages were classified according to per capita income, and 2 villages were randomly selected. Finally, within the selected villages, farmers were classified according to their cultivated area and were randomly selected. The interview questions covered characteristics of farm households, aspects of farm management, agricultural production expenditure and revenues, pesticide application, and farmers’ knowledge about fertilizer application, etc.

This survey was assisted by the local government, and all the farmers selected participated in the survey, i.e., 100% response rate. The sample consisted of 1,123 maize farmers. Given the research purpose and variables of this study, missing values and invalid observations were excluded, leaving a final sample consisting of 824 maize farmers. The sampled provinces in this study account for 63% of China’s maize production in 2018 (National Bureau of Statistics of China, 2022) (Figure 3.2).

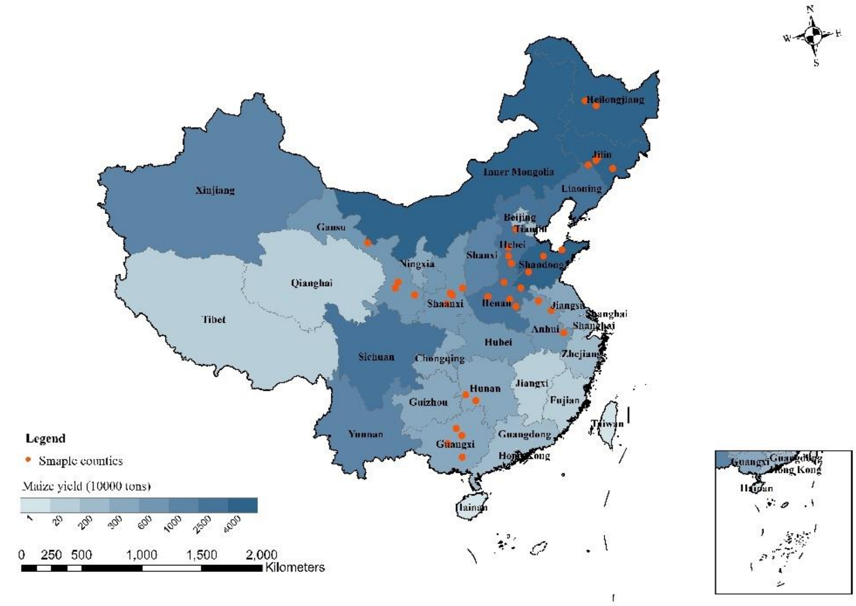

Figure 3.2 Maize yield in different provinces of China in 2018 and sample counties in this study.
Data source: National Bureau of Statistics of China (2022).

3.2.2 Definitions and descriptive statistics of variables

Table 3.1 presents the definitions and descriptive statistics of variables in this study. The *t*-test was performed to check the mean differences of variables between farm machinery adopters and non-adopters. More than half of maize farmers in this study adopted farm machinery in land preparation, fertilizer application, or pesticide application. The outcome variables, maize yield and labor productivity, are significantly higher for farm machinery adopters compared to non-adopters. Generally speaking, farm machinery adopters are more educated and younger than non-adopters. Number of agricultural workers within household for adopters is smaller than that of non-adopters. Compared with non-adopters, farm machinery adopters are more likely to be a member of agricultural cooperatives and are more likely to rent land from others. Averagely, farm size of adopters is 2.05 ha compared to 0.90 ha for non-adopters. Moreover, adopters show significant higher fertilizer expenditures compared to non-adopters. Particularly, most of the adopters are located in North of China. However, the direct comparisons between farm machinery adopters and non-adopters can lead to erroneous conclusions because they only base on descriptive statistics without controlling for confounding factors. Hence, this study accounts farm machinery adoption decisions together with other confounding factors to explore the impacts of farm machinery adoption on maize yield and labor productivity.

Table 3.1 Descriptive statistics

Variables	Definitions	Non-adopters (N =341)	Adopters (N =483)	Mean Difference
Dependent variables				
Machinery adoption	1 if the farm adopted farm machinery in any of the production processes: land preparation, fertilizer application, or pesticide application; 0 otherwise	0	1	−1***
Maize yield	Maize yield per hectare (ton/ha)	6.887	7.154	−0.267*
Labor productivity (ln)	Total value of maize output per agricultural worker (yuan/person) in natural logarithm	7.189	7.680	−0.491***
Independent variables				
Age	Age of household head	58.352	56.791	1.561**
Gender	1 if the household head is male; 0 otherwise	0.921	0.925	−0.005
Education	Education of household head in years	7.968	8.402	−0.434*
Agricultural workers	Number of agricultural workers within household	3.323	3.114	0.209**
Cooperative membership	1 if the farm is a member of an agricultural cooperative; 0 otherwise	0.100	0.157	−0.058**
Off-farm employment	1 if the household head has off-farm employment; 0 otherwise	0.188	0.219	−0.032
Plain	1 if the farm is located in plain region; 0 otherwise	0.897	0.845	0.053**
Soil fertility	1 if the soil on the farm is fertile; 0 otherwise	0.390	0.340	0.050
Land fragmentation	Number of discrete field plots on the farm	3.493	3.540	−0.048
Rented land	1 if the farm household rented land from others; 0 otherwise	0.323	0.520	−0.197***
Farm size	Maize grown area on the farm (ha)	0.898	2.050	−1.152***
Fertilizer expenditure	Total fertilizer expenditure per hectare (1000 yuan/ha)	2.140	2.500	−0.360***
Pesticide expenditure	Total pesticide expenditure per hectare (1000 yuan/ha)	0.466	0.508	−0.042
West	1 if the farm is located in Gansu or Shaanxi; 0 otherwise	0.246	0.284	−0.037
Northeast	1 if the farm is located in Jilin or Heilongjiang; 0 otherwise	0.059	0.174	−0.115***
North	1 if the farm is located in Shandong, Hebei or Henan; 0 otherwise	0.563	0.439	0.124***
South	1 if the farm is located in Anhui, Guangxi, or Hunan; 0 otherwise	0.132	0.104	0.028
Instrumental variables				
Private car	1 if the farm household owns a private car; 0 otherwise	0.326	0.398	−0.072**
Village cadre	1 if the farm household is a village cadre; 0 otherwise	0.182	0.284	−0.102***

Note: yuan is the unit of Chinese currency, 1 yuan ≈ $0.15.

3.2.3 Empirical model

3.2.3.1 Impact evaluation and selection bias

Theoretically, farm machinery adoption decisions and their impacts on maize yield or labor productivity can be estimated in two steps. Firstly, assuming that A_{1i}^{*} is the expected utility of farm machinery adoption, and A_{0i}^{*} is the expected utility of not adopting. M_i^* is a latent variable which captures the expected utility difference of farm machinery adoption (A_{1i}^{*}) and non-adoption (A_{0i}^{*}). A farmer adopts farm machinery for maize production if and only if the expected utility of adoption is higher than non-adoption: $M_i^* = A_{1i}^{*} - A_{0i}^{*} > 0$. Although the latent variable M_i^* is unobserved, the binary farm machinery adoption decision (M_i) is observed: M_i = 1 if $A_{1i}^{*} > A_{0i}^{*}$ and M_i = 0 if $A_{1i}^{*} < A_{0i}^{*}$. Thus, farm machinery adoption decision is specified as follows:

$$M_i^* = \boldsymbol{X_i}\boldsymbol{\alpha} + \mu_i \text{ with } M_i = \begin{cases} 1 & \text{if } M_i^* > 0 \\ 0 & \text{otherwise,} \end{cases} \tag{1}$$

where $\boldsymbol{X_i}$ represents a vector of explanatory variables that affect farm machinery adoption decisions (e.g., age, education, gender, soil fertility, and farm size); $\boldsymbol{\alpha}$ is the parameter to be estimated; and μ_i is the error term.

Secondly, the impact of farm machinery adoption on outcome variables is specified as:

$$Y_i = \boldsymbol{Z_i}\boldsymbol{\beta} + M_i\,\boldsymbol{\gamma} + \varepsilon_i \,, \tag{2}$$

where Y_i is maize yield or labor productivity; $\boldsymbol{Z_i}$ is a vector of explanatory variables that affect outcome variables (e.g., farm and farmer characteristics); M_i is the farm machinery adoption denoted before; ε_i is the error term; $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are vectors of parameters to be estimated.

Normally, equation (2) can be estimated by the ordinary least squares (OLS) if the farm machinery adoption (M_i) is exogenous. However, farmers may self-select as farm machinery adopters or non-adopters based on their farm characteristics and other factors rather than being stochastically assigned, and this causes the selection bias. Moreover, some unobservable characteristics (e.g., farmers' motivation, managerial ability, and experience) may also affect the adoption decisions and outcome variables at the same time and cause the correlation of error terms in the selection equation (1) and the outcome equation (2): ρ = corr (μ, ε) $\neq$ 0. In these cases, the OLS estimates of equation (2) are biased if farm machinery adoption is endogenous.

Moreover, OLS fails to consider the possible structural differences between farm machinery adopters and non-adopters in the outcome equation.

3.2.3.2 Endogenous switching regression (ESR) model

Hence, this study used the ESR model (Maddala, 1983) to address the endogeneity of farm machinery adoption and to estimate the determinants and impacts of farm machinery adoption. The ESR model consists of two stages. In the first stage, the selection equation (1) was used to estimate the factors that affect the adoption of farm machinery. In the second stage, two regimes were specified for adopters and non-adopters to estimate the impact of adoption:

Regime 1: $Y_{1i} = \boldsymbol{Z_{1i}\beta_1} + \varepsilon_{1i}$ if $M_i = 1$, (3)

Regime 0: $Y_{0i} = \boldsymbol{Z_{0i}\beta_0} + \varepsilon_{0i}$ if $M_i = 0$, (4)

where Y_i is the outcome variable (maize yield or labor productivity); $\boldsymbol{Z_i}$ is a vector of variables (e.g., age, gender, education, labor intensity, fertilizer expenditure, and pesticide expenditure) that affect the outcome variables; ε_i is the error term; μ_i, ε_{1i}, and ε_{0i} are assumed to have trivariate normal distribution with zero means.

For the identification of ESR model, $\boldsymbol{X_i}$ in the selection equation (1) must have at least one instrumental variable that does not appear in the $\boldsymbol{Z_i}$, and instrumental variables are supposed to affect the adoption only but not the outcome variables. Here, private car and village cadre were chosen as instrumental variables respectively. Private car and village cadre are expected to affect a farm household’s machinery adoption decision but not a farmer’s maize yield or labor productivity. Table A1 of the appendix reports the test on the validity of instrumental variables. Private car and village cadre both have statistically significant effects on adoption, but not of maize yield or labor productivity by the farmers that did not adopt farm machinery. Thus, the instrumental variables were valid.

The ESR model calculated the impacts of farm machinery adoption by constructing conditional expectations of outcome variables in respect of actual scenarios and counterfactual scenarios:

Farm machinery adopters (actual):

$$E(Y_{1i} | M_i = 1) = \boldsymbol{Z_{1i}\beta_1} + \sigma_{1\mu}\lambda_{1i} , \tag{5}$$

Farm machinery non-adopters (actual):

$$E(Y_{0i} | M_i = 0) = \boldsymbol{Z_{0i}\beta_0} + \sigma_{0\mu}\lambda_{0i} , \tag{6}$$

Farm machinery adopters if they had chosen not to adopt (counterfactual):

$$E(Y_{0i} | M_i = 1) = \boldsymbol{Z_{1i}\beta_0} + \sigma_{0\mu}\lambda_{1i} , \quad (7)$$

Farm machinery non-adopters if they had chosen to adopt (counterfactual):

$$E(Y_{1i} | M_i = 0) = \boldsymbol{Z_{0i}\beta_1} + \sigma_{1\mu}\lambda_{0i} , \quad (8)$$

where $\sigma_{1\mu}$ and $\sigma_{0\mu}$ indicate the covariance of μ_i with ε_{1i} and ε_{0i} respectively; λ_1 and λ_0 represent the inverse Mills ratio derived from the selection equation (1) and are plugged into equation (3) and (4) to correct the selection biases.

Following Heckman *et al*. (2001), the impact of farm machinery adoption on outcome variables (maize yield or labor productivity) was defined in (9), which is also called the average treatment effect on the treated (ATT).

$$\text{ATT} = E(Y_{1i} | M_i = 1) - E(Y_{0i} | M_i = 1) = \boldsymbol{Z_{1i}(\beta_1 - \beta_0)} + (\sigma_{1\mu} - \sigma_{0\mu})\lambda_{1i}, \quad (9)$$

Similarly, the average treatment effect on the untreated (ATU) for farmers that actually did not adopt farm machinery is defined as:

$$\text{ATU} = E(Y_{1i} | M_i = 0) - E(Y_{0i} | M_i = 0) = \boldsymbol{Z_{0i}(\beta_1 - \beta_0)} + (\sigma_{1\mu} - \sigma_{0\mu})\lambda_{0i}, \quad (10)$$

Although the ESR model can be estimated by two-stage OLS or maximum likelihood estimation, these approaches are not efficient and require complicated calculations to achieve consistent standard errors. Thus, full information maximum likelihood (FIML), an efficient method, developed by Lokshin and Sajaia (2004) was performed to estimate the selection equation and two regime equations simultaneously to yield consistent standard errors.

3.3 Empirical results and discussion

3.3.1 Estimation of maize yield function

Table 3.2 reports the estimates of ESR model for farmers' adoption of farm machinery and its impacts on maize yield. ρ_1 is negative and significantly different from zero which suggests the presence of selection bias. The likelihood ratio of independence test rejects the null hypothesis of farm machinery adoption and maize yield are independent at the 10% significance level. The results of selection equation suggest that farm households with more agricultural workers are less likely to be farm machinery adopters because they have sufficient labor supply in agricultural production, and there is no need to adopt farm machinery to replace manual labor. Likewise, Zhou et al. (2020) and Ma et al. (2018) also found that household size has a negative effect on farm machinery adoption. Cooperative membership shows a positive effect on farm machinery adoption may be because agricultural cooperatives often perform various field operations jointly among cooperative members, and are considered to stimulate the farm machinery adoption. This result is in line with Zhang et al. (2020) and Manda et al. (2020) who found that the cooperative membership facilitates the adoption of agricultural technology. Land fragmentation is found to be an obstacle for farm machinery adoption because it increases the difficulty of plot to plot machinery operation. Lai et al. (2015) also support this finding. Farm households who rented in land have higher probability to use farm machinery in maize production, and this may be because the expansion of farm size needs farm machinery to replace manual labor. This result is in line with Zhou et al. (2020) and Ma et al. (2018) who found that farm size has a significant positive effect on farm machinery adoption. Fertilizer expenditure is significantly positive corelated with farm machinery adoption. This finding is consistent with Zhou *et al*. (2020) who found that maize farmers with higher fertilizer expenditure are more likely to adopt farm machinery. Private car has a significantly positive effect on farm machinery adoption, and this indicates its validity as an instrumental variable.

In maize yield equations, most of the coefficients show expected signs. For non-adopters, age, soil fertility, farm size, and fertilizer expenditure have positive effects on maize yield. This result is consistent with the practical experience. In particular, farm size positively affects maize yield of non-adopters but negatively affects maize yield of adopters. This may be because most non-adopters have a relatively small farm size, and the increased farm size can boost maize output. Compared to non-adopters, farm machinery adopters have a relatively large farm size, and the increased farm size may lead to resource misallocation and management inefficiency and finally to a declined maize yield (Sheng et al., 2019). However, rented land has a negative effect on maize yield for both adopters and non-adopters. Likely, Jacoby et al. (2002) also found that insecure land use discourages farmers to invest more on land and decreases the productivity. On the other hand, Feng et al. (2010) argue that farmers who rented in land are more capable of obtaining high benefits from agricultural activities, and rented land can increase production. For adopters, maize yield is positively corelated with gender and soil fertility because male farmers are considered to be physically superior to female farmers in agricultural production, and fertile soil is beneficial for maize production. Interestingly, maize yield of farm households that adopt farm machinery is positively corelated with land fragmentation may be because more field plots provide enough space for machinery operation that can reduce the damage to maize plants.

Table 3.2 Estimates of ESR model for farm machinery adoption and its impacts on maize yield

		Maize yield	
	Selection	Non-adopters	Adopters
Age	0.006	0.034***	0.004
	(0.006)	(0.013)	(0.013)
Gender	−0.174	−0.309	0.697*
	(0.205)	(0.483)	(0.409)
Education	0.012	0.035	0.048
	(0.016)	(0.032)	(0.029)
Number of agricultural workers	−0.079**	−0.036	0.010
	(0.034)	(0.068)	(0.066)
Cooperative membership	0.346**	−0.210	0.229
	(0.154)	(0.286)	(0.282)
Off-farm employment	0.211	−0.045	−0.276
	(0.132)	(0.295)	(0.275)
Plain	−0.210	0.014	0.128
	(0.155)	(0.430)	(0.363)
Soil fertility	−0.188*	0.619**	0.575**
	(0.108)	(0.240)	(0.224)
Land fragmentation	−0.017**	−0.007	0.093***
	(0.008)	(0.011)	(0.027)
Rented land	0.414***	−1.016***	−0.435*
	(0.114)	(0.272)	(0.240)
Farm size	0.002	0.117***	−0.030*
	(0.014)	(0.035)	(0.016)
Fertilizer expenditure	0.137***	0.346***	0.086
	(0.050)	(0.133)	(0.120)
Pesticide expenditure	0.097	0.198	0.566
	(0.133)	(0.326)	(0.406)
West	0.127	1.671***	1.409***
	(0.188)	(0.401)	(0.510)
Northeast	0.724***	2.942***	2.515***
	(0.235)	(0.494)	(0.541)
North	0.024	1.670***	1.267**
	(0.177)	(0.322)	(0.507)
Private car	1.081***		
	(0.101)		
Constant	−0.853*	2.571**	3.864***
	(0.467)	(1.293)	(1.055)
$\ln\sigma_0$		0.628***	
		(0.059)	
ρ_0		−0.034	
		(0.241)	
$\ln\sigma_1$			0.788***
			(0.056)
ρ_1			−0.231**
			(0.102)
Log likelihood		−2106.003	
Wald χ^2 (16)		122.35***	
Likelihood ratio of independence		χ^2 (2) = 4.77*	
Observations		786	

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; south is the reference region; ρ_0 is the correlation coefficient between ε_{0i} and μ_i; ρ_1 is the correlation coefficient between ε_{1i} and μ_i.

3.3.2 Estimation of labor productivity function

Table 3.3 presents the estimates of ESR model for farmers' adoption of farm machinery and its impacts on labor productivity. ρ_1 is negative and significantly different from zero which suggests the presence of selection bias. The likelihood ratio of independence test rejects the null hypothesis of farm machinery adoption and labor productivity are independent at the 1% significance level. Similarly, the results of selection equation suggest that cooperative membership, off-farm employment, and rented land have significantly positive effects on farm machinery adoption, while land fragmentation has a significantly negative impact on farm machinery adoption. Farm household heads with off-farm employment have higher chance to adopt farm machinery may be because they need machinery to substitute the lost labor from off-farm employment (Su et al., 2016). On the other hand, Ji et al. (2012) reported that off-farm employment decreases farmers' odds of owning farm machinery due to the alternative machinery services from market. In particular, the coefficient of fertilizer expenditure is significantly positive, indicating that more fertilizer use promotes the adoption of farm machinery. Maize farmers from West and Northeast of China have higher probability to be farm machinery adopters compared to farmers from South because these regions are mainly plains. Private car and village cadre both have significantly positive effects on farm machinery adoption, and this suggests that they are valid instrumental variables.

Table 3.3 Estimates of ESR model for farm machinery adoption and its impacts on labor productivity

		Labor productivity (ln)	
	Selection	Non-adopters	Adopters
Age	0.005	0.008	−0.005
	(0.005)	(0.006)	(0.005)
Gender	−0.193	−0.521**	−0.115
	(0.200)	(0.239)	(0.189)
Education	0.006	0.034**	0.004
	(0.016)	(0.016)	(0.015)
Cooperative membership	0.372**	0.074	0.146
	(0.150)	(0.190)	(0.146)
Off-farm employment	0.257**	0.184	−0.202*
	(0.125)	(0.158)	(0.120)
Plain	−0.162	0.111	0.202
	(0.152)	(0.192)	(0.132)
Soil fertility	−0.104	0.043	0.370***
	(0.103)	(0.112)	(0.103)
Land fragmentation	−0.015*	0.015	0.079***
	(0.008)	(0.020)	(0.015)
Rented land	0.385***	−0.226	−0.162
	(0.105)	(0.160)	(0.116)
Farm size	0.030	0.207***	0.131***
	(0.026)	(0.030)	(0.012)
Fertilizer expenditure	0.160***	−0.018	−0.134***
	(0.050)	(0.061)	(0.044)
Pesticide expenditure	0.134	0.152	0.422***
	(0.123)	(0.106)	(0.118)
West	0.305*	0.184	−0.136
	(0.174)	(0.193)	(0.181)
Northeast	0.662***	1.552***	0.821***
	(0.236)	(0.306)	(0.212)
North	0.022	0.500***	0.027
	(0.159)	(0.182)	(0.172)
Private car	0.184*		
	(0.112)		
Village cadre	0.359***		
	(0.119)		
Constant	−0.735*	5.991***	7.693***
	(0.439)	(0.536)	(0.492)
$\ln\sigma_0$		−0.118*	
		(0.066)	
ρ_0		−0.214	
		(0.379)	
$\ln\sigma_1$			0.052
			(0.075)
ρ_1			−0.667***
			(0.136)
Log likelihood		−1514.658	
Wald χ^2 (15)		172.75***	
Likelihood ratio of independence		χ^2 (2) = 11.20***	
Observations		786	

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; south is the reference region; ρ_0 is the correlation coefficient between ε_{0i} and μ_i; ρ_1 is the correlation coefficient between ε_{1i} and μ_i.

In labor productivity equations, farm size has a significant positive effect on labor productivity of both adopters and non-adopters because increased farm size leads to more total maize output and indirectly increases labor productivity of each agricultural worker. Soil fertility and pesticide expenditure have positive effects on labor productivity for those who adopted farm machinery because good pest and disease control and fertile soil can boost maize productivity. However, off-farm employment seems to decrease the labor productivity of adopters. A possible explanation is that farmers who have off-farm employment would invest less time and less efforts in agricultural production, and this causes the reduction of labor productivity.

3.3.3 Impacts of farm machinery adoption on maize yield and labor productivity

The impacts of farm machinery adoption on maize yield and labor productivity are shown in Table 3.4. The expected maize yield produced by adopters is 7.159 tons/ha, while these farmers would have produced 6.942 tons/ha of maize yield if they did not adopt farm machinery under the counterfactual scenario. Hence, the average impact of farm machinery adoption for adopters is 0.216 tons/ha. Under the counterfactual scenario, farmers who did not adopt farm machinery would increase maize yield by 0.833 tons/ha if they had adopted. These results support that farm machinery adoption did benefit farmers through increased maize yield. Similarly, farm machinery adoption is also found to increase the labor productivity of maize farmers. The ATT of farm machinery adoption on adopters is 0.450, suggesting that adopters would decrease the expected labor productivity by 5.86% (The formula is: (7.227−7.677)/7.677*100%) if they did not adopt. Likewise, labor productivity of non-adopters would increase by 18.65% (The formula is: (8.530−7.189)/7.189*100%) if they had adopted farm machinery.

Table 3.4 Impacts of farm machinery adoption on maize yield and labor productivity

	Decision stage		Treatment effects
	To adopt	Not to adopt	
Maize yield (ton/ha)			
Adopters	7.159	6.942	ATT=0.216***
	(0.041)	(0.053)	(0.067)
Non-adopters	7.697	6.864	ATU= 0.833***
	(0.051)	(0.052)	(0.072)
Labor productivity (ln)(yuan/person)			
Adopters	7.677	7.227	ATT= 0.450***
	(0.054)	(0.065)	(0.085)
Non-adopters	8.530	7.189	ATU= 1.341***
	(0.051)	(0.045)	(0.068)

*** $p<0.01$; standard errors in parentheses using 50 bootstrap replications.

3.3.4 Heterogeneous impacts of farm machinery adoption on maize yield and labor productivity

The ATTs of maize yield and labor productivity in Table 3.4 only show the average impacts of farm machinery adoption on all adopters. However, many studies have shown that the impacts of farm machinery use may differ across farm households because of the heterogeneous farm characteristics and social-economic conditions (Adekunle et al., 2016; Adu-Baffour et al., 2019; Kienzle et al., 2013; Qing et al., 2019; Takeshima et al., 2020; Zhou et al., 2020). The impacts of farm machinery adoption on maize yield and labor productivity may not be the same for all adopters, and it remains unclear how the ATTs differ across farm households. If farm machinery adoption had positive effects exclusively for large farms or high productive farmers, the undifferentiated farm machinery extension program which fails to consider the farm-level heterogeneity would cause the inequity among farmers. Thus, understanding the heterogeneous effects of farm machinery adoption contributes to formulate different sets of extension services which fit various types of farm households.

Table 3.5 Heterogeneous treatment effects of farm machinery adoption

Variables	Maize yield ATT	Labor productivity (ln) ATT
Age	−0.031***	−0.013***
	(0.002)	(0.001)
Gender	0.853***	0.295***
	(0.077)	(0.050)
Education	0.017***	0.022***
	(0.006)	(0.004)
Number of agricultural workers	0.018	
	(0.015)	
Cooperative membership	0.645***	0.296***
	(0.092)	(0.061)
Off-farm employment	−0.228***	−0.346***
	(0.047)	(0.032)
Plain	0.058	0.110***
	(0.059)	(0.035)
Rented land	0.836***	0.278***
	(0.060)	(0.040)
Farm size	−0.059***	−0.019
	(0.019)	(0.013)
Farm size square	−0.002***	−0.001***
	(0.001)	(0.000)
West	−0.415***	−0.487***
	(0.092)	(0.061)
Northeast	−0.661***	−0.840***
	(0.098)	(0.064)
North	−0.551***	−0.538***
	(0.085)	(0.056)
Constant	1.113***	1.535***
	(0.181)	(0.122)
R−squared	0.779	0.675
Observations	464	464

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; south is the reference region.

Inspired by Verhofstadt and Maertens (2015), this study uses ATTs of maize yield and labor productivity, generated from the ESR model, as dependent variables in two OLS regressions respectively to explore the heterogeneous treatment effects of farm machinery adoption across farm and farmer characteristics. Table 3.5 shows the heterogeneous treatment effects of farm machinery adoption across farm and farmer characteristics. Young, male, and more educated farm households gain higher maize yield and labor productivity from farm machinery adoption. The results also imply that farm machinery adoption is more productive in increasing maize yield and labor productivity among the farms which are located in plain regions with cooperative membership and rented land. This can be explained by that plain regions are favorable for mechanized operations, and jointly mechanical operations within cooperative members improve the effects of farm machinery use. In particular, the coefficients of farm size square terms are significant negative and the axes of symmetry of the quadratic functions are on the left side of y-axes. It indicates that the impacts of farm machinery adoption on maize yield and labor productivity decrease with farm size slightly. This may be because the expansion of farm size leads to resource misallocation and management inefficiency, and finally to a decline in the impacts of farm machinery adoption (Sheng et al., 2019). Likewise, Huang and Ding (2016) found an inverse relationship between farm size and maize yield in China because of distortions in small-scale farming transformation, and policies are needed to assist small farms to adapt to large farms by improving resource use efficiency and farming productivity. To achieve the best economic effects of adopting farm machinery, an appropriate farm size is better than the oversized one in the context of Chinese agriculture.

3.3.5 Robustness test

Table 3.6 Propensity score matching: impacts of farm machinery adoption on maize yield and labor productivity

Outcome variables	Matching algorithm	ATT
Maize yield (ton/ha)	Kernel matching	0.329*
	(Bandwidth = 0.06)	(0.171)
	Nearest neighbor matching	0.304*
	(N=10, with replacement)	(0.215)
	Radius matching	0.347**
	(caliper=0.08)	(0.171)
Labor productivity (ln)	Kernel matching	0.347***
(yuan/person)	(Bandwidth = 0.06)	(0.086)
	Nearest neighbor matching	0.343***
	(N=10, with replacement)	(0.094)
	Radius matching	0.367***
	(Caliper=0.08)	(0.083)

*** p<0.01; standard errors in parentheses using 50 bootstrap replications; ATT: average treatment effect on the treated.

Propensity score matching was performed to check the robustness of results from ESR models. The results of propensity score matching (Table 3.6) show that the impact of farm machinery adoption on maize yield for adopters is 0.304-0.347 tons/ha, which is close to the result of ESR model 0.216 tons/ha. Similarly, the impact of farm machinery adoption on labor productivity for adopters is 0.343-0.367, which is also close to the result of ESR model 0.450. Findings from propensity score matching suggest the robustness of estimates from ESR models.

3.4 Conclusions

This article aims to identify the drivers and barriers of Chinese maize farmers' farm machinery adoption decisions and to estimate the impacts of farm machinery adoption on maize yield and labor productivity by using the ESR models. Rented land and cooperative membership are main facilitators of farm machinery adoption, while land fragmentation is a barrier for adoption. Farm machinery use has shown significantly positive impacts on maize yield and labor productivity, but the impacts differ across farm households and slightly decrease with farm size. To achieve the best economic performance of adopting farm machinery, Chinese farmers need to find appropriate scales in maize production.

Some policy implications can be drawn from this study. Firstly, promoting moderate scale maize production. Moderate scale maize production enlarges the land scale and makes it easier to implement large scale mechanization and promotes the adoption of farm machinery. Notably, the land size is not the bigger the better. Farmers need to explore an appropriate scale to maximize profitability and to avoid resource misallocation and inefficiency of management and thus to increase the returns of farm machinery adoption. Secondly, establishing farm machinery cooperatives or initiating mechanization services. Joint farm machinery ownership in farm machinery cooperatives or mechanization services from the third party would significantly reduce the investment and operation expenditure of farm machinery and can boost the adoption of farm machinery. Thirdly, facilitating land consolidation and land circulation. Land consolidation merges many small and discrete field plots into a relatively large field plot which makes machinery operation easier and efficient. Flexible land circulation systems enable farmers to expand their land scale through renting in land from free market, and enlarged land scale would promote farmers to use farm machinery to substitute manual labor and to facilitate mechanization. Finally, formulating customized farm machinery extension services for different farm households to promote the adoption of farm machinery and to optimize its economic effects. Policy makers should appreciate that farmers who are not cooperative members, not renting in land, and having fragmented land parcels face more challenges in farm machinery adoption.

Conflict of interest

The authors declare that they have no conflict of interest.

Data availability

The datasets used in study are available from the corresponding author on reasonable request.

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Table A1 Test on the validity of instrumental variables

	Probit model	Ordinary least squares	
	Machinery adoption	Maize yield (Non-adopters)	Labor productivity (ln) (Non-adopters)
Private car	0.228**	0.006	−0.183
	(0.103)	(0.231)	(0.118)
Village cadre	0.270**		0.239
	(0.123)		(0.138)
Constant	−0.545	2.615**	6.207***
	(0.443)	(1.256)	(0.526)
Wald test	χ^2 (18) = 83.83***	F = 6.82***	F = 10.96***
R−squared	Pseudo R^2 = 0.093	R^2 = 0.196	R^2 = 0.462
Observations	800	322	322

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Due to brevity, coefficients of all other variables are not reported.

Chapter 4 Unmanned aerial vehicle (UAV) technical applications, standard workflow, and future developments in maize production – water stress detection, weed mapping, nutritional status monitoring and yield prediction

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Abstract: As a consequence of rapid ongoing technological developments and increasing integration into agricultural mechanization and agricultural intelligence, UAVs are gradually starting to play an increasingly important role in field crop management and monitoring. This review introduces and covers the development in four major applications of UAVs in maize production: (i) water stress detection, (ii) weed mapping, (iii) nutrient status monitoring and (iv) yield prediction. In addition, this review summarizes UAV data management methods, explains how expert systems work in UAV systems, and provides standardized workflow data for farmers in maize production. In addition, the strengths, weaknesses, opportunities, and threats of UAV use in maize production are analyzed. Based on more than eighty publications and our own research, the discussion and conclusions point out key issues in UAV usage in maize cropping and research gaps that need to be filled, along with a number of recommendations for the development of UAVs in maize production in the future.

Keywords: Unmanned aerial vehicles (UAVs), maize, field management, data management, expert systems.

Unmanned aerial vehicles (UAVs) can be fitted with specific functional sensors (multispectral, hyperspectral, and thermal, etc.) suitable for agricultural purposes to enable image acquisition and data collection while flying across crop fields at a low altitude. In addition to remote sensing, UAVs can also be used for other agricultural activities such as field surveillance, plant counting, weed mapping, yield prediction, irrigation management, plant disease detection, plant health monitoring, and crop spraying (Tsouros et al., 2019a). Crop spraying is an important application of UAVs. UAVs equipped with tanks fly to the sites where weeds grow and spray variable rates of herbicides based on weed maps instead of uniform blanket application

(Castaldi et al., 2017; Yang et al., 2018). However, due to the potential environmental hazards of pesticide drift, aerial spraying is forbidden in European countries (Remáč, 2018). It is only allowed if there are no viable alternatives but reduced impacts on human and the environment as compared with ground-based pesticide application should be proved (Reger et al., 2018). Nevertheless, as the progress of technology (e.g. smart drones, high-performance UAVs, and longer flight durations, etc.) and changes of legal boundaries, UAV-based crop spraying applications will be an important aspect in the future.

Most studies have shown that low agricultural water use efficiency (Fang et al., 2010), excessive nitrogen application (Cui et al., 2008), and pesticide overuse (Brauns et al., 2018) are the main problems of maize production all over the world. Given the constraints imposed by these problems, more sustainable maize production needs to find innovative ways of solving them. Since UAVs have so many benefits in agricultural production, it is natural to use them in maize cropping. Moreover, maize has significant size and leaf area make it the most promising crop to work with UAV technologies because large size and leaf area are easy for UAVs to execute remote sensing and spraying. Some new applications of this system have been used in maize cropping, for example, water stress detection (Shi et al., 2019), yield prediction (Maresma et al., 2016), weed mapping (Castaldi et al., 2017), and height estimation (Wang et al., 2019). *Table 4.1* shows the differences between traditional ground level precision maize production and UAV-based maize production in field management. Traditional ground level precision maize production relies on tractor-mounted sensors, field deployed sensors, or portable test devices for field monitoring. However, the movement of tractors on the field could cause soil compaction and crop damage. On the contrary, UAV-based maize production uses UAVs fitted with sensors to fly across crop fields at a low altitude and this avoids the problems in ground level precision maize production. UAVs can cover more areas in a short time and can provide more comprehensive field information than ground level precision technologies. Furthermore, UAV-based site-specific aerial spraying is more flexible and faster than tractor-based variable-rate spraying.

Table 4.1 Differences between traditional ground level precision maize production and UAV-based maize production in field management

	Ground level precision maize production	UAV-based maize production	References
Water stress detection	Tractors, handheld infrared thermometer, portable air temperature meter	UAV multispectral sensors	Zhang et al. (2019)
Yield prediction	Yield monitors and yield maps	UAV multispectral sensors	Jeffries et al. (2020); Vergara-Díaz et al. (2016)
Weed mapping	Tractors, spectrometers, fluorescence sensors	UAV multispectral sensors	Castaldi et al. (2017)
Nutrient status monitoring	Tractors, handheld chlorophyll leaf clip sensors	UAV multispectral and hyperspectral sensors	Gabriel et al. (2017)
Crop spraying	Tractor-based variable-rate spraying	UAV-based site-specific spraying	Castaldi et al. (2017)

However, the review of recent UAV technology progress in maize production is very limited. Up to now, UAVs do not have a standardized workflow in maize production, and this can cause confusion when farmers are trying to use UAV systems because a high level of expertise is needed at different field management stages to choose the suitable strategies and to process data (Orakwe and Okoye, 2016; Tsouros et al., 2019b; Zhang and Kovacs, 2012). This increases the difficulty of UAV use and reduces labor productivity because not all farmers possess this kind of professional knowledge. Therefore, a well-structured standardized workflow is urgently needed to guide farmers and to improve system efficiency in UAV-based maize production.

This review compiles the recent UAV studies in maize production in a systematic approach, summarizes the data acquisition and processing methods, designs a standard workflow for maize production, and offers a clear guide for maize producers. The aims of this paper are (i) to review scientific literature about the current use and development of UAV technologies in maize production; (ii) to explain how UAV technologies can solve problems in maize production; (iii) to design a standard UAV workflow for farmers in maize production; and (iv) to provide estimations for the future development of UAVs in maize production.

4.1 Uses of UAVs in maize production field management

Based on sixty-two studies published over the last 10 years on the use of UAVs in maize production, UAV research can be classified as the following types (*Figure 4.1*): water stress detection (10%), nutrient status monitoring (18%), weed mapping (19%), yield prediction (27%), height estimation (13%), plant distance estimation (3%), maize lodging estimation (3%), maize number counting (3%), and others (3%). This review focuses solely on the introduction of UAVs in water stress detection, nutrient status monitoring, weed mapping, and yield prediction, which are considered to be the dominant factors that impact production costs.

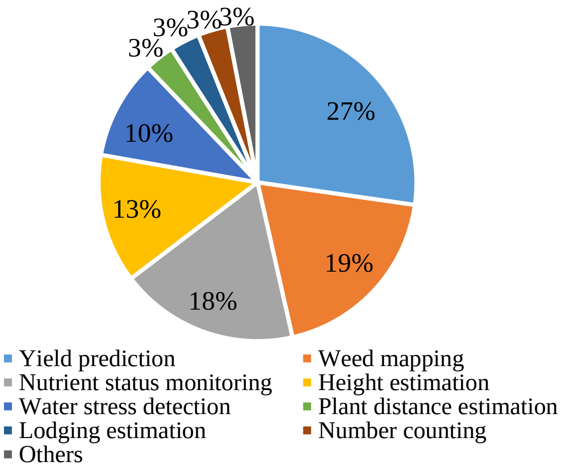

Figure 4.1 Proportions of UAV application types in maize production (Based on 62 studies published over the last 10 years).

4.1.1 Maize water stress detection

Accurate crop water stress detection is needed in a comprehensive irrigation management to achieve maximum water use efficiency and thus reduce costs. In recent years, two methods have been predominantly applied to detect water stress in plant: on-site measurement of soil water content and plant-based physiological indicators measurement (Ihuoma and Madramootoo, 2017). However, these conventional methods are time-consuming, costly, and failed to depict the crop water status of the entire field (Zhang et al., 2019a, 2019b). Due to the benefits of being easy to operate, flexible, and non-invasive coupled with high-resolution images, UAVs have been increasingly used as an alternative production practice in crop water stress monitoring (Park et al., 2017; Poblete et al., 2018; Zhang et al., 2019b). Under different water availability conditions, crop leaves reflect different light spectrums and show different canopy temperatures and UAV sensors are able to differentiate water stress plants from water sufficient plants (Sylvester et al., 2018).

The research on UAV-based maize water status monitoring is very limited. Zhang et al. (2019b) established crop water stress index regression models to map maize water status at the reproductive and maturation stages based on nine vegetation indices (e.g. normalized difference vegetation index, soil-adjusted vegetation index, etc.) extracted from UAV multispectral images. Comparing the maize water stress estimation results derived from regression models with ground-based data, the R^2 value could reach 0.81. It proves the feasibility of UAV-based maize water status monitoring. However, this research does not demonstrate to what extent these maize water stress estimation regression models can be used under varying conditions (e.g. other maize cultivars, other locations, etc.). Furthermore, most of the UAV-based maize water stress detection studies only concentrate on single critical growth stage instead of the whole growth period of maize and the prediction models can only be used under certain circumstances.

Based on the literature available so far, a general standardized procedure of UAV-based maize water stress detection is summarized as: (i) using UAVs equipped with sensors to collect data from maize fields, (ii) measuring field level maize ground-truth data, (iii) modelling and calibrating the UAV data with ground level maize truth data, and (iv) generating maize water status maps that indicate the exact amount of water which should be site-specifically irrigated in different plots or even spots instead of widely applied.

4.1.2 Maize weed mapping

Weeds are estimated to cause approximately 30% to 60% of potential yield losses in maize production worldwide (Castaldi et al., 2017; Chikoye et al., 2005; Oerke, 2006; Safdar et al., 2015; Usman et al., 2001). Some farmers carry out uniform blanket herbicide spraying for weed control instead of site-specific spraying and this causes the excessive use of synthetic chemical herbicides on the fields (Castaldi et al., 2017; Pelosi et al., 2015). Herbicides have significantly reduced weed infestation in fields but the excessive use of herbicides has led to environmental and ecological problems such as groundwater pollution, soil contamination, and biodiversity loss (Castaldi et al., 2017; Pelosi et al., 2015; Peña et al., 2013). Consequently, site-specific and efficient weed management is a measure of major importance when it comes to reducing the frequency and amount of herbicide usage in maize production (Burgos-Artizzu et al., 2011).

UAVs equipped with image sensors fly at low altitudes and are capable of distinguishing weed patches from crops in a less expensive way (Prince Czarnecki et al., 2017). Next, UAVs equipped with tanks filled with liquid herbicide fly to the field to spray precise amounts of herbicide based on observed weed site, weed density, and weed spatial distribution (Pelosi et al., 2015; Peña et al., 2013). UAV-based weed mapping and spraying help to reduce the amount of herbicides applied to fields and reduce environmental pollution (Castaldi et al., 2017; Pelosi et al., 2015).

The accuracy of UAV maize weed mapping ranges from 61% to 98% in seven studies and the accuracy is evaluated by comparing the weeds estimated from UAV images with actual on-ground weed counting (*Table 4.2*). Castaldi et al. (2017) observed herbicide savings of between 14% and 39.2% in UAV-based weed map patch spraying (spraying herbicides only on the site where weeds grow) in maize fields compared to conventional blanket application (evenly spraying herbicides on the entire field). Due to weed heterogeneity within the field, the saved amount of herbicide was different. Compared with uniform blanket application, site-specific patch spraying did not identify any significant differences in maize and weed biomass (Castaldi et al., 2017; Pelosi et al., 2015). This means that patch spraying does not compromise maize yield and has the same weed control effects as blanket application. UAV weed mapping is a possible option to support precision herbicide patch spraying in maize fields without any economic yield loss. Mink et al. (2018) found that UAV weed mapping reduced herbicide use by 90% in post-emergence maize weed treatments. They developed a canopy height model combined with vegetation indices and crop geographic coordinates in the field to distinguish weeds from maize by their height at maize three leaf stage. It demonstrated 96% accuracy in maize weed mapping (Mink et al., 2018).

Table 4.2 UAVs used in maize weed mapping

Sensors	Weed mapping methods	UAV remote indices	Accuracy	References
Visible light (RGB)[1)], NIR[2)]	Support vector machine algorithm (SVM)	NDVI[3)]	82%	Pelosi et al. (2015)
Visible light (RGB), NIR, multispectral	Support vector machine algorithm (SVM)	NDVI	61%	Castaldi et al. (2017)
Multispectral	Object-based image analysis	NDVI	95%	Peña-Barragán and Kelly (2012)
Multispectral	Object-based image analysis	NDVI	86%	Peña et al. (2013)
Visible light (RGB), multispectral	Object-based image analysis	NDVI, ExG[4)]	98%	Peña et al. (2014)
Visible light (RGB), multispectral	Canopy height model, weed height model	NDVI, ExR[5)], ExG	96%	Mink et al. (2018)
Hyperspectral	Support vector machine (SVM), machine learning (ML)	Cnorm[6)] and GRDB[7)]	64%	Casa et al. (2019)

[1)]RGB: red, green and blue; [2)] NIR: near infrared; [3)] NDVI, normalized difference vegetation index; [4)] ExG, excess green index; [5)] ExR, excess red index; [6)] Cnorm, (700 – 515) / (700 + 515); [7)] GRBD, band depth 540 – 690.

However, the main obstacle to UAV weed mapping is finding effective algorithms to identify pixels which depict weeds in the digital images and remove unrelated background (Burgos-Artizzu et al., 2011). Because some weeds are similar in appearance (e.g. shape, color, etc.) to crops in the early stages of development, it is difficult to discriminate weeds from crops (Burgos-Artizzu et al., 2011; Peña-Barragán et al., 2012). The accuracy of discrimination affects the outcomes of weed mapping and site-specific treatment (Hamuda et al., 2016).

4.1.3 Maize nutritional status monitoring

At different development stages, maize has varying nutrient demands (Rhezali and Lahlali, 2017). In order to ensure sufficient nutrient supply, it is crucial to monitor the site-specific nutrient needs at different critical stages of maize growth. With the assistance of UAVs, maize real-time nutrient status in each plot can be detected by sensors. Comprehensive nutritional status monitoring maps extracted from UAV images could be valuable tools in variable rates of fertilizer application.

Most of the UAV nutrient monitoring studies in maize concentrated on maize nitrogen status assessment (Cilia et al., 2014; Corti et al., 2018; Gabriel et al., 2017; Krienke et al., 2017; Quemada et al., 2014; Rhezali and Lahlali, 2017) because nitrogen nutrient indices are the best indicators to assess maize nutritional status (Gabriel et al., 2017) (*Table 4.3*). Cilia et al. (2014) highlighted the potential of using UAVs to obtain maize nitrogen status maps of the entire field, because the estimated nitrogen content derived from UAV images showed good correlation with field level maize nitrogen measurements (R^2=0.70) (Cilia et al., 2014). Quemada et al. (2014) also confirmed the reliability of UAVs in nitrogen status assessment at maize flowering stage because the UAV image derived index (TCARI/OSAVI) was negatively correlated with maize nitrogen balance index (R=−0.84).

Table 4.3 UAVs used in maize nitrogen status monitoring

Sensors	UAV remote indices	Prediction models	Phenology stage of maize	References
Multispectral	BNDVI[1)], GNDVI[2)], GC[3)]	Linear regression, least square regression	V6+V9	Corti et al. (2018)
Hyperspectral	MCARI/MTVI2[4)], NNI[5)]	Ordinary least squares regression	Pre-flowering stem elongation	Cilia et al. (2014)
Hyperspectral	TCARI[6)]/OSAVI[7)]	Polynomial regression	Flowering	Gabriel et al. (2017)
Hyperspectral, thermal	TCARI/OSAVI	Linear regression	Flowering	Quemada et al. (2014)

[1)] BNDVI: Blue Normalized Difference Vegetation Index; [2)] GNDVI: Green Normalized Difference Vegetation Index; [3)] GC: Ground Cover; [4)] MCARI/MTVI2: Modified Chlorophyll Absorption Ratio Index/Modified Triangular Vegetation Index 2; [5)] NNI: nitrogen nutrition index; [6)] TCARI: Transformed Chlorophyll absorption in reflectance index; [7)] OSAVI: Optimized soil-adjusted vegetation index.

Although these studies showed the feasibility of UAV-based maize nitrogen status monitoring, the prediction accuracy can be affected by canopy structure, pigment concentration, leaf water content, and other nutrient deficiencies except nitrogen (Gabriel et al., 2017). To minimize the impact of these interfering factors, further research should use more UAV remote indices as independent variables in maize nitrogen status estimation models. Using more remote indices to predict maize nitrogen status has been proved to be more stable and more reliable than using single one because a single index is easily affected by the factors mentioned above (Cilia et al., 2014; Gabriel et al., 2017; Quemada et al., 2014).

Based on the four references presented in *Table 4.3*, the basic workflow of UAVs in maize nitrogen monitoring is summarized as (i) UAV sensors capture images above maize fields, then derive vegetation indices which characterize the nitrogen status of maize; (ii) determine maize nitrogen concentration using ground level destructive measurements in some representative plots; (iii) by means of a series of regression analyses, selecting the best index or combined indices to predict maize nitrogen status which leads to the results that strongly correlate with ground level maize nitrogen measurements.

4.1.4 Maize yield prediction

Maize yield prediction prior to harvest is very important for farmers to enable them to take decisions about the input of water, fertilizers, pesticides, labor, transportation, space for storage as well as for predicting market constellation and developing optimal economic strategies (Geipel et al., 2014). In most cases, some farmers estimate the yield based on their experience, yield maps, or partly field sampling (Ping and Dobermann, 2005). These methods are over-reliance on experience and the results cannot convey accurate information about fields and proved to be labor-intensive and time-consuming (Li et al., 2016; Wahab et al., 2018). Compared to these methods, the UAV-based system reduces labor and there by improve economic performance (Tsouros et al., 2019a), saves time (Tsouros et al., 2019a), and expands the area of field investigation (Barbedo, 2019). The yield is inferred through its correlation with UAV data in mathematical modeling, then a maize yield prediction model can be given to decision makers (Herrmann and Bdolach, 2019).

Table 4.4 UAVs used in maize yield prediction

Sensors	UAV remote indices	Image/ data processing software tools	Prediction models	R^2	Phenology stages of maize	References
Multispectral	Wide dynamic range vegetation index (WDRVI)	JMP Pro 12 statistical package	Linear and quadratic regression	0.92	V12	Maresma et al. (2016)
Visible light (RGB)[1)]	Excess green (ExG) color feature	Curve Fitting Toolbox of Matlab	Linear regression	0.37	R2, R3, R6	Zhang et al. (2020)
Multispectral, Hyperspectral	Structure of motion (SfM) mean point height	Smart3DCapture software	Random forest regression	0.78	R3, R4	Li et al. (2016)
Multispectral	Normalized difference vegetation index (NDVI)	ENVI software	Exponential regression	0.72	R2-R3	Vergara-Díaz et al. (2016)
Multispectral	LiDAR point clouds	Python 2.7, and R × 64 3.5.3	Linear regression	0.85	Jointing period of summer maize	Zhu et al. (2019)
Visible light (RGB), multispectral, hyperspectral	Vegetation indices (VIs)	Matlab 7.6, PLS-toolbox	Partial least squares regression	0.73	R2	Herrmann and Bdolach (2019)
Multispectral	Blue and near infrared wavelength bands (BNDVI)	Agisoft PhotoScan professional software	Partial least squares regression	0.4-0.69	Entire growing season	Wu et al. (2019)
Multispectral	BIOVP: a volume metric used to estimate crop biomass within a plot	Pix4D software	Random forest regression	0.94	V12, VT	Han et al. (2019)

[1)]RGB: red, green and blue; R^2 is the coefficient of determination of the maize yield prediction model.

Vegetation indices (e.g. WDRVI, BNDVI, NDVI, ExG, etc.) derived from UAV images are considered to be effective variables in different forecast models for yield prediction (*Table 4.4*) (Geipel et al., 2014; Herrmann and Bdolach, 2019; Vergara-Díaz et al., 2016; Wu et al., 2019; Zhang et al., 2020). During vegetative growth stages, different prediction models were developed to predict maize yield, such as linear regressions (Zhang et al., 2020; Zhu et al., 2019), random forest regressions (Han et al., 2019; Li et al., 2016), partial least squares regressions (Herrmann and Bdolach, 2019; Wu et al., 2019), etc. The R^2 ranges from 0.37 to 0.94 because the goodness of fit of the models is affected by many variables (e.g. maize growth stages, sensor sensitivity, weather conditions, locations, etc.) (Zhang et al., 2020).

However, in case of using only UAV derived vegetation indices in maize yield prediction models is not sufficient to get convincing results (Geipel et al., 2014). Maize height, canopy cover, and other structural information extracted from UAV remote sensing can be considered as independent variables in yield prediction models simultaneously with UAV derived vegetation indices to improve yield prediction accuracy (Geipel et al., 2014; Han et al., 2019; Zhu et al., 2019). Some studies have shown the correlation of maize yield with maize height before mid-season stage (Katsvairo et al., 2003; Yin et al., 2011a, 2011b).

4.2 Standard workflow of UAVs in maize production

Recently, the most widespread commercial application of UAVs in maize production on the market has followed this standard workflow: UAV-based field data collection→Farm Management Information Systems → UAV field operation management (DJI, 2020; PrecisionHawk, 2020; XAG, 2020).

4.2.1 UAV-based field data collection

UAVs fitted with multispectral sensors fly across the entire field at a low altitude to collect images and data from crops. The sensors then transmit the collected information to locally installed software such as Agisoft PhotoScan and this a common and valid option for most UAV users (Kaimaris et al., 2017; Radoglou-Grammatikis et al., 2020). Apart from processing the data on local personal computers or workstations, some UAV companies provide cloud services which can also assist in data processing (DJI, 2020; PrecisionHawk, 2020; XAG, 2020). UAVs could be operated by farmers themselves or farmers could source professional licensed operators nearby from an UAV commercial service platform to operate the UAVs for them (Zhang et al., 2020).

4.2.2 Farm Management Information Systems (FMIS)

FMIS are databases designed to manage, implement, and record farm operations systematically (Burlacu et al., 2014; Pedersen and Lind, 2017; Sørensen et al., 2010; Zhai et al., 2020). In UAV-based maize production, FMIS are integrated systems with different functional components to assist farmers in real time decision making (DJI, 2020; PrecisionHawk, 2020; XAG, 2020): automated data processing, expert systems, user-controlled interfaces, and farm recordkeeping systems, etc. (Sørensen et al., 2011, 2010). The inputted farm data in FMIS are analyzed automatically by expert systems (Boursianis et al., 2020; Kenneth and Chinecherem, 2018). Expert systems are powerful tools based on human expert analytical experience, agronomic data from previous years, and computer simulated human expert reasoning process, etc. to predict crop nutritional status, generate prescription maps, design customized expert reports, and give suggestions on fertilization, irrigation, and plant protection, etc. (DJI, 2020; Prasad and Babu, 2006; Rani et al., 2011). Other artificial intelligence methods can also involve in UAV data processing, such as artificial neural networks for predicting crop nutritional status (Jha et al., 2019), random forest for modelling maize above-ground biomass (Han et al., 2019), fuzzy logic for forecasting crop water requirements (Talaviya et al., 2020), etc. User-controlled interfaces allow farmers to control and to access processing and analysis functions (Murakami et al., 2007). All field work executed in a plot is recorded in farm recordkeeping systems (Saiz-Rubio and Rovira-Más, 2020). The data generated in a current year production cycle in the FMIS are used to assess performed field work and will be stored on local personal computers, laptops, or cloud-based storage systems as baseline information for next season production (XAG, 2020). All storage options are valid; farmers can choose appropriate data storage paths depending on their needs (DJI, 2020).

4.2.3 UAV field operation management

Farmers can manage and supervise UAVs in the performance of their field tasks through a smart remote controller (PrecisionHawk, 2020). Mission planning software designs automated missions for UAVs so that they can carry out field tasks automatically without manual operation (Srivastava et al., 2020). Farmers send instructions from smart remote controllers to manipulate UAVs to execute the requested movements (e.g. take-off, speeding, spraying, and landing, etc.) (DJI, 2020). After receiving the radio signals sent from remote controllers, UAVs move automatically along designated routes to execute remote sensing or spraying. During the mission, UAVs share the real-time location with smart remote controllers (XAG, 2020). If the

UAVs were out of the designated tracks, farmers can adjust the flight paths by sending instructions from smart remote controllers.

4.3 Strengths, weaknesses, opportunities, and threats (SWOT) analysis of UAVs in maize production

Based on the literature available so far, a SWOT table can be elaborated, depicting the major strengths, weaknesses, opportunities, and threats of UAV use in maize production (*Table 4.5*).

Table 4.5 SWOT analysis of UAVs used in maize production

Strengths	Weaknesses
• Minimize labor input	• Data processing
• Increase productivity	• Data interpretation
• Reduce resource wastage	• Weather reliant
• Accurate real-time field monitoring	• High investments for small-scale farmers
• Fewer working hours	• Special education and training
Opportunities	**Threats**
• Yield prediction	• UAV crash
• Nutrient status monitoring	• UAV maintenance
• Irrigation management	• Unstable UAV performance
• Identify weeds and diseases	• Short flight time of each mission
• Generate prescription maps	• Unclear data ownership regulations

The strengths of UAVs in maize production are the reduction of labor input, higher productivity and thus higher economic performance, reduced resource wastage, accurate real-time field monitoring, and fewer working hours. Complicated data processing and data interpretation are the weaknesses that restrict the development of UAVs. A weakness of UAV operation is that it is weather dependent. Windy and rainy weather conditions are not ideal for UAVs and flights should be suspended under these circumstances (Tsouros et al., 2019a). Depending on platforms and sensors, the price of UAVs can be different. In 2018, the average price of a domestic brand crop spraying UAV was $14815 in China (Yang et al., 2018). A basic GPS guidance system in precision agriculture costs $800 to $1500 in the US in 2017 (Andrews, 2017). The investments of UAVs are quite high especially for small size farmers because their production scale is small and the benefit they could get from UAV technologies is limited (Yang et al., 2018). Farmers need special education and training, and this is another weakness of UAV adoption in maize production because not all farmers are willing to acquire new knowledge (Michels et al., 2020; Tamirat et al., 2018).

The UAV system offers opportunities for maize yield prediction, maize nutrient status monitoring, maize irrigation management, identification of maize weeds and diseases, and generation of prescription maps. But it also comes with some threats. Farmers need to run the risk of their UAV crashing; this happens sometimes (Barbedo, 2019). UAV maintenance is an essential expense if an UAV were to be out of action. Unstable UAV performance also bothers farmers from time to time. The UAV flight time in each mission ranges from 8 to 60 minutes at full load (Candiago et al., 2015; Norasma et al., 2019; Tsouros et al., 2019a). Short flight time of each mission is another threat which affects UAV application because farmers need to refill application materials or to recharge energy frequently after each flight (Yang et al., 2018). This reduces the working efficiency. Longer flight time of each mission could be desirable for farmers. Fixed wing UAVs have long flight time, high speeds, high load capacity, stable performance and can cover large areas in a single mission, but they need wide space for takeoff and landing (Boon et al., 2017). Comparing with fixed wing UAVs, multi-copter UAVs have slower speeds, shorter flight time, less payloads, but they are more flexible and more manoeuvrable because they can take off and land off vertically in constrained areas (Tsouros et al., 2019a). Therefore, fixed wing UAVs are best for large scale field investigation or spraying; instead multi-copter UAVs are good for small areas precise mapping or site-specific spraying. Finally, data ownership regulations have to be clarified in standard regulations to avoid conflicts of interest.

4.4 Discussion

Compared with traditional ground level precision maize production, UAVs offer an innovative way in irrigation management, nutrient status monitoring, weed mapping, and yield prediction. With the support of UAV precision technologies and FMIS, farmers can improve their work efficiency, reduce labor, and lower resource wastage. UAVs provide farmers greater access to real-time information on maize fields in a few hours, and carry out comprehensive digital field monitoring and intelligent management. Farmers are released from the burden of complex data processing and intricate agricultural task planning, and all the agricultural activities are managed, planned, and recorded by the FMIS. This is the most significant merit of UAV-based agricultural production systems.

However, there are some severe limitations when using UAVs in maize production. UAV data management and UAV operations are very complicated. Without special training and education, farmers will not be able to handle it properly. The high purchase cost restricts UAV development in small scale farmers because their production scale is small and the benefit they could get from UAV technologies is limited (Yang et al., 2018). Unstable performance bothers farmers from time to time when they are using UAVs (Sinha et al., 2016). Furthermore, UAV-based field management is not a general practice in maize production currently and it is not clear if they can replace the traditional ground level precision agriculture technologies in the future. Unclear data ownership regulations may cause conflicts of interest between farmers and data management platforms (Saiz-Rubio and Rovira-Más, 2020; Wiseman et al., 2019). All of these factors added together could increase the difficulty of UAV use in maize production and reduce work efficiency.

4.5 Conclusions and recommendations

This article contributes to the use, research, and development of UAVs in maize production, and leads to better understanding of the role of UAVs in maize production. The application of UAV technologies can solve some, but not all, problems in maize production. The advantages and potential of UAVs should not be overestimated. Compared to traditional ground level precision agriculture technologies, most of the UAV systems are still in the preliminary development and experimental stages. Moreover, the conclusions of UAV-based studies are only drawn from limited researches on specific field and maize variety conditions. The applicability of these conclusions in different circumstances needs to be verified. The large-scale commercial use of UAVs in maize production still has a long way to go. Up to now, most of the studies have focused on the technical level of UAV use, and not on the economic, social, ecological aspects or impact of UAVs in maize production systems. Future research is needed in these areas: education and training, impact assessment, technology assessment, economic evaluation, ecological evaluation, sustainable scheme, proper data ownership regulations, etc.

Overall, there are some recommendations regarding UAV use in maize production in the future:

(i) Development of cost-effective UAVs, to make them more commercially acceptable to small-scale farmers;

(ii) Improvement of UAV performance, increases in the working time and load capacity of UAVs in a single flight, and reduction of UAV crashes; UAV unsupervised operation also needs to be improved because most countries only allow UAVs to be operated under supervision and this makes operation costly;

(iii) Improvement of UAV spraying accuracy and avoid drifting, to promote the adjustment of aerial spraying legal regulations;

(iv) Construction of user-friendly and high efficiency data management platforms to accelerate the ability of data transmission, processing, and interpretation;

(v) Offer of special training and education to farmers who have purchased UAVs, ensuring they get sufficient technical guidance and support services;

(vi) Clearer legal and regulatory frameworks to govern data management, which includes data collection, sharing, using, control, and accessibility;

(vii) Enhancement of network connections between UAV data management platform members and promotion of data sharing and benefit sharing among them;

(viii) Building of UAV system-based field management demonstration sites or farms and provision of consultancy and extension services to farmers.

Declaration of interests

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.

CRediT authorship contribution statement

Xiuhao Quan: conceptualization, methodology, formal analysis, investigation, writing-original draft, visualization, writing - review& editing. Reiner Doluschitz: conceptualization, validation, resources, writing-review & editing, supervision.

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Chapter 5 The determinants of unmanned aerial vehicle (UAV) adoption and status quo of UAV-based pattern management in Chinese agriculture: insights from expert interviews

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Abstract

In China, unmanned aerial vehicles (UAVs) are increasingly used for broadcast application of agricultural inputs such as pesticides, fertilizers, and seeds. In addition, UAVs have the potential to be used for site-specific precision agriculture such as field pattern management to precisely manage fertilization, plant protection, and irrigation, which could help to reduce environmental footprint of farming. There has been research on the use of UAVs in agriculture, but less is known about UAV-based precision agriculture, particularly pattern management. To close the research gaps, this paper conducted structured in-depth interviews with 18 experts from various fields related to UAVs and agriculture in China to study the status quo, drivers, and barriers of adopting UAVs in agriculture, focusing on UAV-based precision agriculture, especially pattern management. The results show that the adoption of UAVs in China is influenced by farmers' production characteristics, farmers' perceptions about UAVs, and social factors. UAV-based precision agriculture is at the initial stage in China, and the promotion of this approach still needs to break technical barriers such as improving the accuracy of crop monitoring, developing real-time UAV positioning systems, and enhancing the response time of variable-rate spraying systems, as well as socio-economic barriers such as farmers' limited UAV-related knowledge, small farm sizes, and lack of technical assistance.

Key words: unmanned aerial vehicles, adoption, determinants, pattern management, China, precision agriculture

5.1 Introduction

UAVs mounted with tanks and sensors can be used in a range of agricultural practices (Michels et al., 2021; Rejeb et al., 2022; Tsouros et al., 2019a) such as pesticide spraying (Faiçal et al., 2014), fertilizer spraying (Abd. Kharim et al., 2019), seeding (Huang et al., 2020), and crop monitoring (Maimaitijiang et al., 2020). China has been using UAVs in agriculture since 2010

(Zheng et al., 2019). Over a decade of development in China, agricultural UAVs have become cheaper, smarter, and better than before (Chung, 2019). UAVs, which can only be used in pesticide spraying at the beginning, can now be applied in seeding, fertilizer spraying, and crop monitoring, etc. (Sylvester et al., 2018; Zhang and Kovacs, 2012). Up to now, China's agricultural UAV industry has become the first in the world in terms of the number of UAVs, flight control technology, and cumulative operating area per year (Ministry of Agriculture and Rural Affairs of People's Republic of China, 2019). In 2020, 70,344 UAVs were being used in China for plant protection purposes and they were treating14.48 million hectares of cropland (China Agricultural Machinery Industry Association, 2021) (Figure 5.1).

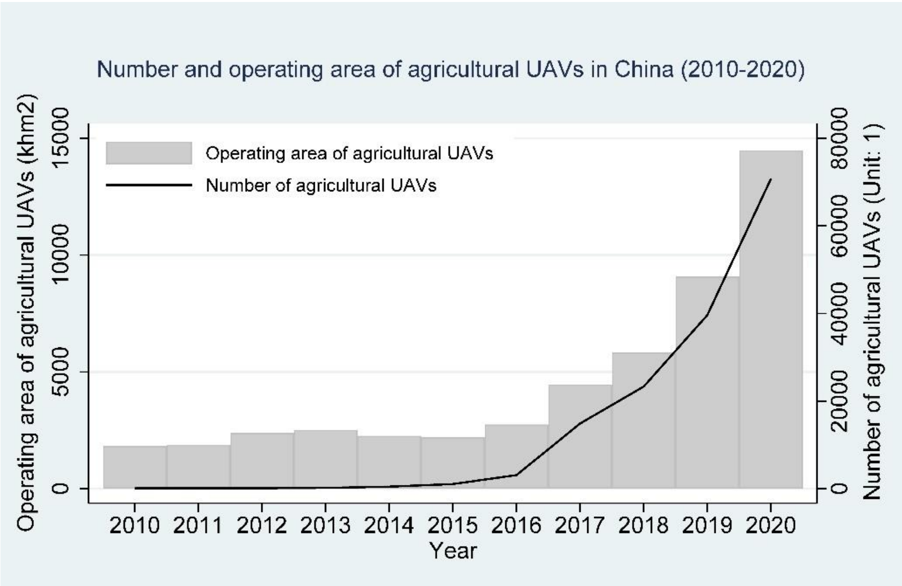

Figure 5.1 Number and operating area of agricultural UAVs in China (2010-2020).
Data source: China Agricultural Machinery Industry Association (2021).

Next to supporting research and development, there are different aspects that explain the rise of agricultural UAVs in China. In 2017, China launched nationwide agricultural UAV purchase subsidies in six provinces to promote the use of UAVs in agricultural production. Agricultural cooperatives and plant protection organizations are eligible to apply for these subsidies and can be granted a subsidy amounting to up to 30% of the purchase price for UAVs, whereby the maximum sum of the subsidy does not exceed 4,370 $ per UAV (Ministry of Agriculture and Rural Affairs of People's Republic of China, 2017). UAV purchase subsidies have had a great impact on the use of UAVs, and their numbers have increased significantly since 2017 (Figure 5.1). The most popular forms of using UAVs among Chinese farmers are either to self-purchase UAVs or to hire UAV services (e.g., pesticide spraying, fertilizer spraying, seeding, and crop monitoring) from UAV service agricultural cooperatives or private UAV pilots (Chung, 2019). Self-purchased UAVs are very common among large-scale corporate farmers, while UAV services are well accepted by small and medium-sized farmers because of the affordable prices (Chen et al., 2020; Chung, 2019).

For the convenience of operation and economic viability, most Chinese farmers adopt UAVs for broadcast spraying (e.g., pesticides, fertilizers, and seeds) instead of site-specific precise spraying (Chung, 2019; Hu et al., 2022; Lan et al., 2019). In addition to the "traditional" use of UAVs in broadcast spraying, UAVs can also be applied in precision agriculture for precise spraying, crop monitoring, and field management (Radoglou-Grammatikis et al., 2020; Sylvester et al., 2018; Tsouros et al., 2019a). Shifting UAVs from "general use" to "precision use" comes with a great potential because precision application rather than broadcasting can greatly improve yield and sustainability of farming (Radoglou-Grammatikis et al., 2020; Roma et al., 2023). One example is UAV-based pattern management, which is an innovative and holistic approach proposed by Spohrer (2019) for sustainable and site-specific precision agriculture in respect of fertilization, plant protection, and irrigation. Pattern management includes three pillars: structured land management, UAV-based image acquisition, and data management (Figure 5.2). Structured land management divides fields into different spatiotemporal patterns. UAVs attached with sensors (e.g., infrared and hyperspectral) fly over fields to capture images and spatiotemporal data of these patterns. Images and field spatiotemporal data are processed by modified algorithms (Zhang and Kovacs, 2012) and stored in the database. Fertilizer, pesticide, and water variable-rate prescription maps are derived from the processed data to instruct fertilization, plant protection, and irrigation (Tsouros et al., 2019b). Data management is responsible for data storage, data retrieval, data processing, data mapping, and UAV flight control, etc. The processed spatiotemporal data will be shown on terminal devices (e.g., tablets, smartphones, and laptops) in a straightforward way, and farmers can manage and monitor different patterns on the field through user-friendly interfaces.

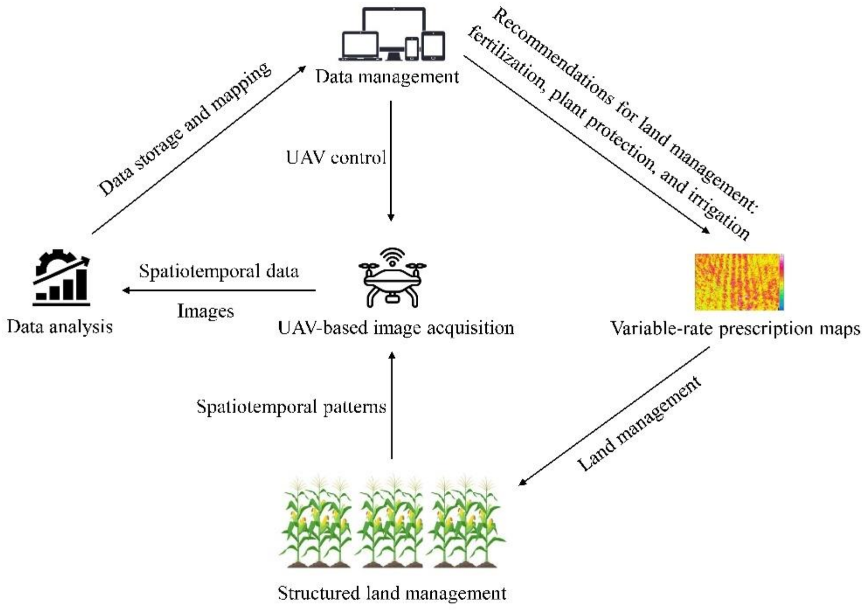

Figure 5.2 UAV-based Pattern Management.

Several studies have explored the determinants of adopting UAVs in Chinese agriculture, finding that perceived usefulness, perceived ease-of-use, UAV-related knowledge level, farm size, agricultural income share, cooperative membership, within-family village leadership, credit availability, government subsidies, extension services, and trainings have positive effects on UAV adoption (Chen et al., 2020; Han et al., 2022; Wachenheim et al., 2021; Zheng et al., 2019). However, these studies only analyzed the determinants of UAV adoption from farmers' perspective but did not explore which other factors are key for the successful and scaling of this technology, including factors related to the enabling environment. For this, it would be important to interview other stakeholders such as agricultural UAV manufacturers, UAV service providers (e.g., UAV service agricultural cooperatives and private UAV pilots), agricultural extension staff from government, and researchers focusing on UAVs. Moreover, although there has been some research on UAVs in Chinese agriculture, the extent to which UAVs are used for precision agriculture (e.g., pattern management) and barriers for adopting UAVs for precision agriculture still remain unclear. To close the research gaps, this study conducted a series of structured in-depth expert interviews with 18 experts from various fields of expertise related to UAVs and agriculture in China to get a holistic view on drivers, barriers, and institutions that are needed for UAV adoption, especially in precision farming for field pattern management.

5.2 Materials and methods

To better understand the status quo of UAV use, determinants of UAV adoption, and development of UAV-based pattern management in China, this qualitative study conducted a series of structured in-depth expert interviews with main stakeholders of agricultural UAVs in China from various backgrounds. Purposeful sampling (Palinkas et al., 2015) was used to select several different types of respondents that are related to agricultural UAVs in China and are able to answer research questions with their practical experience. The sample consisted of 18 experts from China (Table 5.1): university professor (n=1), agricultural UAV manufacturers (n=3), farmers using UAVs (n=4), farmers not using UAVs (n=3), professional UAV pilots (n=3), agricultural extension staff from government (n=1), and managers of UAV service agricultural cooperatives (n=3).

Table 5.1 Characteristics of 18 agricultural experts

ID	Category	Expert information
1	University professor	A pioneer of agricultural UAV research in China and more than 15 years of research experience in agricultural UAVs; Expertise: UAVs for pesticide application and precision variable-rate pesticide spraying technology.
2-4	Agricultural UAV manufacturers	Agricultural UAV industry leaders in China; Expertise: Research and development of agricultural UAVs.
5-8	Farmers using UAVs	Farmer (ID 5): male, 35 years old, 5.3 ha land, college degree, and 2 years of farming experience in rice and black soybean production; Farmer (ID 6): male, 50 years old, 40 ha land, high school degree, and 6 years of farming experience in rice production; Farmer (ID 7): male, around 30 years old, 6.7 ha land, college degree, and 5 years of farming experience in citrus production; Farmer (ID 8): male, 27 years old, 13.3 ha land, college degree, and 6 years of experience in *Areca catechu* plantation.

9-11	Farmers not using UAVs	Farmer (ID 9): male, 38 years old, 66.7 ha land, high school degree, and 12 years of farming experience in potato production; Farmer (ID 10): female, around 60 years old, 0.1 ha land, middle school degree, and 40 years of farming experience in maize, soybean, and vegetable production; Farmer (ID 11): male, 40 years old, 2.7 ha land, master degree, and 3 years of farming experience in loquat plantation.
12-14	Professional UAV pilots	Pilot (ID 12): Male, around 30 years old, middle school degree, and 7 years of work experience as an UAV pilot; Pilot (ID 13): Male, around 30 years old, college degree, and 2 years of work experience as an UAV pilot; Pilot (ID 14): Male, around 30 years old, middle school degree, and 6 months of work experience as an UAV pilot; Expertise: proficient UAV operation skills and working as an individual for farmers in UAV pesticide spraying.
15	Agricultural extension staff from government	12 years of work experience in agricultural extension; Expertise: UAV extension services and trainings.
16-18	Managers of UAV service agricultural cooperatives	Cooperative (ID 16): 5 years of experience in UAV services, 3 UAVs, and 10 employees; Cooperative (ID 17): 6 years of experience in UAV services, 5 UAVs, and 5 employees; Cooperative (ID 18): 3 years of experience in UAV services, 5 UAVs, and 3 employees; Expertise: Teamwork, providing the whole package of UAV services to farmers, including pesticide spraying, fertilizer spraying, and seeding, etc.

The experts were interviewed through phone calls in November and December of 2022. Interview questions were sent to them before the interviews. Expert interviews focused on the following topics (Table 5.2): Status quo, opportunities and challenges of UAVs more generally, and specifically about UAV-based pattern management in Chinese agriculture. During the interviews, experts were asked to answer the related questions in each topic (Table 5.2). Averagely, each phone call was around 25 to 30 minutes. The contents of expert interviews were documented and analyzed by the qualitative content analysis method (Mayring, 2021) to extract the main concepts.

Table 5.2 Interview topics and questions

Topics	Questions
Topic 1	
Status quo of UAVs in Chinese agriculture	UAV: supply, services, operation, work efficiency, maintenance, and training
Topic 2	
Opportunities and challenges of UAVs in Chinese agriculture	Advantages, disadvantages, drivers, and barriers of UAV adoption
Topic 3	
UAV-based precision agriculture and pattern management in Chinese agriculture	Development of UAV-based precision agriculture and pattern management

5.3 Results

5.3.1 "Traditional" or "broadcast" UAVs: status quo, opportunities, and challenges

5.3.1.1 Forms of UAV supply

UAVs are typically supplied in the forms of self-purchasing, renting, and UAV services from third parties. 7 farmers (ID 5-11) were asked about the forms they like to have UAVs. There were four forms for them to choose: self-purchasing, renting, hiring UAV services, and establishing an UAV cooperative. 4 UAV adopters (ID 5-8) preferred self-purchasing than other forms because they have relatively large farms that need UAVs to replace manual labor, and they can use UAVs at any time especially in busy farming seasons. 3 UAV non-adopters (ID 9-11) preferred to hire UAV services than other forms because they only need UAVs several times a year, and they do not want to buy UAVs or to learn how to operate UAVs. The university professor (ID1) mentioned: "*UAV services and UAV renting are two convenient approaches to give farmers access to the latest UAVs at low costs. In addition, the shorter lifespan of an UAV,* *the bigger benefit farmers can obtain from technical progress by frequent replacement"*. Wang et al. (2022) also highlighted that UAV services can reduce production costs, increase production efficiency, lower the threshold price of using UAVs, and accelerate the adoption of UAVs in Chinese agriculture.

Again, 7 farmers (ID 5-11) were asked about the ways they like to learn UAV technology. There were four ways for them to choose: technical manuals or books, online video courses, training programs in UAV demonstration sites, and local professional extension staff. Most of them preferred to learn UAV technology from local professional extension staff and from demonstration sites. They thought it would be easier if local professional extension staff illustrate how to use UAVs for them on the fields, or demonstration sites provide some UAV practical training courses for them. Similarly, Han et al. (2022) emphasized that extension services and promotion programs have positive effects on farmers' intention to adopt UAVs.

5.3.1.2 UAV training, operation, maintenance, and work efficiency

Some important aspects about UAV training, operation, maintenance, and work efficiency were summarized by experts (Table 5.3). An agricultural UAV manufacturer mentioned (ID3): "*All UAV operators have to take training courses which last from 2 to 7 days. The training includes: UAV operation and maintenance, preparation of pesticides, UAV mapping, and UAV security issues. At the end of the course, operators who pass the test will receive a license*". Three UAV pilots (ID12-14) also talked about UAV operation and maintenance. Before UAV flight, 10 to 30 minutes are needed for preparation work such as field observation, marking obstacles, flight planning, and UAV testing. During UAV tasks, one person is responsible for UAV operation, and the other person is in charge of battery replacement, pesticide or fertilizer loading, and field observation. Pilots need 2 to 5 minutes to refill UAV tanks and to replace new batteries. UAV battery capacity affects the time required for charging, and charging habits affect the lifespan of batteries. Charging an UAV battery needs 8 to 30 minutes, and the lifespan of a battery is about 500 to 1500 cycles. Wings and nozzles are the most easily damaged parts of UAVs because wings often hit on obstacles, and nozzles are often clogged by pesticides. UAV work efficiency depends on the types of UAVs and field conditions. One UAV pilot said (ID12): "*Depending on battery capacity, load, and field conditions, a single UAV flight can last from 8 to 25 minutes and can cover 0.5 to 3.3 ha field crops and 0.1 to 0.4 ha fruit trees. The daily flight range of an UAV can reach 10 to 13.3 ha in fields and 3.3 to 6.7 ha in orchards*".

Table 5.3 UAV training, operation, maintenance, and work efficiency

Questions	Answers
UAV training course duration	2-7 days
UAV training contents	UAV operation and maintenance, preparation of pesticides, UAV mapping, and UAV security issues
UAV training tuition fees	300-900 $
Preparation time before flight	10-30 minutes
Single flight time	8-25 minutes; depending on battery capacity and load
Single flight range	0.5-3.3 ha for field crops; 0.1-0.4 ha for fruit trees;
	depending on battery capacity, load, and field conditions, etc.
Time to refill tanks and to replace new batteries	2-5 minutes
Daily flight range of an UAV	10-13.3 ha for field crops; 3.3-6.7 ha for fruit trees
Battery charging time	8-30 minutes
Battery lifespan	500-1500 cycles; depending on battery capacity and charging habits
Which parts of UAVs are easily to damage?	Wings and nozzles

5.3.1.3 The price of UAV services

A manager from an UAV service agricultural cooperative (ID17) said: *"UAV pesticide spraying is the most common UAV service for farmers in China. Other UAV services such as seeding, fertilizer spraying, and crop monitoring are not widespread, but are gradually increasing".* Farmers can hire either UAV pilots or UAV service agricultural cooperatives to spray pesticides for them. An UAV pilot (ID14) emphasized that "*UAV operation fees depend on the types of crops, severity of pests and diseases, topography, and field conditions. In general, UAV operation fee is lower for large fields that are easy to fly UAVs and higher for crops with severe pests and diseases*". An UAV adopter (ID7) mentioned: *"For field crops, UAV operation fees range from 22 $ /ha to 56 $ /ha. For fruit trees, UAV operation fees (78 $/ha to 178 $/ha) are* *more expensive because most orchards are located in hilly regions which makes UAV operations difficult, and fruit trees need more pesticides than field crops due to the large canopies".* Likewise, Chung (2019) found that UAV operation fees depend on types of crops and topographies, and H. Li *et al.* (2022) reported that, compared to plain regions, UAV operation efficiency drops significantly by 30% to 50% in hilly regions.

5.3.1.4 Advantages, disadvantages, drivers, and barriers of UAV adoption

Most farmers in this study adopt UAVs for "traditional" broadcast pesticide spraying, while other UAV applications such as seeding, fertilizer spraying, and crop monitoring are less common but not unimportant. The experts were asked to point out advantages of UAVs in agricultural production (Table 5.4). One expert reported (ID1): *"Labor-saving and time-saving are the most distinctive merits of UAVs. In the context of labor shortages in rural areas, UAVs play an important role in replacing manual labor in agricultural production"*. This is in line with scientific studies. In pesticide application, an UAV can work 4 to 10 hectares in one hour, which is equivalent to the workload of 30 to 100 workers using manual spraying (Yang et al., 2018). The saved labor costs significantly reduce production costs and increase profitability. Four UAV adopters (ID5-8) and three professional UAV pilots (ID12-14) addressed that compared to the slow speed and huge amount labor input of ground-based pesticide application methods, UAVs can conduct timely and effective pest and disease control with considerably fewer labor, water, and pesticide. An UAV adopter (ID5) said: *"Separating operators from pesticides to avoid pesticide poisoning is an advantage of UAVs. In addition, UAVs can be applied in plains, mountains, orchards, and other terrains where people cannot reach".*

The experts were asked to point out disadvantages of UAVs in agricultural production as well (Table 5.4). Nearly all experts acknowledged that pesticide drift is the biggest disadvantage of UAVs because it can damage the crops nearby and cause environment pollution (Biglia et al., 2022; Wang et al., 2020). Three UAV non-adopters (ID9-11) and three agricultural UAV manufacturers (ID2-4) admitted that high prices and unstable performances discourage farmers to use UAVs. An UAV adopter (ID5) said: "*Unstable performances such as safety incidents, unstable flight control systems, repeated and omitted spraying of pesticides are disadvantages of UAVs".* Weather reliant is another drawback of UAVs. An agricultural extension staff from government (ID15) addressed: "*UAVs cannot work in high temperatures and in windy weather because high temperatures could damage batteries, and windy weather exacerbates pesticide drift".* However, traditional ground-based pesticide application methods are constrained by these weather conditions as well. Three professional UAV pilots (ID12-14) mentioned that UAVs are inefficient in scattered field plots because the difficulty of operation. One UAV pilot (ID12) said: "*For treating severe pest and disease outbreaks in some specific areas on the field, UAVs are less effective than ground-based spraying methods. The concentration of pesticide sprayed by UAVs is 5 to 30 times higher than ground-based spraying, but the high concentration and low volume pesticides have undesirable treatment effects due to the low water content".* Likewise, P. Li *et al.* (2022) found that UAV spraying is more effective at controlling mild and moderate cotton Aphis than the severe one. In contrast, Qin *et al.* (2016) reported that UAV spraying shows better control effects than ground-based stretcher sprayer against plant hoppers because the low volume and high concentration pesticides sprayed by UAVs can persist to active for many days after application. Thus, more solid experimental evidence is still needed to compare the controlling effect of UAV spraying and ground-based spraying in pest and disease treatment.

Table 5.4 Advantages, disadvantages, drivers, and barriers of adopting UAVs

Advantages	Disadvantages	Drivers	Barriers
• Saving time • Saving labor • Saving water • Saving pesticides • Avoid pesticide poisoning • Overcoming terrain obstacles • Effective pest and disease control	• High prices • Pesticide drift • Weather reliant • Unstable performances • Inefficient in scattered field plots • Inefficient in treating severe pests and diseases	• Rural labor shortages • Specialized farming • Market demand for UAV services • Expansion of farm size • UAV purchase subsidies • After-sales service or technical support • UAV trainings • Farmers' positive perceptions about UAVs	• Knowledge gap • Small farm size • UAV operation skills are required • Unspecified UAV operating standards • Unfavorable field conditions • UAV pilot shortages

Experts pointed out some drivers of UAV adoption in China (Table 5.4). Social factors such as labor shortages, UAV purchase subsidies, market demand for UAV services, after-sales service or technical support, and UAV trainings are important drivers of UAV adoption. Four farmers using UAVs (ID5-8) highlighted that rural labor shortages are the biggest driver of UAV adoption because farmers need UAVs to cope with missing workers and rising rural wages. An agricultural extension staff from government (ID15) said: *"UAV purchase subsidies are important drivers of UAV adoption because subsidies lower prices and make UAVs more* *affordable for the majority"*. Likewise, H. Li *et al.* (2022) also found that UAV purchase subsidies can boost UAV adoption, and subsidies based on cumulative areas of UAV operation can also promote UAV adoption, especially among small and medium-sized farmers. A farmer not using UAVs (ID10) reported: *"If we could get UAV technical assistance or after-sales service, we might consider to adopt UAVs in our farm".* Han *et al.* (2022) also emphasized that external environment such as UAV technical assistance and after-sales service are the main drivers of UAV adoption. A professional UAV pilot (ID12) said: *"There is a market demand for UAV services. Thus, we adopt UAVs to provide these services to farmers".* Farmers' perceptions about UAVs and production characteristics can also influence UAV adoption. A farmer not using UAVs (ID10) mentioned: *"I would like to use UAVs only if there are convincing benefits of adoption*". This finding is consistent with Han *et al.* (2022), Skevas and Kalaitzandonakes (2020), and Li *et al.* (2020) who found that perceived usefulness can affect farmers' UAV adoption. The university professor mentioned (ID1): *"Specialized farming, where 50% or more of its income derives from a single crop, is a driver of UAV adoption. Specialized farming makes UAVs work easily and efficiently because most of the crops on the farm are the same*". One farmer using UAVs said (ID6): "*The expansion of farm size needs UAVs to replace manual labor and to improve productivity".* This finding is in line with Michels et al. (2020), who expected that UAVs can considerably assist farmers in reducing time costs, labor costs, and management complexity as the increasing of farm size.

Meanwhile, there are several barriers of UAV adoption (Table 5.4). A farmer not using UAVs mentioned (ID9): *"Small farm size makes UAVs less useful because farmers are able to manage all field work by manual labor. Unfavorable filed conditions such as scattered field plots and high voltage lines above fields inhibit the adoption of UAVs".* Four farmers using UAVs (ID5-8) emphasized that UAV operation skills discourage some farmers from using this technology. One farmer reported (ID8): *"The operation of UAVs needs some basic skills, and farmers have to be trained to operate UAVs, but the training discourages some farmers to use UAVs because they think it is too difficult to learn UAV technology".* This finding is consistent with Han *et al.* (2022) and Zheng *et al.* (2019) who reported that perceived ease of use has positive effects on UAV adoption. Three UAV pilots (ID12-14) addressed that specified standards for UAV operation and pesticide application are very important. One UAV pilot (ID13) said: *"Unspecified standards for UAV operation and pesticide application is a barrier of UAV adoption because incorrect UAV operation and pesticide application can cause undesirable results in pest and disease control".* Pilot shortages are obstacles of UAV adoption too. An

UAV pilot (ID12) emphasized: "*The shortage of UAV pilots can also be a barrier of UAV adoption because many farmers do not have UAVs or do not know how to operate UAVs, and they need to hire UAV pilots to work for them".* Chung (2019) also mentioned that the low supply of agricultural UAV pilots does not match with the fast speed of UAV adoption in China, and more UAV training institutes are needed to educate more pilots.

5.3.2 Development of UAVs in precision farming: the case of pattern management

UAV-based pattern management is still at the experimental phase, and it will take some time to achieve commercial use in precision farming. The university professor (ID1) mentioned: *"UAV-based pattern management is an innovative approach and has great potential in the future, but this concept needs time to elaborate. In China, UAV-based pattern management is only partially used in some large-scale farms for specialized farming, where 50% or more of its income derives from a single crop".* According to answers from experts in this research, there are three main socio-economic prerequisites to apply the UAV-based pattern management. Firstly, farmers' good UAV-related knowledge and the convincing benefits of using UAVs. The application of UAV-based pattern management requires good knowledge about UAV operations, UAV image processing, and data management, etc. Farmers' UAV-related knowledge affects the quality of UAV-based pattern management. The convincing benefits of using UAV-based pattern management can promote farmers to use this approach. Most farmers do not adopt UAV-based pattern management because of the huge investment and unforeseen returns from adoption (Sylvester et al., 2018), and they concern that the economic benefits of adoption may not offset the investment. However, up to now, limited studies have analyzed the economic returns of using UAVs in precision agriculture (Andújar et al., 2019; Späti et al., 2021), and more empirical analysis should be conducted in the future to estimate the economic benefits of using UAVs (Kerry and Escolà, 2021). Secondly, a relatively large arable land size (≥ 2 ha) and high-value crops producing on the farm. A relatively large arable land size makes UAVs more convenient to use, and high-value crops producing on the farm make farmers more willing to invest in UAVs to improve profitability. Thirdly, social facilitating conditions such as UAV purchase subsidies, after-sales UAV service or support, UAV trainings, and relatively mature agricultural UAV markets are also important prerequisites to implement UAV-based pattern management.

Based on answers from three agricultural UAV manufacturers (ID2-4), there are also three main technical prerequisites to apply UAV-based pattern management. Firstly, accurate crop monitoring. UAV monitoring systems should be able to accurately monitor pests, diseases, and nutrients of crops. Fertilizer and pesticide variable-rate prescription maps are made based on the monitoring data, and the accuracy of monitoring can affect the following field operations such as spraying and irrigation. Due to the limitations of current technology, UAV-based crop monitoring still needs to improve its accuracy in some cases (Maimaitijiang et al., 2020; Xie et al., 2021). Secondly, precise real-time UAV positioning systems. When UAVs are flying above fields to perform site-specific precise spraying, real-time positioning systems are needed to guide UAVs to the right site (Yang et al., 2018). However, it is difficult to make real-time positioning systems to work precisely when UAVs are flying. Thirdly, fast response time of variable-rate spraying systems. UAVs operate at a high speed and require a quick response time of variable-rate spraying systems to match with the speed of UAVs, but it is still difficult to achieve this.

5.4 Discussion and conclusions

This paper conducted structured in-depth expert interviews with 18 experts in China from various field of expertise related to UAVs and agriculture to study the status quo of UAV use, determinants of UAV adoption, and development of UAV-based pattern management in China. Most Chinese farmers adopt UAVs for pesticide spraying; other UAV applications such as seeding, fertilizer spraying, and crop monitoring are not widespread, but are gradually increasing. The determinants of UAV adoption come from these major aspects: farmers' production characteristics (e.g., land size and specialized farming), farmers' perceptions about UAVs (e.g., perceived ease of use and perceived usefulness), and social factors (e.g., UAV purchase subsidies, trainings, and technical support). In this study, the determinants of UAV adoption and their effects on UAV adoption are consistent with Han *et al.* (2022), H. Li *et al.* (2022), Li *et al.* (2020), Michels *et al.* (2020), Skevas and Kalaitzandonakes (2020), Wachenheim *et al.* (2021), Zheng *et al.* (2019), and Zuo *et al.* (2021).

UAV-based pattern management is at the initial stage in China, and the promotion of this approach still needs to break technical barriers (e.g., accurate crop monitoring, precise real-time UAV positioning systems, and fast response time of variable-rate spraying systems) and socio-economic barriers (e.g., farmers' limited UAV-related knowledge, small farm sizes, and lack of technical assistance). At this stage, UAV-based pattern management can be promoted first in large-scale farms for specialized farming because of its high expected returns. Given economic viability, UAV service agricultural cooperatives can provide UAV-based pattern management services for small and medium -sized farms.

To effectively promote the shifting of UAVs from “general use” to “precision use” in China’s agriculture, joint efforts are needed from all stakeholders (Figure 5.3). Government is the head of all stakeholders and is expected to formulate laws and regulations to instruct the development of agricultural UAV industry in China. For example, investing in UAV research and development, formulating standards for UAV operating and pesticide application, providing UAV extension programs and UAV related subsidies (e.g., UAV purchase subsidies, subsidies based on cumulative areas of UAV operation, and UAV training subsidies), and establishing UAV demonstration sites. UAV manufacturers are supposed to develop UAVs with stable and good performances but affordable prices. UAVs should have user-friendly interfaces that are easy to learn and to operate. UAV trainings and after-sales service or support are also expected from UAV manufacturers. Professional UAV pilots should be proficient in standards of UAV operating and pesticide application. UAV service agricultural cooperatives are expected to provide cheap, efficient, and high-quality UAV services for farmers, including crop spraying and crop monitoring, etc. Farmers are encouraged to expand arable land size appropriately, to consolidate scattered field plots together, to conduct specialized farming, or to attend UAV extension programs.

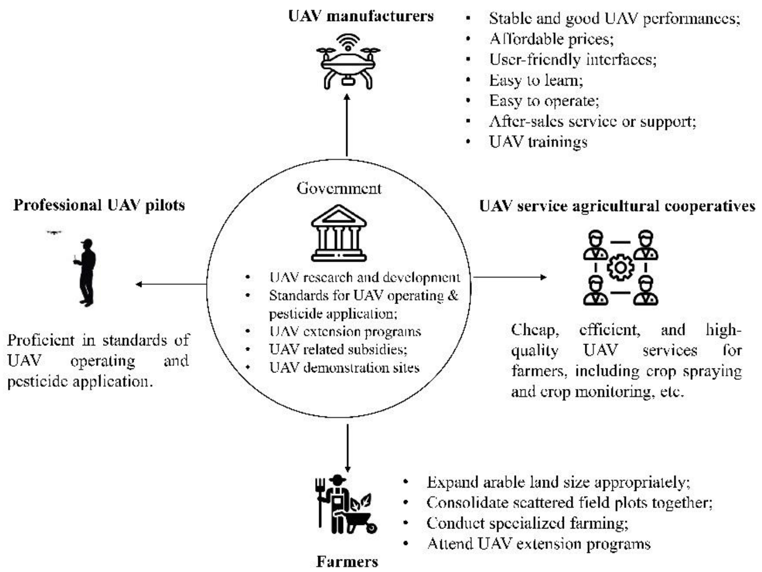

Figure 5.3 UAV promotion model in China

However, the results of this article are from interviews with a small group of 18 experts and cannot represent all stakeholders of China’s agricultural UAV sector. In addition, this qualitative study is based on answers of experts and is inevitably somewhat subjective. Nevertheless, this study sets the foundation for the future research of UAV adoption in Chinese agriculture and provides an overview of UAV-based pattern management in China, and it opens the flow for further investigation and research fields, e.g., a more comprehensive questionnaire based quantitative survey with a large number of participants.

Conflict of interest

The authors declare that they have no conflict of interest.

Author contributions

Xiuhao Quan: conceptualization, methodology, software, validation, formal analysis, investigation, data curation, writing—original draft, writing—review and editing, and visualization; Reiner Doluschitz: conceptualization, supervision, writing—review and editing, resources, project administration, and funding acquisition; Xiongkui He: investigation, resources, and project administration; Zhichong Wang: conceptualization, methodology, investigation; Thomas Daum: conceptualization, methodology, investigation, writing—original draft.

Data availability

The data used in study are available from the corresponding author on reasonable request.

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Chapter 6 The economic effects of unmanned aerial vehicles in pesticide application: evidence from Chinese grain farmers

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Abstract

Unmanned aerial vehicles (UAVs) are a recent innovation in precision agriculture technology. They are being used in a wide range of agricultural practices, whereby pesticide application is one of the most common uses of UAVs in China's agriculture. However, the economic effects of UAVs in pesticide application have not been sufficiently investigated. To address the gap, this paper used propensity score matching to evaluate the economic effects of UAV adoption on outcome variables including revenue, pesticide costs, time spent on pesticide application, and pesticide application frequency based on a dataset covering over 2,000 grain farmers across 11 provinces of China. Furthermore, generalized propensity score matching was used to evaluate the heterogeneity of outcome variables arising from differing UAV adoption intensities. The empirical results show that adoption of UAV increased revenue by approximately 434-488 dollars per hectare and reduced the time spent on pesticide application in the range of 14.4-15.8 hours per hectare. Depending on the area with use of UAVs for pesticide spraying, UAV adoption has heterogeneous impacts on grain farmers' revenue and the time spent on pesticide application. In terms of marginal revenue and marginal time spent on pesticide application, the optimal area with use of UAVs for pesticide spraying is estimated to be 20 hectares of arable land.

Keywords: unmanned aerial vehicles, propensity score matching, precision agriculture, adoption, pesticide application, Chinese grain farmers

6.1 Introduction

Unmanned aerial vehicles (UAVs) equipped with sensors or tanks can be used in a range of agricultural activities such as pesticide application, fertilizer spraying, irrigation, and field monitoring (Michels et al., 2021). China has been using UAVs in agriculture since 2010 (Zheng et al., 2019). After 10 years of rapid development, 70,344 UAVs were being used in China for plant protection purposes and by 2020 they were treating14.48 million hectares of cropland (China Agricultural Machinery Industry Association, 2021). Pesticide application is one of the most common uses of UAVs in Chinese agriculture (Yang et al., 2018). UAVs equipped with tanks can fly over fields at a low altitude to ensure uniform rate of pesticide application and can treat 20-33 hectares per day, which is 30-60 times faster than manual spraying (Zheng et al., 2019). UAVs' intelligent spraying system makes pesticide application more accurate and reduces pesticide residue (Chen et al., 2020). In addition, UAVs can overcome topography barriers and can be used in hilly or mountainous regions.

Although pesticide application with UAVs has many advantages compared with backpack sprayers, such as high efficiency and flexibility, low labor requirements, and reduced pesticide exposure, most Chinese farmers still apply pesticides manually using backpack sprayers (Wachenheim et al., 2021). Backpack sprayers can be operated in almost any situation with low operating costs. However, their inferior efficiency is one of the main sources of pesticide overuse, and it is estimated that China's average pesticide use per hectare is more than three times above the world average (Wu et al., 2018). Nevertheless, UAV spraying also has disadvantages. For example, spray drift is more severe with UAVs than with aircraft spraying or ground based application due to the vortex airflow generated by the UAV rotors (Carvalho et al., 2020; Wang et al., 2021). This is one reason why UAV spraying is prohibited in many European countries as exposure to this drift is considered to be a hazard both for the environment and human health (Remáč, 2018). China's regulations on UAV spraying are less stringent than in Europe and it is permitted as long as the operation is carried out in accordance with national operational specifications (The Civil Aviation Administration of China, 2019). Specifically, UAV pilots must be trained and licensed, and UAV spraying must adhere to national operational specifications and avoid harming people on the ground.

In 2017, China launched nationwide agricultural purchase subsidies in six provinces to promote the use of UAVs in agricultural production. Agricultural cooperatives and plant protection organizations are eligible to apply for these subsidies and can be granted a subsidy amounting to up to 30% of the purchase price for UAVs, whereby the maximum sum of the subsidy does not exceed 4,370 $ per UAV (Ministry of Agriculture and Rural Affairs of People's Republic of China, 2017). The agricultural UAV purchase subsidies have had a great impact on the use of UAVs, and their numbers have increased significantly since 2017. Given the small size of farms in China, it is not economically viable for individual farmers to own UAVs. Thus, some agricultural UAV companies and plant protection organizations provide on-farm UAV spraying services which have become popular leading to a huge market demand (Lan et al., 2019). Prices of UAV spraying services (labor and machinery costs) range from \$15 to \$30 per hectare depending on crop types and topography (Chung, 2019; Wang et al., 2022). In addition to UAV purchase subsidies, some provinces also partially subsidize UAV spraying services based on the cumulative area of UAV operations. For example, in the Guangdong province subsidies for UAV pesticide spraying services range from \$32 to \$43 per hectare (Li et al., 2022).

Given the benefits of UAVs, some studies have investigated the adoption of this technology for pesticide application. Zheng et al. (2019) used a probit model involving 897 farmers in Jilin province of China to estimate the factors influencing the adoption of UAVs for plant protection. Their results suggest that perceived usefulness, perceived ease-of-use, UAV-related knowledge level, and agricultural income ratio have a positive influence on UAV adoption. Likewise, Wachenheim et al. (2021) used a probit model to estimate the effects of social networks, resource endowment, and perceptions on Chinese farmers' intention to adopt UAVs for pesticide application. The results indicate that arable land area, agricultural income share, within-family village leadership, perceived usefulness, and credit availability have positive effects on UAV adoption. Chen et al. (2020) employed logit models to investigate the factors that influence Chinese farmers' willingness to adopt UAVs for pesticide application. The results show that arable land area and cooperative membership are positively correlated with farmers' adoption intention, and the land threshold for UAV adoption is estimated to be 2 hectares. Han et al. (2022) used a technology acceptance model and found that perceived usefulness, perceived ease-of-use, and external environment (e.g., government subsidies, extension services, and training) have positive effects on UAV adoption for pesticide application among Chinese farmers in Shaanxi province. To sum up, these studies reveal that farmers' characteristics, farm household characteristics, and external environment are the main factors influencing UAV adoption.

The abovementioned studies focus on identifying factors that facilitate or constrain the adoption of UAVs for pesticide application. However, the economic effects of adoption still remain unclear. To address this research gap, propensity score matching (PSM) based on a dataset of over 2,000 Chinese grain farmers was used to identify the factors that influence their adoption of UAVs and to analyze the economic effects of adoption on outcome variables, including farmers' revenue, pesticide costs, time spent on pesticide application, and pesticide application frequency. Furthermore, generalized propensity score matching was used to estimate the heterogeneity of outcome variables arising from differing UAV adoption intensities. Finally, the conclusions present some policy suggestions that are apt to promote the use of UAVs in China.

6.2 Materials and methods

6.2.1 Data source

The data used in this study is based on the "National Scientific Fertilizer Application Research Project 2019" headed by the Ministry of Agriculture and Rural Affairs of China. This national survey focused mainly on evaluating the farm-level impact of a scientific fertilizer application project. The survey was carried out in 2019 by the National Academy of Agriculture Green Development, China Agricultural University and was based on face-to-face interviews with farmers from 11 of the country's main grain producing provinces: Heilongjiang, Jilin, Hebei, Henan, Shandong, Shaanxi, Gansu, Anhui, Jiangsu, Hunan, and Guangxi. This survey applied stratified multi-stage sampling and random sampling. Firstly, within each province, counties were classified according to the cultivated area, and 4 counties were randomly selected. Secondly, within the selected counties, townships were classified according to per capita income, and 3 townships were randomly selected. Thirdly, within the selected townships, villages were classified according to per capita income, and 2 villages were randomly selected. Finally, within the selected villages, farmers were classified according to their cultivated area and were randomly selected. The interview questions covered characteristics of farm households, aspects of farm management, agricultural production expenditure and revenues, pesticide application, and farmers' knowledge about fertilizer application, etc.

This survey was assisted by the local government, and all the farmers selected participated in the survey, i.e., 100% response rate. The sample consisted of 3,061 farmers: 1,123 maize farmers, 817 rice farmers, and 1,121 wheat farmers. Given the research purpose and variables of this study, missing values and invalid observations were excluded, leaving a final sample consisting of 1,078 maize farmers, 763 rice farmers, and 1,045 wheat farmers.

6.2.2 Variable definitions and descriptive statistics

Table 6.1 presents definitions of the variables in this study and their descriptive statistics. The descriptive analysis shows significant differences between UAV adopters and non-adopters in many variables. UAV adopters are more likely to be male, young, fulltime farmers, and better educated than non-adopters and they also seem to have higher net incomes, bigger farm size, and fewer land parcels than non-adopters. Concerning the outcome variables, adopters show higher revenues and less time spent on pesticide application than non-adopters.

Table 6.1 Description of variables

Variables	Definitions	Non-adopters (n=2777)		Adopters (n=109)		*t*-test
		Mean	Std. dev.	Mean	Std. dev.	Mean difference
Independent variables						
Land parcel	1 if the farm has more than one land parcel; 0 otherwise	0.726	0.446	0.642	0.482	0.083*
Land lease	1 if the farm leases land from others; 0 otherwise	0.193	0.395	0.743	0.439	−0.550***
Land expansion	1 if the household head wants to expand the farm land area; 0 otherwise	0.141	0.348	0.220	0.416	−0.079**
Soil fertility	1 if the soil on the farm is fertile; 0 otherwise	0.380	0.486	0.624	0.487	−0.244***
Net income	Family annual net income (dollars)	8185.069	16713.34	34902.62	37772.46	−26717.551 ***
Farm size	Area of farm's arable land (hectares)	4.493	44.378	28.383	75.722	−23.889***
Membership of agricultural cooperative	1 if the farm is a member of an agricultural cooperative; 0 otherwise	0.162	0.368	0.239	0.428	−0.077**
Plain	1 if the farm is located in plain region; 0 otherwise	0.868	0.338	0.908	0.290	−0.040
Gender	1 if the household head is male; 0 otherwise	0.924	0.266	0.982	0.135	−0.058**
Age	Age of household head	57.499	10.467	48.927	10.592	8.572***
Education level	Education of household head in years	8.175	3.342	9.312	2.316	−1.137***
Fulltime farmer	1 if agricultural activities are the household head's sole main source of income; 0 otherwise	0.739	0.439	0.890	0.314	−0.151***

Pest & disease	1 if the crops suffered from pests or diseases; 0 otherwise	0.131	0.337	0.064	0.246	0.066**
Insurance	1if the farm bought agricultural insurance; 0 otherwise	0.602	0.489	0.771	0.422	−0.168***
Pesticide subsidy	1if the farm received subsidies for pesticide use; 0 otherwise	0.049	0.216	0.028	0.164	0.021
Pesticide training	1 if the household head has received pesticide application training; 0 otherwise	0.316	0.465	0.248	0.434	0.068
Outcome variables						
Revenue	Average gross income per hectare (dollars / hectare)	2119.101	1196.897	2615.937	815.737	−496.836***
Pesticide costs	Total pesticide expenditure per hectare (dollars / hectare)	128.765	129.943	145.016	100.598	−16.251
Time spent on pesticide application	Average time spent on pesticide application per hectare (hours/ hectare)	24.761	53.582	4.814	24.773	19.947***
Pesticide application frequency	The number of times pesticide is applied during the growing season	3.896	2.810	4.404	1.479	−0.508*
Treatment variable						
UAV adoption	1 if the farm used UAVs for pesticide application; 0 otherwise	0.000	0.000	1.000	0.000	−1.000***
UAV adoption intensity	Area with UAVs used for pesticide spraying (hectare) in natural logarithm, ln (area with UAVs used for pesticide spraying)	0.000	0.000	2.905	1.5117	−2.905***

*** p<0.01, ** p<0.05, * p<0.1.

6.2.3 Empirical model

In this study, propensity score matching (PSM) was used to estimate the impacts of UAV adoption on outcome variables. PSM applied a set of observed covariates to construct a counterfactual comparison group to match against the treatment group based on the probability of UAV adoption (Khandker et al., 2009). The probability or propensity score, then served as the basis for matching UAV adopters with non-adopters using three different matching algorithms. The average treatment effects of UAV adoption are the mean difference of outcome variables between the treatment group and the comparison group.

Assuming farmers are risk neutral and rational, farmer i will only adopt UAVs for pesticide spraying if the expected utility of adoption (D_1^*) is greater than non-adoption (D_0^*): $D_i^* = D_1^* - D_0^* > 0$, where D_i^* is the latent variable which captures the utility difference between adoption and non-adoption. D_i^* is unobserved, but it can be denoted as a function of observed covariates. Thus, a latent variable model is given as follows (El-Shater et al., 2016; Zheng et al., 2021):

$$D_i^* = \beta \boldsymbol{z_i} + \varepsilon_i \text{ with } D_i = \begin{cases} 1 & \text{if } D_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

where D_i is a binary variable and equals 1 if farmer i adopts UAVs and 0 otherwise; $\boldsymbol{z_i}$ is a vector of observed covariates that affect UAV adoption; β is a vector of parameters to be estimated; ε_i is the error term.

Firstly, a probit model was employed to estimate the probability of farm households adopting UAVs for pesticide spraying. Secondly, UAV adopters and non-adopters were matched based on the probability or propensity score derived from the probit model. The robustness of the results was checked using three different matching algorithms, including kernel matching, nearest-neighbor matching, and radius matching to compare UAV adopters with non-adopters (Caliendo and Kopeinig, 2008). Finally, the average treatment effects on the treated (ATT) for the outcome variables were estimated according to (Khandker et al., 2009):

$$\text{ATT} = \text{E}\,(\text{Y}\,(1) - \text{Y}\,(0) \mid D_i = 1) = \text{E}\,(\text{Y}\,(1) \mid D_i = 1) - \text{E}\,(\text{Y}\,(0) \mid D_i = 1) \tag{2}$$

where $\text{E}\,(\text{Y}\,(1) \mid D_i = 1)$ is the potential outcome of adopters in the treatment group and $\text{E}\,(\text{Y}\,(0) \mid D_i = 1)$ is the potential outcome of adopters had they decided not to adopt and become part of the counterfactual comparison group.

It is important to note that the effectiveness of PSM relies on two fundamental assumptions: conditional independence and common support (Khonje et al., 2015). Conditional independence assumes that, given a set of observable covariates (X_i) which are not affected by UAV adoption (D_i), outcome variables are independent of the UAV adoption status. If $Y_i\,(1)$ is the outcome of UAV adopters and $Y_i\,(0)$ is the outcome of non-adopters, the conditional independence can be expressed as: $(Y_i\,(1), Y_i\,(0)) \perp D_i \mid X_i$ (Caliendo and Kopeinig, 2008). Common support assumes that the number of UAV adopters is approximately equal to the number of non-adopters with whom they are matched. PSM attempts to estimate the difference between outcome variables of UAV adopters and non-adopters with similar characteristics, but bias cannot be avoided if unobservable covariates affect UAV adoption (Khandker et al., 2009).

Although the UAV adoption rate is low, at 3.8% of the full sample, PSM can still generate unbiased estimates of treatment effects if the appropriate variables are selected into the model (Gitonga et al., 2013; Pirracchio et al., 2012).

6.3 Empirical results and discussion

6.3.1 Estimates of probit model

In the first stage of PSM, the probit model was used to analyze the determinants of UAV adoption and to calculate the propensity score of adoption for each farmer. The results of the probit analysis are reported in Table 6.2. The Wald χ^2 test (254.29) indicates the joint significance of independent variables (p = 0.000). Farmers who lease land from others, and therefore hold a larger area of arable land, are more likely to adopt UAVs than their non-adopter counterparts. This finding is in line with Skevas *et al.* (2021) who pointed out that farmers who rent out land to others are less likely to be willing to use UAVs. As expected, family net income and farm size are positively correlated with the probability of adoption. Young farmers are more likely to adopt UAVs, suggesting that they are more open-minded and skilled with digital agricultural technology than older farmers. These results are consistent with Michels *et al.* (2020) who found that farm size has a positive effect and a farmer's age has a negative effect on the UAV adoption process in German agriculture. Similarly, Skevas and Kalaitzandonakes (2020) observed that household income has a positive impact on American farmers' intention to adopt UAVs and Skevas and Kalaitzandonakes (2020) and Chen et al. (2020) found that cooperative members are more likely to adopt UAVs than non-members. On the other hand, in this study, membership in an agricultural cooperative has a negative effect on UAV adoption, indicating that most of the UAV adopters did not participate in agricultural cooperatives and that agricultural cooperatives did not play a significant role in UAV extension. Soil fertility has a positive relationship with UAV adoption, implying that the probability of adoption is higher on a farm with fertile soil. Fulltime farmers are also more inclined to adopt UAVs. This could be due to the fact that farmers whose main source of income is earned in agriculture are more willing to try UAVs to enhance productivity.

Table 6.2 Probit regression model for UAV adoption

	Coefficient	Std. Err.	z	P>|z|
Land parcel	−0.102	0.118	−0.86	0.388
Land lease	0.383**	0.148	2.58	0.010
Land expansion	0.019	0.132	0.14	0.887
Soil fertility	0.279**	0.112	2.49	0.013
ln (net income)	0.116**	0.051	2.29	0.022
ln (farm size)	0.239***	0.050	4.74	0.000
Membership of agricultural cooperative	−0.327**	0.135	−2.43	0.015
Plain	0.066	0.164	0.40	0.687
Gender	0.556	0.347	1.60	0.109
Age	−0.019***	0.006	−3.16	0.002
Education level	0.002	0.019	0.08	0.933
Fulltime farmer	0.507***	0.155	3.28	0.001
Pest & disease	−0.241	0.193	−1.24	0.214
Insurance	0.123	0.124	1.00	0.319
Pesticide subsidy	−0.130	0.291	−0.44	0.657
Pesticide training	−0.152	0.123	−1.24	0.217
Constant	−3.337***	0.702	−4.75	0.000
Log likelihood		−323.619		
LR $\chi^2(16)$		254.29		
Prob > χ^2		0.0000		
Pseudo R^2		0.282		
Number of observations		2,635		

*** p<0.01, ** p<0.05.

6.3.2 Balancing tests

In the second stage of PSM, UAV adopters and non-adopters were matched on the basis of their propensity scores. The results of balancing tests before and after matching are shown in Table 6.3. Regardless of which matching algorithm is used, *Pseudo* R^2, which reveals how well the independent variables explain UAV adoption (Caliendo and Kopeinig, 2008), fell from 0.282

before matching to a range of 0.019-0.025 after matching. The likelihood ratio test of the joint significance of covariates was not rejected before matching but it was rejected after matching. The mean standardized bias was below 8% after matching. The total percentage of bias reduction ranges from 4.6% to 13.7%. Thus, the PSM has significantly reduced the biases of covariates in the treatment group and the control group, suggesting a good matching quality.

Table 6.3 Balancing tests

Outcome variables	Matching Algorithms	Pseudo R^2		LR χ^2		$p > \chi^2$		Mean standardized bias		Total% |bias| reduction
		Before matching	After matching	Before matching	After matching	Before matching	After matching	Before matching	After matching	
Revenue (dollars / hectare)	KM	0.282	0.021	254.29	6.16	0.000	0.986	47.3	6.5	6.2
	NNM	0.282	0.019	254.29	5.56	0.000	0.992	47.3	6.5	4.6
	RM	0.282	0.025	254.29	7.24	0.000	0.968	47.3	7.8	13.7
Pesticide costs (dollars / hectare)	KM	0.282	0.021	254.29	6.16	0.000	0.986	47.3	6.5	6.2
	NNM	0.282	0.019	254.29	5.56	0.000	0.992	47.3	6.5	4.6
	RM	0.282	0.025	254.29	7.24	0.000	0.968	47.3	7.8	13.7
Time spent on pesticide application (hours/ hectare)	KM	0.282	0.021	254.29	6.16	0.000	0.986	47.3	6.5	6.2
	NNM	0.282	0.019	254.29	5.56	0.000	0.992	47.3	6.5	4.6
	RM	0.282	0.025	254.29	7.24	0.000	0.968	47.3	7.8	13.7
Pesticide application frequency	KM	0.282	0.021	254.29	6.16	0.000	0.986	47.3	6.5	6.2
	NNM	0.282	0.019	254.29	5.56	0.000	0.992	47.3	6.5	4.6
	RM	0.282	0.025	254.29	7.24	0.000	0.968	47.3	7.8	13.7

Note: kernel matching (KM), bandwidth = 0.06; nearest neighbor matching (NNM), N=10, with replacement; radius matching (RM), caliper=0.08.

6.3.3 Common support

Figure 6.1 shows the density distributions of propensity scores for UAV adopters and non-adopters before and after matching. It reveals substantial overlaps in the density distributions of the propensity scores of UAV adopters and non-adopters after matching. Obviously, the common support assumption is satisfied after matching.

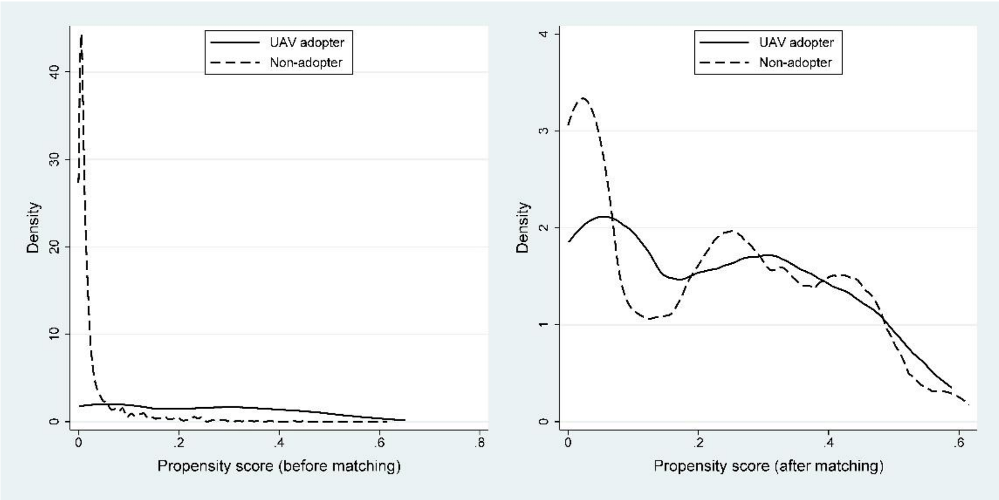

Figure 6.1 Density distributions of propensity scores for UAV adopters and non-adopters before and after matching

6.3.4 The economic effects of UAVs in pesticide application

Table 6.4 reports the impacts of UAV adoption on revenue, pesticide costs, time spent on pesticide application, and pesticide application frequency. The results derived from kernel matching, nearest neighbor matching, and radius matching are very close, suggesting that the results are robust. The use of UAVs in pesticide application did have some positive economic effects. Firstly, UAV adoption significantly improved grain farmers' revenue by approximately 434-488 dollars per hectare, possibly because the grain yield per unit area increased thanks to the effective pest and disease control it offers. Subtracting the cost of UAV spraying (labor and machinery), the net revenue of UAVs in pesticide application is 404-473 dollars per hectare. Secondly, the adoption of UAVs noticeably reduced the time spent on pesticide application in the range of 14.4-15.8 hours per hectare, and thus it indirectly reduced labor costs for this task. This is mainly due to the fast, accurate, and efficient pesticide spraying performed by UAVs compared to traditional approaches. Finally, although UAV adoption reduced the costs and application frequency of pesticides, the impacts were not statistically significant. The fact that UAV spraying did not noticeably reduce pesticide costs could be due to the fact that a lot of Chinese farmers use UAVs for uniform rate pesticide application instead of site-specific spraying (Yang et al., 2018).

Table 6.4 The impacts of UAV adoption on revenue, pesticide costs, time spent on pesticide application, and pesticide application frequency

Outcome variables	Matching algorithm	Adopters	Non-adopters	ATT	Matched observations		
					Adopters	Non-adopters	Total
Revenue (dollars/hectare)	KM	2620.789	2186.352	434.436*** (105.288)	106	2,527	2,633
	NNM	2620.789	2133.152	487.637*** (129.837)	106	2,527	2,633
	RM	2620.789	2169.142	451.646*** (81.146)	106	2,527	2,633
Pesticide costs (dollars/hectare)	KM	145.511	150.088	−4.576 (15.516)	106	2,527	2,633
	NNM	145.511	157.108	−11.597 (17.061)	106	2,527	2,633
	RM	145.511	148.708	−3.197 (14.093)	106	2,527	2,633
Time spent on pesticide application (hours/ hectare)	KM	4.808	20.432	−15.623*** (4.457)	106	2,527	2,633
	NNM	4.808	19.257	−14.449*** (4.422)	106	2,527	2,633
	RM	4.808	20.572	−15.764*** (3.499)	106	2,527	2,633
Pesticide application frequency	KM	4.406	4.456	−0.051 (0.205)	106	2,527	2,633
	NNM	4.406	4.483	−0.077 (0.321)	106	2,527	2,633
	RM	4.406	4.426	−0.021 (0.245)	106	2,527	2,633

*** $p<0.01$; standard errors in parentheses using 50 bootstrap replications; kernel matching (KM), bandwidth = 0.06; nearest neighbor matching (NNM), N=10, with replacement; radius matching (RM), caliper=0.08.

However, it is quite likely that some important causal factors are missing (e.g., management ability and entrepreneurial capability) and these factors both boost profits and increase the likelihood of adoption. That is, while UAVs may have little to do with increased profits for the average farmer, profits and UAV use are nevertheless correlated. Further tests are needed to check if the possible unobserved covariates (e.g., farmer's ability, risk preferences, and motivation) influence UAV adoption and, at the same time, outcome variables.

6.3.5 Sensitivity analysis

PSM assumes that UAV adoption and outcome variables are solely affected by the observable covariates. However, hidden bias may be a problem if the possible unobserved covariates (e.g., farmer's ability, risk preferences, and motivation) influence UAV adoption and outcome variables simultaneously (Chagwiza et al., 2016; Gitonga et al., 2013; Mishra et al., 2016; Schreinemachers et al., 2016). Thus, the Rosenbaum bounds test was performed to check the robustness of results to hidden bias (Rosenbaum, 2002). The PSM results show that UAV adoption only has statistically significant effects on grain farmers' revenue and the time spent on pesticide application. Thus, the Rosenbaum bounds test was performed to assess the sensitivity of these two outcome variables to unobserved variables. Since the impact of UAV adoption on grain farmers' revenue is positive, focus should concentrate on the upper bound (sig+) in this case (Caliendo and Kopeinig, 2008). Likewise, the lower bound (sig−) should be the focus for the time spent on pesticide application. Gamma represents log odds of differential assignment arising from unobserved factors (Becker and Caliendo, 2007).

Table 6.5 Sensitivity analysis of the outcome variables to hidden bias, p-values

Gamma	Revenue		Time spent on pesticide application	
	sig+	sig−	sig+	sig−
1	0.000	0.000	0.000	0.000
1.1	0.000	0.000	0.000	0.000
1.2	0.000	0.000	0.000	0.000
1.3	0.000	0.000	0.000	0.000
1.4	0.000	0.000	0.000	0.000
1.5	0.001	0.000	0.000	0.000
1.6	0.001	0.000	0.000	0.000
1.7	0.003	0.000	0.000	0.000
1.8	0.006	0.000	0.000	0.000
1.9	0.010	0.000	0.000	0.000
2	0.017	0.000	0.000	0.000

Gamma, log odds of differential assignment due to unobserved factors; sig+, upper bound significance level; sig−, lower bound significance level.

When Gamma is up to 2, the sig+ of revenue is still significant at 5% level and the sig− of time spent on pesticide application remains significant at 1% level, indicating that grain farmers' revenues and time spent on pesticide application are insensitive to hidden bias (Table 6.5).

6.3.6 Continuous treatment effects

PSM uses a binary treatment variable (UAV adoption) in the model and can only estimate the average treatment impact of UAV adoption on outcome variables. However, the heterogeneous treatment impact of UAV adoption is unclear (Shiferaw et al., 2014). The generalized propensity score (GPS) matching (Hirano and Imbens, 2004) serves as an extension to PSM. It uses a continuous treatment variable in the model and thus allows the heterogeneous treatment impact of UAV adoption on outcome variables to be explored. In this study, a continuous treatment variable, UAV adoption intensity (natural logarithm of area using UAVs for pesticide spraying) was used in the GPS matching to study the heterogeneous treatment impact of UAV adoption. Other covariates were the same as those previously used in the PSM.

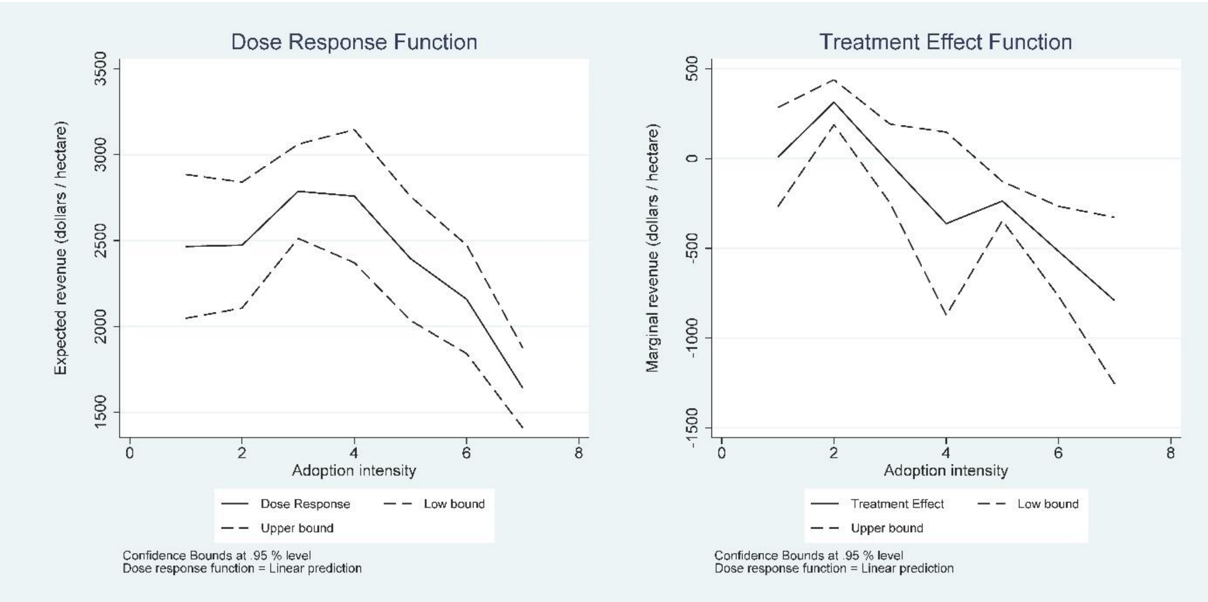

Figure 6.2 Dose response (average treatment effects) function and marginal treatment effects function for revenue. Standard errors and confidence intervals were estimated by 100 bootstrap replications. Adoption intensity: natural logarithm of area with use of UAVs for pesticide spraying.

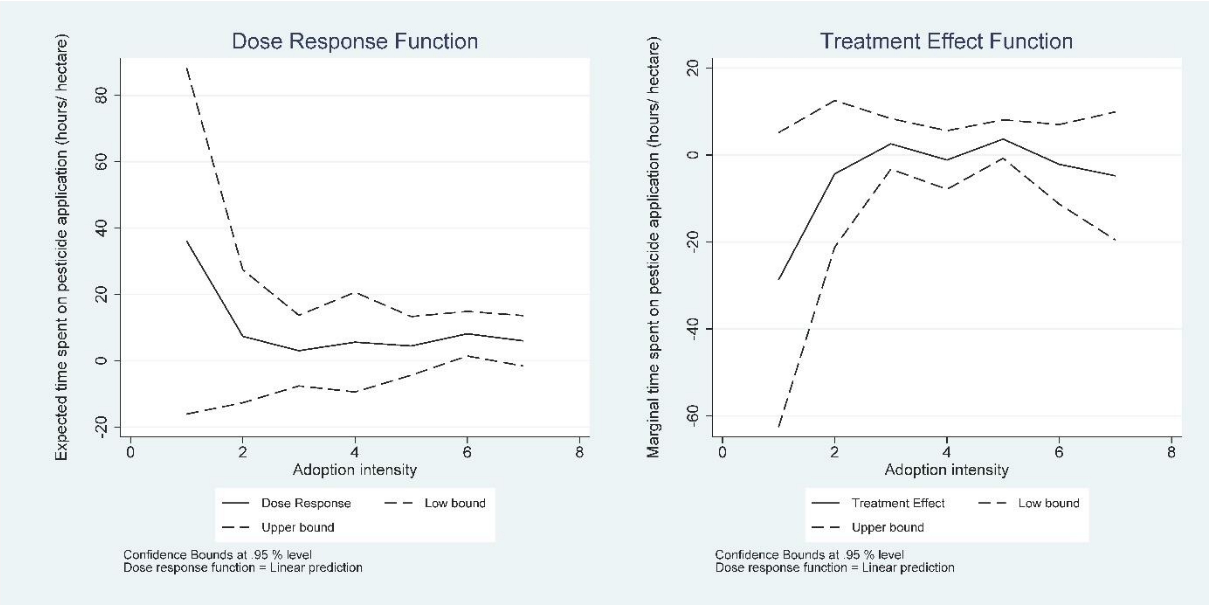

Figure 6.3 Dose response (average treatment effects) function and marginal treatment effects function for time spent on pesticide application. Standard errors and confidence intervals were estimated by 100 bootstrap replications. Adoption intensity: natural logarithm of area with use of UAVs for pesticide spraying.

Figure 6.2 shows that revenue and UAV adoption intensity have an inverted U-shaped relationship. The revenue increases from 2,500 dollars/hectare at adoption intensity of 1 to 2,750 dollars/hectare at adoption intensity of 3. After that, revenue drops from 2,750 dollars/hectare to 1,500 dollars/hectare as the adoption intensity increases. The marginal revenue decreases as the adoption intensity increases, declining from 250 dollars/hectare at adoption intensity of 2 to −750 dollars/hectare at adoption intensity of 7. Figure 6.3 shows that the time spent on pesticide application decreases as the adoption intensity increases. The time spent on pesticide application decreases from 38 h/hectare at adoption intensity of 1 to 2 h/hectare at adoption intensity of 2. Once the adoption intensity of 2 has been reached, the time spent on pesticide application does not show any visible fluctuations, remaining at 2 h/hectare. The marginal time spent on pesticide application increases gradually and reaches a diminishing return at adoption intensity of 3.

These empirical results reveal that UAV adoption intensity has heterogeneous impacts on grain farmers' revenue and the time spent on pesticide application. This may be due to the fact that increased farm size leads to resource misallocation and management inefficiency, and finally to a decline in the impacts of UAV adoption (Sheng et al., 2019). Likewise, Abdul Mumin and Abdulai (2022), Mohammed and Abdulai (2022), Shahzad and Abdulai (2021), and Wu (2022) also reported heterogeneous returns for adoption of agricultural technologies due to differences in resource endowments, such as farm size, financial resources, and social networks. The results of this study suggest that, in terms of marginal revenue and marginal time spent on pesticide application, the optimal UAV adoption intensity for Chinese grain farmers is estimated to be 3, referring to 20 hectares of arable land.

6.4 Conclusions

This article uses the PSM method to identify the factors that influence Chinese grain farmers' adoption of UAVs and to analyze the impacts of UAV adoption on farmers' revenue, pesticide costs, time spent on pesticide application, and pesticide application frequency. The UAV adoption rate among the grain farmers in this survey was relatively low at only 3.8%. The empirical results show that UAV adoption is significantly and positively correlated with arable land area, family annual net income, soil fertility, rented land, fulltime farmer status, and young farmers. Policy makers aiming to increase UAV adoption should appreciate that older farmers, small-scale farmers, part-time farmers, and low-income farmers face more barriers in UAV adoption. In the future, more UAV extension services and education programs should target at these groups. However, membership in an agricultural cooperative has a significant negative impact on UAV adoption, indicating that most of the UAV adopters in this study did not participate in agricultural cooperatives. Traditional agricultural cooperatives did not play a significant role in UAV extension. Thus, benefit-risk sharing UAV agricultural cooperatives should be established to promote UAV adoption. Farmers who are interested in using UAVs for pesticide application can set up an agricultural cooperative and buy UAVs together, whereby members jointly cover the purchase and maintenance costs and share the use of their UAVs. This reduces the cost and risk for each famer and makes UAVs more affordable for the majority.

The use of UAVs can increase revenue and reduce the time spent on pesticide application, and these results are insensitive to hidden bias arising from unobserved variables. On average, the adoption of UAVs increases revenue by approximately 434-488 dollars per hectare and reduces time spent on pesticide application by about 14.4-15.8 hours per hectare. UAV adoption should therefore be encouraged. The GPS matching indicates that UAV adoption has heterogeneous effects on revenue and time spent on pesticide application. In terms of marginal revenue and marginal time spent on pesticide application, the optimal adoption intensity of UAV in Chinese grain farming is estimated to be 20 hectares, suggesting that small and medium-scale farmers are the main beneficiaries of UAV adoption. Large farms are advised to improve resource allocation and management efficiency to increase the returns of UAV adoption.

Conflict of interest

The authors declare that they have no conflict of interest.

Author contributions

Xiuhao Quan: conceptualization, methodology, software, validation, formal analysis, investigation, data curation, writing—original draft, writing—review and editing, and visualization; Reiner Doluschitz: conceptualization, supervision, writing—review and editing, resources, project administration, and funding acquisition; Ji Ma: investigation, data curation, and resources; Qiaoling Guo: investigation.

Data availability

The datasets used in study are available from the corresponding author on reasonable request.

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Chapter 7 General discussion

This chapter will comprehensively discuss the key findings of each chapter and compare them with other relevant studies and consolidate the conclusions of individual chapters. The pros and cons of different agricultural machinery and strategies will be discussed. The contributions are highlighted, and limitations and future research are also discussed.

7.1 Discussion of the results

The research questions of this dissertation will be discussed from a broader perspective in this section, following a pros and cons approach.

- The factors that influence the adoption of farm machinery by Chinese maize farmers

In Chapter 2, multivariate probit models were performed to identify the factors that affect maize farmers' adoption of four machinery technologies as well as the interrelation between these adoption decisions. The empirical results indicate that maize sowing area, arable land area, crop diversity, family labor, subsidy, technical assistance, and economies of scale have positive effects on machinery adoption, while the number of discrete fields on the farm has a negative impact. The adoption of these four machinery technologies are interrelated and complementary. Pro and cons of adopting different machinery technologies at the same time can be identified as that adopting a machinery technology can facilitate the adoption of other complementary machinery technologies, but will inhibit the adoption of other substitutable machinery technologies.

Many studies have similar findings as in Chapter 2. Using household survey data of 493 Chinese maize farmers, Ma et al. (2018) found that farm size has a significantly positive impact on farm machinery adoption, while household size is negatively correlated with machinery use. Zhang et al. (2019) reported that off-farm work, farm size, and extension contact have significantly positive effects on farm machine use in maize production, but farmers' risk preference has a negative impact on farm machinery adoption. Wang et al. (2020) showed that land fragmentation constrains mechanization and influences the substitution effects of machinery for labor in Chinese agriculture.

In light of diversified agricultural production conditions in China, the factors that influence the adoption of farm machinery by Chinese maize farmers may be varied in different contexts. The adoption of different machinery technologies might be complementary or substitutable, and extension programs should take advantage of these characteristics to promote the use of agricultural machinery.

- The economic effects of adopting farm machinery on maize yield and labor productivity

Farm machinery use significantly increased maize yield by 0.216 tons/ha and improved labor productivity by 18.65%, but the impacts of machinery use differ across farm households. Young, male, and better-educated farm households benefit more from farm machinery adoption. These results also imply that farm machinery adoption is more productive in increasing maize yield and labor productivity among the farms which are located in plain regions with cooperative membership and rented land. In addition, the impacts of farm machinery adoption on maize yield and labor productivity slightly decrease with farm size. This may be because farm size expansion leads to resource misallocation and management inefficiency, finally resulting in a decline in the impacts of farm machinery adoption (Sheng et al., 2019). To attain optimal economic returns from adopting farm machinery, an appropriate farm size is better than the oversized one in the context of Chinese agriculture.

Many studies have shown the differing impacts of farm machinery use across farm households due to the heterogeneous farm characteristics and socio-economic conditions (Adekunle et al., 2016; Adu-Baffour et al., 2019; Kienzle et al., 2013; Qing et al., 2019; Takeshima et al., 2020; Zhou et al., 2020). Huang and Ding (2016) found an inverse relationship between farm size and maize yield in China because of distortions in small-scale farming transformation, and policies are needed to assist small farms to adapt to large farms by improving resource use efficiency and farming productivity. Zhou et al. (2020) reported that farm machinery use significantly increased maize yield, but low productivity farmers gained more yield from farm machinery adoption than the high productivity farmers.

As a conclusion, the pros and cons concerning adoption can be stated as that the adoption of agricultural machinery has significantly positive impacts on maize yield and labor productivity, but the impacts may not be the same for all adopters. The undifferentiated farm machinery extension program which fails to consider the farm-level heterogeneity would cause the inequity among farmers. It is necessary to understand the heterogeneous effects of farm machinery adoption and to formulate customized extension services tailored to various types of farm households.

- An overview of UAV applications in maize production

UAVs have been using in some important aspects of maize production such as water stress detection, weed mapping, nutrient status monitoring, and yield prediction. The benefits of UAVs in maize production are higher productivity, accurate real-time field monitoring, reduced labor use, and fewer working hours, etc. These favorable factors facilitate the use of UAVs. On the other hand, disadvantages include complex data processing and interpretation, high prices, and unstable performance, etc. These unfavorable factors increase the difficulty of UAV use and reduce work efficiency. Unspecified UAV operating standards could lead to inefficiencies. For the efficient use of UAVs in maize production, a standard workflow needs to be followed.

In addition to UAV applications in maize farming specifically, other research also studied the applications of UAVs in agriculture generally. Delavarpour et al. (2021) mentioned that UAVs can be used as platforms to attach with sensors for field monitoring and to equip with tanks for crop spraying. Likewise, UAVs have many merits such as flexible, accurate, and efficient, but high financial investment, complexity of UAV technology, and complex data interpretation constrain the adoption of UAVs in precision agriculture. In addition, they highlighted that the potential benefits of using UAVs and the compatibility of UAV technology with farmers' exiting agricultural technologies can affect the adoption of UAVs. Rejeb et al. (2022) and Maddikunta et al. (2021) pointed out that UAV operating regulations and farmers' acceptance and knowledge of UAV technology can influence the use of UAVs in agriculture. To conclude, the pros of using UAVs in agriculture are flexible, accurate, and efficient, while the cons are high investment, complex data interpretation, and the possible poor compatibility of UAV technology with farmers' exiting agricultural technologies. Future research about the applications of UAVs should focus on socio-economic effect evaluation, operating regulations, education and training, and technology assessment, etc.

- Drivers and barriers of UAV adoption in China

The determinants of UAV adoption derive from three major aspects: farmers' production characteristics, farmers' perceptions about UAVs, and social factors. Drivers for UAV adoption are rural labor shortages, expansion of farm size, specialized farming, UAV purchase subsidies, market demand for UAV services, after-sales service or technical support, and UAV trainings. Taking into account the observed structural change in Chinese agriculture, especially the growing of medium- and large-scale farms (Huang and Ding, 2016; Ji et al., 2016) and agricultural specialization (Liu et al., 2021; Wang et al., 2017), the promotion of UAVs in China will have a positive perspective. Barriers for UAV adoption are knowledge gap, small farm size, sophisticated UAV operations, unspecified UAV operating standards, unfavorable field conditions, and UAV pilot shortages. The determinants of UAV adoption and their effects on UAV adoption are consistent with Han *et al.* (2022), H. Li *et al.* (2022), Li *et al.* (2020), Michels *et al.* (2020), Skevas and Kalaitzandonakes (2020), Wachenheim *et al.* (2021), Zheng *et al.* (2019), and Zuo *et al.* (2021). In addition to the above determinants, however, Delavarpour et al. (2021) and Rejeb et al. (2022) emphasized that compatibility and interoperability of UAV technology with farmers' existing technologies are also determinants of UAV adoption.

Due to the barriers discussed above, UAVs have not been widely adopted by most Chinese farmers. In the future, the establishment of a comprehensive socio-economic institution to integrate a range of beneficial factors for UAV adoption is important. Balancing the pros and cons, the tackling of priorities would be as follows: to improve farmers' UAV-related knowledge, to enhance user experience of UAVs, to define UAV operation specifications, to consolidate scattered field plots, and to educate more UAV pilots.

- The prerequisites for adopting and implementing UAV-based pattern management in China's agriculture

18 experts mentioned that there are some socio-economic and technical prerequisites for adopting and implementing UAV-based pattern management in Chinese agriculture. Socio-economic prerequisites include farmers' good UAV-related capabilities, convincing benefits of using UAVs, a relatively large arable land size (≥ 2 ha), and social facilitating conditions such as UAV purchase subsidies, after-sales UAV service or support, and UAV trainings. Likewise, Han *et al.* (2022), Skevas and Kalaitzandonakes (2020), and Li *et al.* (2020) reported that perceived usefulness can affect farmers' UAV adoption. Sylvester et al. (2018) showed that most farmers do not adopt UAVs because of the huge investment and unforeseen returns from adoption, and they concern that the economic benefits of adoption may not offset the investment. H. Li *et al.* (2022) found that UAV purchase subsidies can boost UAV adoption. Han *et al.* (2022) emphasized that external environment such as UAV technical assistance and after-sales service can facilitate UAV adoption. To conclude, educating farmers on UAV-related capabilities, expanding farm size appropriately, and providing UAV-related social facilitating conditions are important for implementing UAV-based pattern management in China. In addition, the observed structural change in Chinese agriculture such as the growing

of medium- and large-scale farms (Huang and Ding, 2016; Ji et al., 2016) and agricultural specialization (Liu et al., 2021; Wang et al., 2017) would be supportive for implementing UAV-based pattern management.

On the other hand, three main technical prerequisites are needed for implementing UAV-based pattern management, including accurate crop monitoring, precise real-time UAV positioning systems, fast response time of variable-rate spraying systems. Due to the limitations of current technology, Maimaitijiang et al. (2020) and Xie et al. (2021) addressed that UAV-based crop monitoring still needs to improve its accuracy in some cases. Yang et al. (2018) highlighted that real-time positioning systems are needed to guide UAVs to the right site when UAVs fly above fields to perform site-specific precise spraying. UAVs operate at a high speed and require a quick response time of variable-rate spraying systems to match with the speed of UAVs, but it is still difficult to achieve this.

UAV-based pattern management is still at the experimental phase, and it will take some time to achieve commercial use in precision farming. At this stage, UAV-based pattern management can be promoted first in large-scale farms for specialized farming due to the high expected returns and structural change in Chinese agriculture. Given economic viability, UAV service agricultural cooperatives can provide UAV-based pattern management services for small and medium-sized farms.

- The economic effects of adopting UAVs in pesticide application in China's agriculture

The use of UAVs in pesticide application did have some positive economic effects. The empirical results in Chapter 6 show that adoption of UAV increased revenue by approximately 434-488 USD/ha and reduced the time spent on pesticide application in the range of 14.4-15.8 hours/ha. This finding is in consistent with Wang et al. (2020) who found that UAV-based pesticide application increased the effect of pest and disease control in citrus production by 20.3% and saved cost by 266 USD/ha. Likewise, Wang et al. (2019) reported that UAV-based pesticide application decreased pesticide use by one-third, increased work efficiency by three times, and reduced machinery operation cost by 8.70 USD/ha in cotton production. However, in Chapter 6 UAV spraying did not noticeably reduce pesticide costs could be due to the fact that a lot of Chinese farmers use UAVs for uniform rate pesticide application instead of site-specific spraying (Yang et al., 2018). One conclusion would be that promoting the use of UAVs in precision agriculture has a great potential in China.

Another conclusion is that UAV adoption has heterogeneous impacts. Small and medium-scale farmers are the main beneficiaries of UAV adoption, and the optimal area with use of UAVs for pesticide application is estimated to be 20 hectares. On the other hand, Zheng et al. (2018) found that farmers' UAV adoption intention is positively correlated with farm size, and the land threshold for UAV adoption is about 2 hectares in China. Hence, small farms are expected to expand farm size appropriately to facilitate UAV adoption, and large farms are advised to improve resource allocation and management efficiency to increase the returns of UAV adoption.

7.2 Methodological considerations and contributions

- Multivariate models were performed to study the factors that influence the adoption of machinery in four key production processes (e.g., seeding, plowing, harvesting, and pesticide spraying) in China's maize production and the potential interrelation among these adoption decisions. This study analyzed factors that influence the adoption of machinery in each production stage and the interrelation among these adoptions, which helps to obtain a thoroughly understanding of Chinese maize farmers' machinery adoption decisions.
- An endogenous switching regression (ESR) model was used to quantitatively explore the economic effects of adopting farm machinery on maize yield and labor productivity. In addition, the heterogeneous effects of farm machinery adoption were analyzed across farms and farmers' characteristics. This study contributes to understand the heterogeneous effects of farm machinery adoption and to develop customized extension services tailored to various types of farm households to prevent the inequity among farmers.
- The literature review introduces the development of four major UAV applications (e.g., water stress detection, weed mapping, nutrient status monitoring, and yield prediction) in maize farming, summarizes UAV data management methods, explains how expert systems work in UAV systems, and provides standardized workflow data for farmers in maize production. In addition, the strengths, weaknesses, opportunities, and threats of UAV use in maize production were analyzed. This review paper provides an overview of the latest UAV applications in maize production and serves as a general introduction to farmers who are interested in using UAVs in maize farming.
- A series of structured in-depth expert interviews were conducted with 18 experts from various backgrounds related to UAVs and agriculture in China. This study included different types of UAV stakeholders (e.g., farmers, agricultural UAV manufacturers, UAV service providers, agricultural extension staff from government, and researchers focusing

on UAVs) into expert interviews and provided a holistic view on determinants and institutions that are needed for UAV adoption, especially in precision farming for UAV-based pattern management.

- Propensity score matching and generalized propensity score matching were used to quantitatively estimate the economic effects of UAV adoption on outcome variables (e.g., revenue, pesticide costs, time spent on pesticide application, and pesticide application frequency) respectively. Propensity score matching estimated the average effects of UAV adoption on outcome variables, while generalized propensity score matching estimated the heterogeneous economic effects of outcome variables arising from differing UAV adoption intensities. The joint use of these two methods provides a comprehensive evaluation of the economic effects of UAV adoption.

7.3 Conclusions, discussion, and recommendations

By utilizing farm household data, qualitative methods, and econometric quantitative methods, this dissertation explored the factors that influence the adoption of agricultural machinery, namely farm machinery in maize production and UAVs in precision agriculture, estimated the economic impacts of adoption, provided an overview of UAV applications in maize production, and studied the prerequisites for adopting and implementing UAV-based pattern management in Chinese agriculture.

The determinants of farm machinery adoption and UAV adoption can be attributed by three major aspects: farmer characteristics (e.g., age, education level, and perceptions about agricultural machinery), farm characteristics (e.g., farm size, land fragmentation, and cooperative membership), and other external socio-economic factors (e.g., subsidies, technical assistance, and labor shortages). A conclusion would be that for the widespread implementation of UAV-based pattern management in precision agriculture, certain socio-economic and technical prerequisites are necessary. These include farmers possessing adequate UAV-related capabilities, relatively large farm sizes, availability of UAV-related subsidies, and superior UAV performance.

Although the adoption of farm machinery and UAVs shows positive impacts on farm performance, the impacts differ across farm households due to the heterogeneous farm characteristics and socio-economic conditions. Small and medium-scale farmers are the main beneficiaries of agricultural machinery adoption, while large-scale farmers are advised to improve resource allocation and management efficiency to increase the returns of agricultural machinery adoption. It is necessary to formulate customized extension services tailored to various types of farm households to prevent inequity among farmers. Policy makers aiming to increase the adoption of farm machinery and UAVs should appreciate that older farmers, small-scale farmers, part-time farmers, and low-income farmers face more barriers. To conclude, in the future, more agricultural machinery extension services and education programs should target at these groups.

Balancing the pros and cons, it can be derived that some strategies provided by public or private sectors are in favor of agricultural machinery adoption. These strategies include the implementation of land consolidation, the establishment of agricultural machinery cooperatives for benefit-risk sharing, the provision of practical training and education on agricultural machinery, and subsidies for the purchase of agricultural machinery. Priorities should focus on the establishment of a comprehensive socio-economic institution. This institution should integrate strategies from both the public and private sectors to leverage their respective strengths for the effective promotion of agricultural machinery. The land consolidation launched by public sectors creates favorable field conditions for machinery operation and facilitates agricultural mechanization. Agricultural machinery cooperatives established by private sectors can jointly cover the purchase and maintenance costs and share the use of machinery, and this approach reduces the cost and risk for each famer and makes machinery more affordable for the majority, especially for expensive precision agriculture facilities. Precision agriculture is a knowledge-based technology, and thus practical training and education provided by public sectors to farmers are important. Machinery purchase subsidies provided by public sectors to farmers lower machinery prices and make it more affordable for the majority.

7.4 Limitations and future research

- This dissertation only used cross-sectional data to model the adoption of farm machinery and UAVs and treated farmers' adoption as a binary choice. However, the dynamic adoption process across years remains unclear. Depending on economic returns and other factors, farmers may continue to use or drop the technologies they have adopted (Khanal et al., 2019; Munguia et al., 2021). In addition, the factors that influence the adoption of agricultural machinery may have changed over time (Walton et al., 2008).

Thus, it is meaningful to investigate farmers' dynamic adoption process across years in the future.

- This dissertation only studied the qualitative relation between farmers' perceptions about UAV technology and their adoption intentions, but the quantitative relation between them is vague. In the future, the technology acceptance model (Davis et al., 1989) can be used as a framework to quantitatively estimate how farmers' perceptions about UAV technology (e.g., perceived usefulness, perceived ease-of-use, and perceived benefits) affect their adoption intentions.
- No work has done to compare farmers' adoption intentions and actual adoption rates in this dissertation. However, farmers' intended adoption and actual adoption might differ (Bagheri and Teymouri, 2022). Understanding the discrepancies between farmers' intended adoption and actual adoption can ensure to formulate effective agricultural machinery extension programs (Niles et al., 2016).
- Due to the low adoption rates of UAVs, it would be interesting to investigate the resistance of UAV adoption in the future (Michels et al., 2021). For example, modeling the main reasons for farmers' non-adoption decisions such as high investment, unpredictable benefits, and complex UAV operation.

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Annex 1 Declaration in lieu of an oath on independent work

According to Sec. 18(3) sentence 5 of the University of Hohenheim's Doctoral Regulations for the Faculties of Agricultural Sciences, Natural Sciences, and Business, Economics and Social Sciences

1. The dissertation submitted on the topic

"The adoption of agricultural machinery and its economic impacts in China"

is work done independently by me.

2. I only used the sources and aids listed and did not make use of any impermissible assistance from third parties. In particular, I marked all content taken word-for-word or paraphrased from other works.

3. I did not use the assistance of a commercial doctoral placement or advising agency.

4. I am aware of the importance of the declaration in lieu of oath and the criminal consequences of false or incomplete declarations in lieu of oath.

I confirm that the declaration above is correct. I declare in lieu of oath that I have declared only the truth to the best of my knowledge and have not omitted anything.

Stuttgart, 01.12.2023	Xiuhao Quan
Place, Date	Signature

Total list of all publications

Quan, X., Doluschitz, R. (2021). Unmanned aerial vehicle (UAV) technical applications, standard workflow, and future developments in maize production – water stress detection, weed mapping, nutritional status monitoring and yield prediction. LANDTECHNIK, 76(1). https://doi.org/10.15150/lt.2021.3263

Quan, X., Doluschitz, R. Factors Influencing the Adoption of Agricultural Machinery by Chinese Maize Farmers. Agriculture. 2021; 11(11):1090. https://doi.org/10.3390/agriculture11111090

Quan, X., Guo, Q., Ma, J., Doluschitz, R. The economic effects of unmanned aerial vehicles in pesticide application: evidence from Chinese grain farmers. Precision Agriculture (2023). https://doi.org/10.1007/s11119-023-10025-9

List of publications included in the doctoral thesis

Quan, X., Doluschitz, R. (2021). Unmanned aerial vehicle (UAV) technical applications, standard workflow, and future developments in maize production – water stress detection, weed mapping, nutritional status monitoring and yield prediction. LANDTECHNIK, 76(1). https://doi.org/10.15150/lt.2021.3263

Quan, X., Doluschitz, R. Factors Influencing the Adoption of Agricultural Machinery by Chinese Maize Farmers. Agriculture. 2021; 11(11):1090. https://doi.org/10.3390/agriculture11111090

Quan, X., Guo, Q., Ma, J., Doluschitz, R. The economic effects of unmanned aerial vehicles in pesticide application: evidence from Chinese grain farmers. Precision Agriculture (2023). https://doi.org/10.1007/s11119-023-10025-9

List of publications in process in the dissertation

Quan, X., Wang, Z., Daum, T., He, X., Doluschitz, R. The determinants of unmanned aerial vehicle (UAV) adoption and status quo of UAV-based pattern management in Chinese agriculture: insights from expert interviews. (Manuscript)

Quan, X., Ma, J., Doluschitz, R. Farm machinery adoption and its impacts on maize yield and labor productivity: insights from China. (Manuscript)

Curriculum Vitae

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Research interests

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- Precision agriculture extension
- Technology adoption and its socio-economic effects analysis.

Language skills

Chinese (Mother tongue), English (Proficient), German (B1)

Additional skills

R project for statistical computing (Moderate), STATA for statistical computing (Proficient).

Conferences

The 97th Annual Conference of The Agricultural Economics Society, University of Warwick, UK - 27th - 29th March 2023. Poster presentation on "The adoption of unmanned aerial vehicles (UAVs) in China's agriculture: insights from expert interviews".

Publications

Quan, X., Doluschitz, R. (2021). Unmanned aerial vehicle (UAV) technical applications, standard workflow, and future developments in maize production – water stress detection, weed mapping, nutritional status monitoring and yield prediction. LANDTECHNIK, 76(1). https://doi.org/10.15150/lt.2021.3263

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Stuttgart, 01.12.2023   Xiuhao Quan