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Abstract

Market uncertainty in agriculture has been suggested to influence farmers to allocate their lands and cultivate different crops each season, thus threatening food production. However, little is known about the effects of such uncertainty on farmers' land-fragmentation decisions. We examine how input-price uncertainty affects land fragmentation along with crop diversification, considering that this uncertainty is approximated by an "input-price deviations," i.e., a difference between the realized market price and the initial expectation of each farmer in a season. It is hypothesized that farm sizes matter in that small-size farms respond to the deviations in a contrasting way compared to large-size ones. Data were collected from a questionnaire survey of 800 Tajikistan farmers, enabling us to develop a new indicator for land fragmentation in addition to a Simpson indicator for crop diversification. Econometric analyses highlight the importance of farm sizes, demonstrating that medium- and small-size farms adjust their land allocation by fragmenting (consolidating) lands for diversifying (specializing) crops against positive (negative) input-price deviation. In contrast, large-size farms are less likely to fragment (consolidate) their lands and display the opposite pattern for diversification in response to input-price deviations. Overall, input-price deviations and the interactions with farm sizes are keys not only in land allocation for agriculture, but also in causing substantial fluctuations for crop productions — consistent with the observed patterns in Tajikistan. Thus, implementing price ceilings or subsidies for agricultural inputs should be considered to mitigate land fragmentation for stable and sustainable food production, as a majority of farms are not large-sized.

Keywords: Land fragmentation; Farm sizes; Input-price deviations; Tajikistan

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Contents

1 Introduction

Agricultural land fragmentation has become a growing global issue and is recognized as being influenced by population growth, policies and market uncertainty, particularly in developing countries (Blarel et al., 1992, Gomes et al., 2019). This fragmentation can be a major problem for developing sustainable agricultural production and achieving food security, hindering mechanization and increasing production costs (Mayele et al., 2024). Conversely, crop diversification has been reported as a sustainable agricultural strategy, as it can improve adaptation to uncertainty and risk minimization, as well as crop rotation to meet agronomy requirements (Shah et al., 2021, Liang et al., 2023, Mihrete and Mihretu, 2025). Market uncertainty is among the main drivers of crop diversification through land fragmentation to minimize risks and avoid income loss (Villa et al., 2019, Kurdyś-Kujawska et al., 2021). In contrast, land fragmentation in semiarid and arid regions significantly affects irrigation water availability and adaptation to climate change for sustainable food production (Sharofiddinov et al., 2024, 2025). Considering these circumstances, we aim to address how input-price uncertainty influences farmers' land-allocation decisions.

In the past few decades, land allocation decisions have been studied in relation to policies and socioeconomic factors, such as land reforms, population growth, production instabilities and market uncertainty. Several approaches, such as multicriteria decision making, the analytical hierarchy process, linear programming, simulated annealing and empirical analysis, have been used to address land allocation decisions (Dhakal, 2016, Kaim et al., 2018, Gebre et al., 2021). For instance, empirical analyses have been used to study land allocations under price and production uncertainty (Babcock et al., 1987, Messina and Bosetti, 2003, Vassalos et al., 2013, Lu et al., 2014). Agricultural activities are subjected to a variety of risks and uncertainty, to which farmers respond by making various decisions, such as whether to fragment or consolidate land and diversify or specialize crops, to maximize their production or profit (Hamsa and Bellundagi, 2017, Zonneveld et al., 2020).

In the literature, agricultural land fragmentation is known as parcelization and is defined as the existence of numerous of plots that are small in size and irregular in shape (Demetriou et al., 2013, Postek et al., 2019). Different methods are used to measure and determine the degree of land fragmentation, including the number of plots and average plot sizes under each farm, as well as land fragmentation indices (Kalantari and Abdollahzadeh, 2008, Demetriou et al., 2013, Looga et al., 2018). Crop diversification is known as a green agricultural strategy and is defined in the literature as the practice of growing different types of crops on a farm (Mzyece et al., 2023). Crop diversification is also measured in the literature via various approaches, such as considering the number of plots and their size on a farm (Mesfin et al., 2011, Hufnagel et al., 2020). However, there is no universally accepted threshold for determining when a farm or plot is considered fragmented. The degree of land fragmentation and/or diversification depends on several context-specific factors, such as land availability, infrastructure, landscape and soil characteristics, mechanization and irrigation methods and types (Ntihinyurwa et al., 2019).

A group of studies demonstrate that changes in policies, land availability, demography, precipitation, income and labor force are considered as the driving forces of land fragmentation (Tan et al., 2006, Gu et al., 2023). To ensure rural employment, economic growth and food security in the transition period from a centralized economy to a market-based economy, some countries in Central Europe, Eastern Europe and Asia have implemented a land reform by privatizing and restructuring large state farms (Gorgan and Hartvigsen, 2022, Sharofiddinov et al., 2025). Kalantari and Abdollahzadeh (2008) investigate the determinants of farmers' land allocation decisions for fragmentation practices using a questionnaire survey with 151 farmers in Iran, indicating that farmers' income, household labor force and family size contribute to land fragmentation. Tacconi et al. (2022) explore the driving forces and constraints of crop diversification by conducting a literature review of 97 studies, finding that in response to the risks associated with the market, farmers implement crop diversification as a risk management strategy. Furthermore, this review indicates that small-size farms tend to diversify their crops when faced with production limitations and that farmers tend to specialize in production when they have comparative advantages, such as financial capital and access to technologies and markets.

Land fragmentation and crop diversification have been reported to be among the critical decisions of farmers under market uncertainty. Thus, understanding how farmers allocate their lands under price uncertainty is important for stable and sustainable food production. However, little is known about the effects of such uncertainty on farmers' land allocation decisions. Given this paucity in the literature, we examine how input-price uncertainty affects land fragmentation along with crop diversification, considering that this uncertainty is approximated by an "input-price deviation," i.e., a difference between the realized market price and the initial expectation of each farmer in a given season. To this end, we conduct a questionnaire survey with 800 farmers in the two river basins of Tajikistan and collect data on their land allocations, perceptions of input-price deviations, farm sizes and cognitive and socioeconomic variables. We develop a new indicator for land fragmentation in addition to a Simpson indicator for crop diversification, hypothesizing that farm sizes matter in that small-size farms respond to positive input-price deviation by fragmenting their lands compared to large-size ones. Addressing this question and hypothesis is beneficial for the development of agricultural policies in not only Tajikistan but also other countries experiencing similar issues in terms of food security and Sustainable Development Goals (SDGs).

2 Land fragmentation and input issues in Tajikistan's agriculture

Despite its challenging environment and limited agrarian land availability, the agricultural sector in Tajikistan remains among the leading components of the national economy, providing 46 % of employment and forming a significant portion of the gross domestic product (GDP) (World Bank, 2021). Irrigated agriculture plays an important role in the socioeconomic development of the country, resulting in the production of approximately 80 % of agricultural commodities (MEDT, 2013). The agricultural sector is considered the largest water user in Tajikistan, utilizing approximately 90 % of the country's extracted water resources (MEWR, 2019). Food security and nutrition are among the main priorities of the country's national development strategy (MEDT, 2013). Nevertheless, the agricultural sector has been facing challenges, including vulnerability to climate change, poor irrigation infrastructure, market uncertainty and strong dependency on importing inputs (MEDT, 2013, World Bank, 2022).

After gaining independence from the Soviet Union in 1991, the country has been undergoing a period of various economic reforms. In 1995, the government of Tajikistan began a land reform by adopting national policies and programs to reorganize former collective and state farms and distribute agricultural land to individuals, households or groups of farms and enterprises. A series of the President's decrees and programs were adopted to reduce the unemployment rate, develop profitable farm production processes, and grant freedom to farmers to plant their chosen crops and set their own product prices. In particular, the agricultural sector reform program (2012−2020) was adopted to increase agricultural output and enhance the export environment (Babu and Akramov, 2022). The transition to new economic relations, the establishment of new economic forms and the privatization of assets have led to a complete transformation of the agricultural sector. However, the institutional mechanism, infrastructure, mechanization, input supply and product processing that were established for the large-size farms during the Soviet era remain critical issues in Tajikistan.

In addition to the negative impacts of external factors, such as climate change, population growth and global competition, the agricultural sector in Tajikistan is facing significant constraints related to market uncertainty. In particular, countries rely on imports to meet food and nutritional needs and are considered net importers of agricultural inputs (fertilizers, seeds, machinery and fuel) (Akramov and Shreedhar, 2012, World Bank, 2022). Agricultural input market disruptions represent a key driver of vulnerability, especially in terms of food and nutritional insecurity. Fluctuations in global input prices, such as those for seeds and fertilizers, cause not only increased production costs but also substantial fluctuations in output prices and crop production (WFP, 2025). Thus, the food and nutritional security of Tajikistan remains vulnerable due to limited access to key agricultural inputs (World Bank, 2022). Moreover, the growing number of small-size farms due increased land fragmentation poses negative threats to irrigation water availability and reduces ability to adapt to climate change (Sharofiddinov et al., 2024, 2025). Despite government efforts, creating a favorable environment, such as one with strong investments and infrastructure, reliable water, market access, technology and knowledge, remains challenging in Tajikistan given the growing number of small-size farms.

Despite the significant progress made in economic reforms through implementation of national programs and strategies, governmental subsidies and investments, promoting sustainable agricultural production remains a major challenge for the country. Agricultural production is constrained by inadequate input supply, increasing input prices, a lack of farmer knowledge, poor infrastructure and technology and inefficient land use patterns (Tashmatov et al., 2000, Husenov et al., 2020, Kawabata et al., 2020). Agricultural production diversification and increased access to improved agricultural inputs are considered the main activities for achieving goals of Tajikistan's National Development Strategy (NDS). Conversely, crop diversification through land fragmentation by medium- and small-size farms may have adverse effects on food security and sustainability in Tajikistan. Furthermore, increasing access to improved agricultural inputs, such as seeds, fertilizers, machinery and labor, becomes challenging with the number of small-size farms increasing over time. Farmers' decisions to implement land fragmentation (or consolidation) and crop diversification (crop specialization) are made considering several factors, such as land availability, farming knowledge and skills and adaptation to uncertainty. Therefore, it is important to examine and understand the relationship between farm sizes and land allocation decisions for production under market uncertainty.

3 Methodology

3.1 Study areas

We conduct a questionnaire survey in the two river basins of Tajikistan –Zarafshon and Kofarnihon (figure 1). We select river basins on the basis of several criteria, including their geographical location, economic activities and production, farm sizes and population density, as suggested by Mr. Muslihiddin Kholiqzoda, the chief of the Water Resources Department of the Ministry of Energy and Water Resources (MEWR). The Zarafshon river basin is located in the central-western part, whereas the Kofarnihon river basin is located in the central-southwest part of the Tajikistan, covering approximately 9 % and 30 % of Tajikistan territory, respectively (MEWR, 2019, 2020).

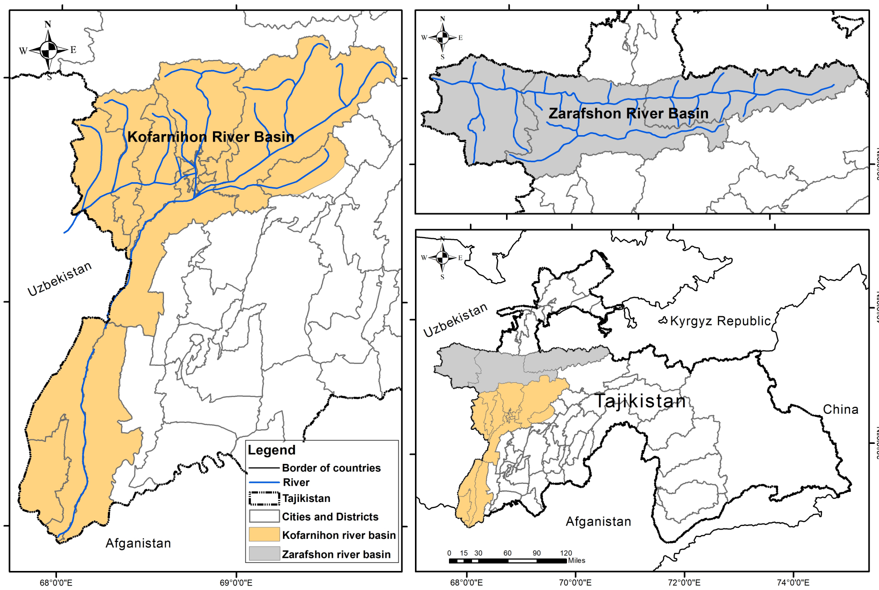
3.2 Data collection

A stratified sampling method was used to conduct our questionnaire surveys in the Kofarnihon and Zarafshon river basins. We collected a list of farmers from the irrigated areas of each of the river basins. A random selection of 800 farmers was utilized with the strata of the river basins. Farmers in these areas cultivate a variety of orchards and crops, including cotton, vegetables, cereals and fodder crops. As a result, 181 and 618 farmers were selected from the Zarafshon and Kofarnihon river basins, respectively, and a simple random sampling within each stratum was applied to finalize the sample selection for our data collection. Because the two basins have unequal numbers of farms and areas, we sought to determine the difference through the above stratified sampling procedures. We organized two-day orientation sessions to train research assistants and administer questionnaire pretests. Surveys were conducted from May 15 to June 14, 2023 in the local Tajik language. The researcher administered the orientation sessions and surveys, coordinating with the research assistants for farm interviews.

3.3 Key variables

We asked the heads of farms (hereafter referred to as “farmers”) a series of questions to obtain data related to their farm sizes, numbers of plots and corresponding areas. We also collected information from farmers related to their cognitive and socioeconomic factors, perceptions of input-price changes, climatic perceptions, farming experience, information access, education, irrigation water availability, equipment and services, primary income sources, market distances, distances to plots, locations in the river basin zone, family sizes and gender (table 1). We asked farmers to indicate their current land allocation for each crop with its corresponding areas. With this in-

Figure 1: A map of study areas in Tajikistan



formation, the key variables of the crop-diversification indicator (CDI)[1] and land-fragmentation indicator (LFI) in our statistical analyses are derived. To measure the CDI and LFI, we used the Simpson diversity index (SDI) and the newly developed LFI, respectively.

The CDI for the i^{th} farmer is calculated as follows:

$$\text{CDI}_i = 1 - \frac{\sum_{j=1}^{n_i} a_{ij}^2}{\left(\sum_{j=1}^{n_i} a_{ij}\right)^2} \tag{1}$$

where subscripts $i = 1, 2, \ldots, 800$ and $j = 1, 2, \ldots, m$ denote the farmer and the plots for the i^{th} farmer, respectively. Symbol a_{ij} represents the size of plot j and n_i is the number of plots with different crops for the i^{th} farmer. The CDI ranges from 0 to 1, and a larger value indicates a higher degree of CDI.

In previous studies, indicators such as Simpson diversity index, Januszewski index or area-weighted mean plot size have been used to measure the degree of agricultural land fragmentation

[1]The crop-diversification indicator is calculated from plot size data (a_{ij}) under the assumption that different plots are typically used for different crops.

(Olarinre and Omonona, 2018, Looga et al., 2018, Lu et al., 2018). However, these indicators cannot be directly applied to measure the degree of land fragmentation for a diverse range of farm sizes and for Tajikistan's irrigated agriculture, where water acts as a bottleneck. Existing indicators can be applied when farm sizes are uniform, but in our sample these sizes range from 0.12 ha to 61 ha, making it difficult to utilize these indicators.

The LFI for the i^{th} farmer is defined as follows:

$$\text{LFI}_i = \sqrt{\left(\frac{n_i}{\bar{n}} \times \frac{1}{\bar{a}_i}\right) \times \left(\frac{1}{\hat{a}_i}\right)} \tag{2}$$

where subscripts $i = 1, 2, \ldots, 800$ denote the farmer. Symbol n_i represents the number of plots for the i^{th} farmer and $\bar{n}$ is the average number of plots per farmer in the study area, $\bar{a}_i$ is arithmetic mean of plot size for the i^{th} farmer and $\hat{a}_i$ is harmonic mean of plot size for the i^{th} farmer (Appendix I). The LFI ranges between 0.06 and 53.09 for our dataset. The larger value of LFI indicates a higher degree of land fragmentation (For the logic behind the definition of LFI, see Appendix I).

In some cases, the LFI becomes fully consistent with the SDI and other well-known indicators, especially when the farm size, number of plots and plot size are similar. In other cases, our LFI extends other indicators by taking water use inefficiency into account, especially when the sample includes a diverse range of farm sizes and when there are large differences in plot size. In particular, existing indicators do not account for the existence of small plots, which contribute to irrigation water losses and reduce the operational efficiency of the irrigation system. For instance, a farm composed of three 0.5 ha plots imposes very different operational demands on the irrigation system compared with a farm composed of three 5 ha plots, even if the number of plots or the SDI values appear similar. As a result, those existing indicators may fail to capture the real-world inefficiencies and water losses that arise in such diverse systems (see Appendix I for these concepts).

To illustrate how water losses vary under different levels of land fragmentation, we developed five hypothetical farms (A, B, C, D and E). All farms are assumed to be located the same distance from the main canal and irrigated through a 500 m on-farm earthen canal with identical hydraulic parameters. We assume that each farm grows different crops on its plots, each requiring irrigation at different times. Figure 2 presents a comparison of indicator values for the Simpson diversity index, the Januszewski index and the new land-fragmentation indicator to measure land fragmentation for hypothetical farms A, B, C, D and E, which differ in terms of both the number of plots and plot size. For instance, the Simpson and Januszewski indices are the same for farms C and E, where the number of plots is the same, while the plot sizes are different[2]. Next, while the SDI and Januszewski indices indicate that farm D is less fragmented than is farm C, the LFI suggests the opposite. Finally, the LFI is greater for farms E and D than for farm C, better reflecting the land fragmentation level in irrigated agriculture considering water losses, such as seepage and system loss. In reality, calculating water losses in Tajikistan agriculture is practically impossible, as the secondary and tertiary distribution systems consist of open canals and ditches without proper water measurement tools. Therefore, we propose a new LFI as a practical and context-specific indicator to measure the degree of land fragmentation, specifically designed for irrigated agriculture reliant on open canals and for a diverse range of farm sizes, integrating not only the structural aspects of fragmentation (e.g., plot size and number of plots) but also its functional consequences, such as the consolidation waste effect and the bottleneck effect of small plots on irrigation efficiency.

Figure 3 shows the relationship between the average weighted water losses and LFI for hypothetical farms A-E. We calculate average weighted water losses by combining plot-level water losses as a weighted mean, normalized by the total withdrawn water, rather than simple sum. Although the direct calculation of water losses is impractical for real farms as mentioned earlier, we computed them for the hypothetical farms by imposing several simplifying assumptions (for the details of this calculation, see Appendix II.) The results indicate that the average water losses increase with LFI. Specifically, the LFI values (corresponding average weighted water losses) for farms A, B, C, D and E are 0.02 (29.87 %), 0.14 (42.13 %), 0.48 (50.45 %), 1.13 (55.44 %) and 5.33 (80.78 %), respectively. This pattern reflects the reality that Tajikistan's irrigation systems

[2]The SDI and Januszewski indices range from 0 to 1, where higher values indicate a greater degree of land fragmentation. For ease of comparison, we transform the Januszewski index by subtracting it from 1, so that a value of 0 represents no fragmentation.

Figure 2: Comparison of indicator values for the Simpson diversity index (SDI), Januszewski index and new land-fragmentation indicator (LFI).

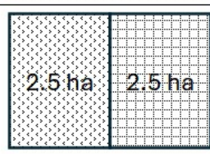
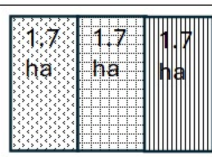
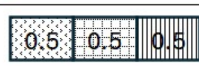
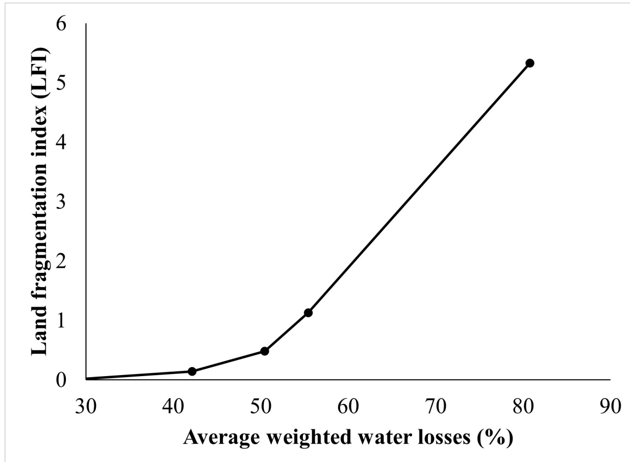
Hypo-thetical farms	Land-allocation structures	Land-fragmentation indicators		
		Simpson Diversity Index (SDI)	Januszewski index	Land-fragmentation indicator (LFI)
A		0	0	0.02
B		0.5	0.29	0.14
C		0.67	0.42	0.48
D		0.34	0.35	1.13
E		0.67	0.42	5.33

Figure 3: Relationships between water losses and the land-fragmentation indicator (LFI) in earth canals

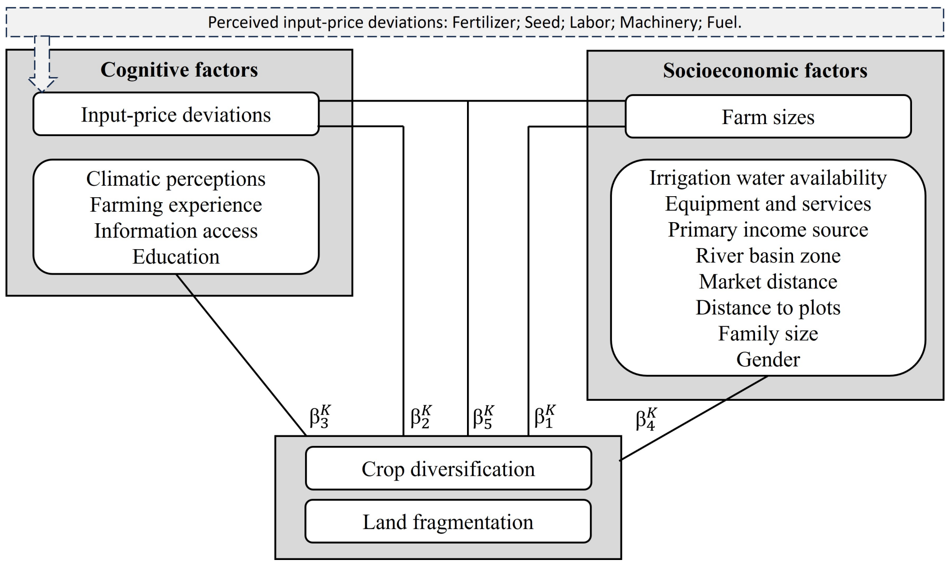


were originally designed for large farms and plot sizes. However, during the country's land reform, the physical infrastructure remained unchanged while land was subdivided. As a result, farmers often withdraw more water than needed to meet the actual requirements, especially when fragmented plots are being irrigated. For instance, when plots smaller than 1 ha are cultivated, farmers often withdraw water equivalent to at least the water required for 1 ha. A portion of the delivered water is used by the farmer, while the remaining portion flows to the drainage network as management loss. Our proposed LFI effectively captures this dynamic, reflecting higher average weighted water losses as plot size decreases below 1 ha. While farmers may sometimes irrigate multiple plots simultaneously, crop-specific irrigation schedules typically prevent complete synchronization. Therefore, we consider this approach to be the best possible approximation for assessing different degrees of water losses under varying levels of land fragmentation[3].

The other key variables in our study are farm sizes and input-price deviations. Following Sharofiddinov et al. (2024), we categorize our farm sizes into three groups, creating two farm-size dummies along with one base group as follows: (i) small-size farm (farm sizes $<$ 1 ha) as the small-size dummy, (ii) medium-size farm (3 ha $\geq$ farm sizes $\geq$ 1 ha) as a medium-size dummy

[3]Detailed calculations of water losses for farms A, B, C, D and E are provided in Appendix II.

Figure 4: A conceptual framework that describes the relationships between variables (farm sizes, input-price deviations, climatic perceptions, farming experience, information access, education, irrigation water availability, equipment and services, primary income source, distance to plots, river basin zone, family size, gender and interactions) and the crop-diversification indicator (CDI) and the land-fragmentation indicator (LFI) by β_j^Ks for $K = \{\text{CDI}, \text{LFI}\}$ and $j = 0, 1, \ldots, \ell$.



and (iii) large-size farm (farm sizes > 3 ha) as a base group. With respect to input-price deviations, we asked the farmers to answer 5 questions about their initial expectations for input prices (three months before the cultivation season) and 5 questions about their realized market prices, such as those for fertilizer, seed, labor, machinery and fuel. Finally, following the calculation method of Gayretli et al. (2019), we computed input-price deviations for each farmer by taking the difference between the realized market price and the initial expectation of each farmer in a given season. These deviations capture both positive (when realized market prices exceed initial expectations) and negative (when realized market prices fall below initial expectations) values.

3.4 Conceptual framework and data analyses

Figure 4 presents a conceptual framework for our empirical analyses, drawing on observations of farmers in Tajikistan and existing theoretical models addressing market uncertainty. Farmers in Tajikistan, much like those in other countries (Solano et al., 2001, Mandryk et al., 2014), pursue di-

Table 1: Description of the variables

Variables	Definitions and descriptions
Dependent variables	
Crop-diversification indicator (CDI)	The Simpson diversity index is used to quantify how evenly land is distributed among different crops. The index ranges between 0 and 1, with higher values indicating a greater of crop diversification.
Land-fragmentation indicator (LFI)	A new indicator is developed based on the number of plots and the area of each plot. The indicator ranges between 0.06 and 53.09, with higher values indicating a greater land fragmentation.
Independent variables	
Input-price deviations	Input-price deviations is calculated based on the initial expected input prices (three month before the cultivation season) and farmers' realized market price, such as for fertilizer, seed, labor, machinery and fuel.
Climate perceptions	A number of perceived changes in temperature, rainfall, snowfall, drought, hot waves and cold waves by the farmer within the last 10 years that range between 0-10.
Farming experience	The level of agricultural experience for the farmer ranges . between $1-5$; 1 - less than five years; 2 - 5 to 10 years; 3 - 11 to 15 years; 4 - 16 to 20 years; 5 - more than 20 years
Information access	An aggregate number of accesses to agricultural information in local, region, province and country levels that range between $0-32$.
Education	The level of schooling for the farmer ranges between $1-4$, 1 - primary school; 2 - middle school; 3 - high school; 4 - university or above.
Irrigation water availability (IWA)	The level of water availability ranges between $1-5$ 1 - water does not reach and 5 - water is abundant.
Equipment and services	Summation of the number of farmers equipment types and received agricultural extension services.
Primary income source ($base\ group = non\ agriculture$)	A variable that takes value 1 if the farmers' primary income is from agriculture; otherwise, 0.
Distance to plots	Distance in kilometers (km) from farmer's home to their land.
Market distance ($base\ group = Long\ distance$)	A dummy variable that takes value 1 if the farmer is located in close to market; otherwise, 0.
River basin zone ($base\ group = Kofarnihon$)	A dummy variable that takes value 1 if the farmer is located in Kofarnihon river basin; otherwise, 0.
Family size	The number of family members of the farmer.
Gender ($base\ group = male$)	A dummy variable that takes value 1 if the farmer is female; otherwise, 0.

verse objectives in their agricultural practices. While some prioritize food security and household consumption –focusing on maximizing food production –others seek to mitigate risks by ensuring that their yields do not fall below certain thresholds. Additionally, some farmers prioritize maintaining stable cash income through supplementary activities. As a result, conventional economic theories of profit maximization and cost minimization do not uniformly apply to land allocation decisions in Tajikistan. In this study, input-price deviations is considered as a cognitive factor, reflecting the difference between farmers' planned input prices and the actual prices they face, representing not only an economic shock but also psychological and decision-making challenges. To explain farmers' land-allocation decisions, we refer to some sociocognitive theories, such as adaptive capacity theory and resilience theory, in our conceptual framework. These theories provide some insights into the role of farmers' land-allocation decisions in relation to cognitive and socioeconomic factors. Prior research further highlights that these factors play a crucial role in how farmers respond to input-price deviations in the agricultural context (Allison and Hobbs, 2004, Duong et al., 2019, Osiemo et al., 2021, Das et al., 2023).

A conceptual framework is developed to offer a comprehensive perspective for understanding how farmers' land-allocation decisions (LAD) are characterized by both cognitive and socioeconomic factors along with their interactions. We apply median regressions to quantitatively estimate parameters β_j^Ks for $j = 0, 1, \ldots, \ell$ and $K = \{\text{CDI}, \text{LFI}\}$, each of which represents the relationship between the crop-diversification indicator and land-fragmentation indicator as the dependent variable and the independent variable is specified in equation (3).[4] Median regression is known to be preferred over mean-based regression for characterizing a nonnormally distributed dependent variable in relation to some independent variables (Sarker et al., 2012, Hirose et al., 2023). Because the CDI and LFI are not normally distributed according to the Shapiro-Wilk test, we believe that the median regression approach is appropriate for our analyses (Corder and Foreman, 2014,

[4]We also apply Poisson regression to estimate the relationship between the land-fragmentation indicator (number of plots) as the dependent variable and the same set of independent variables as that specified in equation (22).

Khatun, 2021). The regression specification is expressed as follows:

$$\text{LAD}_i^K = \mathbf{x}_i \beta^{K\prime} + \epsilon_i \tag{3}$$

where LAD_i^K is the CDI or LFI implemented by the i^{th} farmer, $\mathbf{x}_i = (1, x_{1i}, x_{2i}, \ldots, x_{\ell i})$ represents a vectors of $\ell + 1$ independent variables consisting of intercept, farm-size, input-price deviations, cognitive and socioeconomic variables and the corresponding interaction terms, respectively. Finally, $\beta^K = (\beta_0^K, \beta_1^K, \ldots, \beta_\ell^K)$ is a vector of the coefficients associated with $\mathbf{x}_i$ to be estimated through the least absolute distance estimation method, $K =$ CDI, LFI is the crop-diversification indicator and land-fragmentation indicator, and ϵ_i is the error term. Each coefficient is interpreted as a change in the land-allocations median when one continuous (or dummy) independent variable increases by one unit (or from zero to one), holding the other variables constant.

A conceptual framework illustrated in figure 4 along with the regression specifications in equation (3) help us identify the key determinants for examining the research question and hypothesis in our study. The following further steps are taken. First, we conduct Mann-Whitney non-parametric tests to determine some qualitative relations between the key variables. Second, we apply Shapiro-Wilk tests to determine whether the CDI and LFI are normally distributed (Shapiro and Wilk, 1965). Third, we estimate four regression models for each of the CDI and LFI as a robustness check, with Model 1 including farm-size dummies and input-price deviations as the independent variables along with an intercept, Model 2 additionally including cognitive variables, Model 3 additionally including cognitive and socioeconomic variables and Model 4, to further characterize how the relationship between farm-size dummies and dependent variables changes, including interaction terms between farm-size variables and the input-price deviations in addition to the specifications in Model 3. Finally, we interviewed two experts in the field to gain nuanced insights into farmers' response behaviors and motivations.

Table 2: Summary statistics of the variables

	Farm-size dummy			
	Small-size farm ($N = 261$)	Medium-size farm ($N = 394$)	Large-size farm ($N = 144$)	Overall ($N = 799$)
Dependent variables				
Crop-diversification indicator (CDI)				
Mean (Median) [a]	0.41 (0.50)	0.51 (0.58)	0.61 (0.64)	0.52 (0.59)
SD [b]	0.27	0.24	0.17	0.24
Min	0.00	0.00	0.00	0.00
Max	0.82	0.85	0.86	0.86
Land-fragmentation indicator (LFI)				
Mean (Median)	7.77 (4.71)	4.52 (2.72)	1.23 (0.91)	4.04 (1.90)
SD	8.56	5.43	1.03	5.77
Min	0.52	0.17	0.06	0.06
Max	53.09	35.84	7.26	53.09
Independent variables				
Cognitive variables				
Input-price deviations				
Mean (Median)	0.28 (0.25)	0.30 (0.25)	0.27 (0.21)	0.29 (0.23)
SD	0.28	0.24	0.22	0.24
Climate perceptions				
Mean (Median)	7.80 (8.00)	8.36 (9.00)	8.42 (9.00)	8.27 (9.00)
SD	2.19	2.05	1.89	2.03
Farming experience				
Mean (Median)	3.89 (5.00)	4.04 (5.00)	4.21 (5.00)	4.06 (5.00)
SD	1.27	1.23	1.07	1.19
Information access				
Mean (Median)	3.82 (3.00)	4.25 (4.00)	6.35 (6.00)	4.86 (4.00)
SD	2.80	2.67	2.94	2.97
Education				
Mean (Median)	2.01 (2.00)	1.92 (2.00)	2.10 (2.00)	2.00 (2.00)
SD	0.77	0.81	0.78	0.80
Socioeconomic variables				
Irrigation water availability				
Mean (Median)	3.33 (3.00)	3.42 (4.00)	3.25 (4.00)	3.35 (4.00)
SD	0.78	0.96	1.09	0.98
Equipment and services				
Mean (Median)	3.03 (3.00)	3.10 (3.00)	4.00 (4.00)	3.38 (3.00)
SD	1.23	1.11	1.39	1.30
Primary income source				
Mean (Median)	0.44 (0.00)	0.69 (1.00)	0.92 (1.00)	0.72 (1.00)
SD	0.50	0.46	0.26	0.45
Market distance				
Mean (Median)	0.74 (1.00)	0.79 (1.00)	0.43 (0.00)	0.66 (1.00)
SD	0.44	0.41	0.49	0.47
Distance to plots				
Mean (Median)	1.38 (1.00)	1.78 (1.00)	2.38 (1.50)	1.91 (1.00)
SD	1.31	2.99	3.05	2.81
River basin zone				
Mean (Median)	0.46 (0.00)	0.81 (1.00)	0.89 (1.00)	0.77 (1.00)
SD	0.50	0.39	0.31	0.42
Family size				
Mean (Median)	7.97 (7.00)	9.24 (8.00)	9.57 (8.00)	9.12 (1.00)
SD	3.82	4.51	5.36	4.72
Gender				
Mean (Median)	0.32 (0.00)	0.22 (0.00)	0.09 (0.00)	0.19 (0.00)
SD	0.47	0.41	0.29	0.40

[a] Median in parentheses.

[b] SD stands for standard deviation.

Notes: Small-size farm (farm sizes < 1 ha), medium-size farm (3 ha $\geq$ farm sizes $\geq$ 1 ha), large-size farm (farm sizes $>$ 3 ha).

4 Results

The summary statistics of the variables in our analyses indicate that 799 observations are collected, whereas 261, 394 and 144 correspond to small-, medium- and large-size farms, respectively (table 2). The CDI shows that farmers promote 0.52 crop diversification on average and the median is 0.59. The averages (medians) for small-, medium- and large-size farms are 0.41 (0.50), 0.51 (0.58) and 0.61 (0.64), respectively. The CDI also tends to increase as farm size increases. The LFI indicates that farmers implement 4.04 land fragmentation on average and the median is 1.90. The averages (medians) for small-, medium- and large-size farms are 7.77 (4.71), 4.52 (2.72) and 1.23 (0.91), respectively, illustrating a downward trend as farm size increases. To statistically evaluate the differences in distributions of the CDI and LFI, we perform a non-parametric Mann-Whitney test for each pair of small-, medium- and large-size farms. The null hypothesis states that the distributions of the CDI and LFI are the same across farm sizes. The results indicate that the null-hypothesis is rejected for all pairs at 1 % level, implying significant differences in the distributions of the CDI and LFI across farm sizes.

The average input-price deviations for farmers is 0.29 and the median is 0.23. The averages (medians) are 0.28 (0.25), 0.30 (0.25) and 0.28 (0.25) for small-, medium- and large-size farms, respectively, showing that there are no considerable differences in average or median input-price deviations across farm sizes. The cognitive variables, such as climatic perceptions, farming experience and information access, are likely to increase with farm sizes, whereas education does not display a similar pattern. The socioeconomic variables, such as equipment and services, main income source, river basin zone, distance to plots and family size, except for irrigation water availability (IWA) and gender, increase as the farm size increases (table 2). Overall, the summary statistics reveal that farmers are heterogeneous in terms of the CDI, the LFI, climatic perceptions, farming experience, information access, equipment and services, distance to plots, river basin zone, family size and gender, whereas they are homogeneous in terms of input-price deviations, education and IWA.

4.1 Crop-diversification indicator

Table 3 reports the estimated coefficients, their corresponding standard errors and the statistical significance level of the independent variables on the CDI in median regression models. The estimated coefficients of medium- and small-size farms on the CDI are statistically significant with a negative sign at 1 % level across all models. The results indicate that medium- and small-size farms tend to reduce CDI by 0.06 $\sim$ 0.14 and by 0.12 $\sim$ 0.17 on the median CDI, respectively, compared to large-size farms, holding other variables constant. Overall, the findings suggest that both medium- and small-size farms tend to not diversify their crops compared to large-size farms.

The coefficients of some cognitive variables, such as input-price deviations and farming experience, are statistically significant at 1 % to 5 % levels across all models (table 3). The results reveal that farmers tend to increase the CDI by 0.08 $\sim$ 0.11 when their input price deviates positively by one unit, holding the other variables constant. Previous studies find that input-price uncertainty plays an important role in farmers' crop diversification (Ahsan, 2011), which is consistent with these results. Five years of farming experience tends to induce farmers to diversify their crops by 0.01 $\sim$ 0.02, which is in line with previous studies that show a positive impact on crop diversification (Ibrahim et al., 2009). The socioeconomic variables, such as primary income source, market distance and family size, are statistically significant at 1 % to 5 % levels in Models 3 and 4. The results reveal that farmers' crop-diversification capacities are determined by these factors (Kasem and Thapa, 2011, Nandi and Nedumaran, 2022, Ge et al., 2023).

In Model 4, we include and estimate interaction terms between farm sizes and input-price deviations, which enables us to derive the predicted median CDI over input-price deviations (positive or negative) for each farm size. Model 4 shows that the coefficient of the interaction terms between medium-size farms and input-price deviations is statistically significant at 1 % level. This finding implies that medium-size farms tend to increase the CDI by 0.30 ($= 0.08 + 0.22$) when their input price has a positive deviation by one unit. Similarly, the coefficient of the interaction terms between small-size farms and input-price deviations is statistically significant at 5 % level, implying that small-size farms implement additional crop diversification by 0.27 ($= 0.08 + 0.19$) when

Table 3: Estimated coefficients of the independent variables on the crop-diversification indicator (CDI) in the median regression

	Crop-diversification indicator (CDI)			
	Model 1	Model 2	Model 3	Model 4
Farm-size variables				
Farm-size dummies				
(base group = Large-size farm)				
Medium-size farm	–0.07***	–0.06***	–0.08***	–0.14***
	(0.02)	(0.02)	(0.02)	(0.03)
Small-size farm	–0.13***	–0.14***	–0.12***	–0.17***
	(0.03)	(0.03)	(0.03)	(0.04)
Cognitive variables				
Input-price deviations (IPDv)	0.11***	0.11***	0.08**	–0.08
	(0.04)	(0.04)	(0.04)	(0.07)
Climatic perceptions		0.001	–0.003	–0.002
		(0.004)	(0.004)	(0.005)
Farming experience		0.02***	0.02***	0.01**
		(0.007)	(0.01)	(0.007)
Information access		–0.003	–0.005	–0.004
		(0.003)	(0.003)	(0.003)
Education		0.005	0.01	0.01
		(0.01)	(0.01)	(0.01)
Socioeconomic variables				
Irrigation water availability			0.002	0.003
			(0.01)	(0.008)
Equipment and services			–0.001	0.001
			(0.007)	(0.007)
Primary income source			0.06***	0.06***
(base group = non agriculture)				
			(0.02)	(0.02)
Market distance			0.06***	0.06***
			(0.02)	(0.02)
Distance to plots			–0.002	–0.003
			(0.003)	(0.003)
River basin zone (base group = Kofarnihon)			0.03	0.03
			(0.02)	(0.02)
Family size			0.004**	0.004**
			(0.002)	(0.002)
Gender (base group = male)			0.03	0.03
			(0.02)	(0.02)
Interaction terms				
(base group = Large-size farm)				
Medium-size farm × IPDv				0.22***
				(0.08)
Small-size farm × IPDv				0.19**
				(0.10)
Constant	0.61***	0.52***	0.42***	0.49***
Sample size	792	770	741	741
Pseudo R-squared	0.04	0.05	0.07	0.08

*** significant at 1 % level
** significant at 5 % level
* significant at 10 % level
Standard errors are in parentheses

their input price has a positive deviation by one unit. Overall, crop diversification by medium- and small-size farms can be interpreted as highly dependent on input-price deviations with positive associations, while large-size farms are not. The results suggest that the interaction effects of farm sizes with input-price deviations practically influence crop diversification in farming in Tajikistan.

On the basis of the estimation results from Model 4 of table 3, we compute and graph the predicted median CDI over input-price deviations for each farm size considering the interactions (figure 5a). The predicted median CDI for each of the large-, medium- and small-size farms in figure 5a demonstrates that the intercepts and slopes are idiosyncratic between large-size farms and other-size ones (medium- and small-size farms). In particular, the intercept for large-size farms is higher than that for small- and medium-size farms when farmers perceive a negative deviation in input prices. The predicted median CDI has an upward slope over input-price deviations for medium- and small-size farms when they have positive deviation in input prices. In contrast, the predicted median CDI has a downward slope over input-price deviations for large-size farms that perceive positive deviations. Overall, figure 5a suggests that medium- and small-size farms in Tajikistan increase (reduce) the degree of crop diversification in response to positive (negative) deviations in input prices, whereas large-size farms display the opposite trend. These results can be interpreted as follows: medium- and small-size farms tend to cultivate multiple crop types to reduce input costs by relying on their own labor, whereas large-size farms reduce the number of crops, utilizing machinery. This finding indicates that large-size farms have certain advantages in terms of their response to input-price deviations compared to medium- and small-size farms.

4.2 Land-fragmentation indicator

Table 4 presents the estimated coefficients, their corresponding standard errors and the statistical significance level of the independent variables in the median regression models for the LFI. The estimated coefficients of medium- and small-size farms on the LFI are statistically significant with a positive sign at 1 % level across all models. The results indicate that compared with large-size farms, medium- and small-size farms tend to fragment their land by 1.24 $\sim$ 1.85 and

Table 4: Estimated coefficients of the independent variables on the land-fragmentation indicator (LFI) in the median regression

	Land-fragmentation indicator (LFI)			
	Model 1	Model 2	Model 3	Model 4
Farm-size variables				
Farm-size dummies				
(base group = Large-size farm)				
Medium-size farm	1.85***	1.67***	1.24***	0.45
	(0.31)	(0.30)	(0.38)	(0.53)
Small-size farm	3.76***	3.62***	2.83***	1.91***
	(0.40)	(0.39)	(0.52)	(0.69)
Cognitive variables				
Input price deviations (IPDv)	1.46***	1.11**	1.13*	–0.28
	(0.56)	(0.52)	(0.66)	(1.08)
Climatic perceptions		0.11	0.03	–0.01
		(0.07)	(0.08)	(0.07)
Farming experience		0.30***	0.23*	0.25**
		(0.11)	(0.12)	(0.12)
Information access		–0.07	–0.06	–0.06
		(0.04)	(0.05)	(0.05)
Education		0.05	0.13	0.02
		(0.16)	(0.19)	(0.18)
Socioeconomic variables				
Irrigation water availability			–0.01	–0.01
			(0.15)	(0.14)
Equipment and services			–0.14	–0.06
			(0.12)	(0.11)
Primary income source			–0.91**	–0.75**
(base group = non agriculture)				
			(0.36)	(0.34)
Market distance			–0.16	0.02
			(0.35)	(0.34)
Distance to plots			–0.04	–0.06
			(0.05)	(0.05)
River basin zone (base group = Kofarnihon)			–0.33	–0.67*
			(0.41)	(0.39)
Family size			0.03	0.03
			(0.03)	(0.03)
Gender (base group = male)			0.22	0.12
			(0.38)	(0.36)
Interaction terms				
(base group = Large-size farm)				
Medium-size farm × IPDv				3.19**
				(1.31)
Small-size farm × IPDv				3.68**
				(1.59)
Constant	0.59**	–0.22	1.33	1.90
Sample size	770	770	741	741
Pseudo R-squared	0.10	0.12	0.12	0.13

*** significant at 1 % level
** significant at 5 % level
* significant at 10 % level
Standard errors are in parentheses

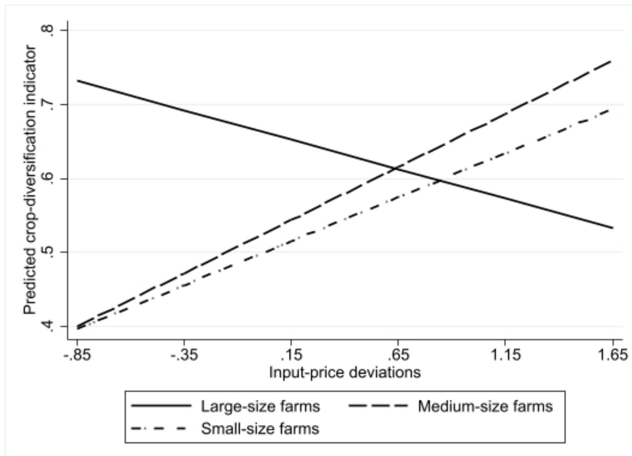
by 1.91 $\sim$ 3.76 on the median LFI, respectively, holding the other variables constant. Overall, the findings suggest that both medium- and small-size farms tend to implement land fragmentation as compared to large-size farms [5].

The coefficients of some cognitive variables, such as input-price deviations and farming experience, are statistically significant at 1 % to 10 % levels across all models (table 4). The results imply that farmers tend to increase the LFI by 1.11 $\sim$ 1.46 when their input price has a positive deviation by one unit, holding the other variables constant. Farmers tend to fragment their land by 0.23 $\sim$ 0.30 when their experience increases by five years. Compared with those with primary income from other sources, those farmers with primary income from agriculture tend to reduce the degree of land fragmentation by 0.75 $\sim$ 0.91. Compared with farmers in the Zarafshon river basin, farmers in the Kofarnihon river basin are likely to reduce the degree of land fragmentation by 0.67. Overall, input-price deviations, farming experience, income source and river basin zone determine the degree of land fragmentation in Tajikistan.

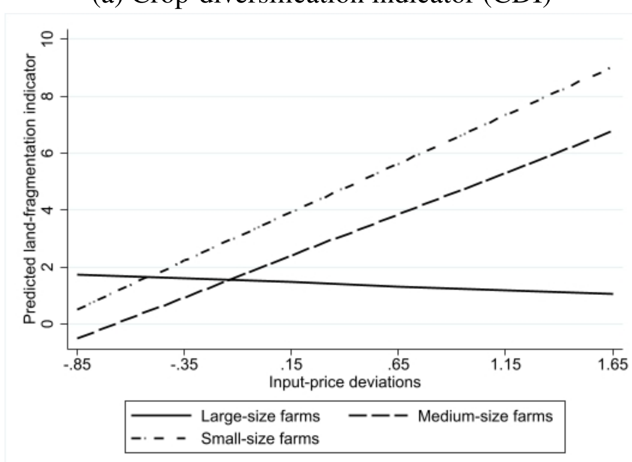
The estimated coefficients of the interaction terms between farm sizes and input-price deviations are statistically significant at 1 % to 5 % levels (see Model 4 of table 4). We derive the predicted median LFI over input-price deviations (positive and negative) for each farm size. The result implies that medium-size farms tend to raise the LFI by 0.30 ($= 0.08 + 0.22$) when their input price has a positive deviation by one unit. Similarly, we find that small-size farms implement additional LFI by 0.27 ($= 0.08 + 0.19$) when their input price has a positive deviation by one unit. Overall, land fragmentation by medium- and small-size farms can be interpreted as highly dependent on input-price deviations with positive associations, while large-size farms are not. The results suggest that the interaction effects of farm sizes with input-price deviations practically influence land allocation in Tajikistan farming.

We compute and graph the predicted median LFI over input-price deviations for each farm size considering the interactions based on the estimation results from Model 4 of table 4 (figure 5b). The predicted median LFI for each of the large-, medium- and small-size farms in figure 5b shows that

[5]The Poisson regression results demonstrate qualitatively similar findings, confirming that differences in land-allocation decisions between large-size farms and other ones exist (table 5)



(a) Crop-diversification indicator (CDI)



(b) Land-fragmentation indicator (LFI)

Figure 5: Predicted degrees of crop diversification and land fragmentation over input-price deviations by farmers across farm sizes.

the intercepts are proximate to one another, while the slopes are idiosyncratic between large-size farms and other-size ones (medium- and small-size farms). In particular, the predicted median LFI has an upward slope over input-price deviations for medium- and small-size farms. Conversely, we find that the predicted median LFI is not sensitive to input-price deviations for large-size farms, being particularly flat. Overall, figure 5b suggests that medium- and small-size farms in Tajikistan are likely to fragment (consolidate) their land in response to positive (negative) deviations in input prices, whereas large-size farms are not. Importantly, large-size farms do not display such a tendency, and we conjecture that they possess structural resilience capacities –reflecting greater robustness, adaptability and transformability –that enable them to withstand stresses, shocks, and risks and manage uncertainty more effectively than can medium- and small-size farms (Candel et al., 2019).

We summarize the statistical and econometric results related to the CDI and LFI, providing answers to our research question (how does input-price uncertainty affect land fragmentation along with crop diversification, considering that this uncertainty is approximated by "input-price deviations," i.e., a difference between the realized market price and the initial expectation of each farmer in a given season.) and hypothesis (Farm sizes matter in that small-size farms respond to the deviations in a contrasting way compared to large-size ones). As outlined in our conceptual framework, the CDI and LFI are influenced by cognitive factors, socioeconomic factors and their interactions. The results demonstrate that farm sizes, input-price deviations and farming experience influence both the CDI and LFI in a robust manner. In particular, the summary statistics and regression results uniformly suggest that farm sizes are key variables to characterize land-allocation decisions; that is, crop diversification and land fragmentation tend to increase or decrease under input-price deviations. We find notable differences in land allocations by farm sizes in the two regressions that characterize farming practices in Tajikistan. First, medium- and small-size farms are less likely to diversify their crops with a higher degree of land fragmentation compared to large-size ones, demonstrating the structural resilience capacities of large-size farms in terms of sustainable agricultural productions and adaptations to uncertainty and risks. Second, farmers whose primary source of income is agriculture tend to adopt greater degrees of crop diversification and exhibit lower levels of land fragmentation than do those whose primary income is derived from nonagriculture. These findings suggest that reliance on agricultural income enhances farmers' engagement with farming practices, enabling them to develop effective strategies to optimize agricultural productivity.

The estimated coefficients on the interaction terms and the associated graphs show that medium- and small-size farms tend to implement crop diversification (specialization) against positive (negative) input-price deviation. In contrast, large-size farms tend to implement crop specialization (diversification) in response to positive (negative) input-price deviation. Likewise, medium- and small-size farms are likely to fragment their land (consolidate) against positive (negative) input-price deviation, while large-size ones do not. These results may be due to the appropriateness of infrastructure and traditional farming practices where farmers are familiar with agricultural production, management and adaptations under large-scale farming (Sharofiddinov et al., 2025). Conversely, small-size farms in Tajikistan are known to suddenly become the owners of newly allocated small agricultural plots, and they do not receive proper instructions or training regarding how to manage and make productions under small-scale farming (Van-Assche et al., 2013, Shtaltovna, 2016). Therefore, such farmers may not possess any embodied knowledge, skills or abilities to respond, particularly under input-price deviations. It is our belief that these statistical analyses present results that are coherent with one another, well reflecting with the current situation in terms of farmers' land allocations by farm sizes in Tajikistan.

Crop diversification is widely recognized in the literature as an effective strategy for enhancing socioeconomic benefits, nutritional security, sustainability and adaptation to market uncertainty and climate change. Depending on policy perspectives, market and environmental conditions and land availability, farmers' land-allocation decisions may be oriented toward either crop diversification or crop specialization. Several studies indicate that crop diversification is an active strategy for smallholder farms to ensure food security and mitigate climate vulnerability through the cultivation of multiple crops (Mango et al., 2018, Molua et al., 2020, Jr et al., 2021, Ferry and de Montalembert, 2025), which often results in land fragmentation. In contrast, land fragmentation is widely established by previous studies as a growing global issue that is influenced by population growth, policies and market uncertainty (Gomes et al., 2019, Sharofiddinov et al., 2024) and is negatively associated with irrigation water availability, agricultural productions, land and labor productivity, machinery efficiency and climate change adaptation (Rahman and Rahman, 2009, Sharofiddinov et al., 2025). Market uncertainty, input-price fluctuations and access to high-quality inputs and markets are considered among the main drivers of land fragmentation. This research suggests some possible countermeasures to improve agricultural production through the optimization of land allocation and increase in the level of government support. First, a land-consolidation policy involving the merging of several small-size farms and the establishment of community collaborative management should be considered to increase the ability of farms to overcome input-price deviations, risks and uncertainty. Another, is to implement price ceilings or subsidies for agricultural inputs to mitigate land fragmentation for stable and sustainable agricultural production, as the majority of farms are not large-sized in Tajikistan.

5 Conclusion

This paper has examined how input-price deviations influence farmers' land-allocation decisions under different farm sizes, hypothesizing that farm sizes matter in that small size farms respond to deviations in a contrasting way compared to large-size ones. We utilize a questionnaire survey from 800 farmers in Tajikistan and collect data on their perceptions of the input-price deviations, farm sizes, and cognitive and socioeconomic factors. To model farmers' land-allocation decisions, we develop a new indicator to quantify the degree of land fragmentation for irrigated agriculture. The analyses imply that farm sizes, input-price deviations, farming experience and primary income source are key determinants for characterizing land-allocation decisions. The findings highlight the importance of farm sizes in land-allocation decisions, demonstrating that medium- and small-size farms adjust their land allocation by fragmenting (consolidating) lands for diversifying (specializing) crops against positive (negative) input-price deviation. In contrast, large-size farms are less likely to fragment (consolidate) their lands and display the opposite pattern for diversification in response to input-price deviations. Overall, this study reveals that input-price deviations and the interactions with farm sizes are important drivers not only of land allocation for agriculture but also of causing substantial fluctuations in crop productions. Our findings suggest that implementing price ceilings or subsidies for agricultural inputs should be considered to mitigate land fragmentation for stable and sustainable food production, as a majority of farms are not large-sized in Tajikistan.

We note several limitations of this study and suggest directions for future research. First, in this study, we do not consider long-term farmers' land-allocation decisions in relation to the realized market price or the initial expectation of input prices. Instead, we utilize cross-sectional data, focusing on farm-level decisions in relation to their cognitive and socioeconomic factors in a given season due to time and resource limitations. Moreover, we do not incorporate farmers' profits and production processes into our analyses. We admit that farmers' land-allocation decisions may go beyond the results of this study. Future studies should consider the long-term (several growing seasons) effects of input- and output-price deviations on land-allocation decisions within a single framework and switching regressions. Finally, it is our belief that this research signifies progress in understanding the importance of farm sizes for input-price deviations and land allocations in Tajikistan.

6 Appendix

6.1 Appendix I: Detailed information about land fragmentation indicator (LFI)

LFI is composed of two factors, which we call consolidation waste effect and bottleneck effect.

The consolidation waste effect (CWE_i) for the i^{th} farmer is defined as follows:

$$CWE_i = \left(\frac{n_i}{\bar{n}} \times \frac{1}{\bar{a}_i} \right) \tag{4}$$

where subscripts $i = 1, 2, \ldots, 800$ denotes the farmer, n_i is the number of plots for the i^{th} farmer, $\bar{n}$ is the average number of plots across all farmers in the sample and $\bar{a}_i$ is the arithmetic mean of plot size for the i^{th} farmer. The arithmetic mean of plot size is defined as follows:

$$\bar{a}_i = \frac{1}{n_i} \sum_{j=1}^{n_i} a_{ij} \tag{5}$$

where subscripts $i = 1, 2, \ldots, 800$ and $j = 1, 2, \ldots, m$ denote the farmer and the plots for the i^{th} farmer, respectively. a_{ij} is a plot size j and n_i is the number of plots for the i^{th} farmer.

$$\bar{n} = \frac{1}{N} \sum_{j=1}^{N} n_i \tag{6}$$

where $N = 800$ is the number of farms in the sample. The CWE_i reflects the inefficiencies arising from land subdivision that prevent the optimal use of irrigation systems and economies of scale in farming. We call it CWE_i because such inefficiency or waste could be avoided if plots were consolidated. The CWE_i is composed of two components –the relative number of plots ($n_i/\bar{n}$), which disrupts scheduling and increases management complexity, and the inverse of the average plot size per farmer ($1/\bar{a}_i$), which captures the loss of irrigation efficiency in small plots. This finding suggests that a high number of plots and small average plot sizes per farmer lead to a wasted consolidation effect. Therefore, CWE_i captures the compounded loss due to having many plots (disrupting scheduling) and small plots (reducing irrigation efficiency), which together exacerbate water and resource losses in irrigated systems. This dual structure allows us to represent both the physical and managerial inefficiencies introduced by fragmentation.

The bottleneck effect (BE_i) for the i^{th} farmer is defined as follows:

$$BE_i = \left(\frac{1}{\hat{a}_i}\right) \tag{7}$$

where subscripts $i = 1, 2, \ldots, 800$ denotes the farmer and $\hat{a}_i$ is the harmonic mean of plot size for the i^{th} farmer. The harmonic mean of plot size is defined as follows:

$$\hat{a}_i = \frac{1}{\frac{1}{n_i}\sum_{j=1}^{n_i}\frac{1}{a_{ij}}} \tag{8}$$

where subscripts $j = 1, 2, \ldots, m$ denote the farmer and the plots for the i^{th} farmer, a_{ij} is a plot size j and n_i is the number of plots for the i^{th} farmer. BE_i arises from the operational inefficiencies disproportionately caused by small plots, which exacerbate irrigation water losses and reduce system performance. We use the harmonic mean of plot sizes $\hat{a}_i$, because it is more sensitive to the size of small plots than it is to that of large plots, emphasizing the importance of small plots. This sensitivity ensures that even a few small plots (less than 1 ha) can significantly increase BE_i, highlighting their disproportionate influence of inefficiency. This finding is particularly important in the context of Tajikistan, where the irrigation infrastructure is typically earthen open canals and was originally designed for large plots. As $\hat{a}_i$ decreases, BE_i rises, reflecting the bottlenecks introduced by land fragmentation into irrigation scheduling and water delivery.

Finally, LFI for the i^{th} farmer is defined as a composite indicator that integrates the consolidation waste effect and the bottleneck effect. Specifically,

$$\text{LFI}_i = \sqrt{CWE_i \times BE_i} \tag{9}$$

The CWE_i represents the compounded inefficiencies caused by having many small plots, while the BE_i emphasizes the disproportionate influence of very small plots. By combining them, LFI_i provides a single measure that quantifies the extent to which land fragmentation reduces irrigation efficiency and agricultural productivity.

6.2 Appendix II: Detailed calculation of water losses

We calculate the weighted average water loss (WL_i) in $\%$ for the i^{th} farmer (A, B, C, D and E) as follows:

$$WL_i = SL_i + ML_i \tag{10}$$

where subscripts $i = 1, 2, \ldots, 800$ denote the farmer in $\%$, SL_i is the weighted relative seepage loss for the i^{th} farmer and ML_i is the weighted average management loss due to inadequate water distribution and scheduling or system design for the i^{th} farmer.

Following Kuznetsov et al. (2009), we calculate SL_i in $\%$ for the i^{th} farmer as follows:

$$SL_i = \frac{\sum_{j=1}^{n_i} W_{ij}^w (P_{ij}/Q_{ij}^w)}{\sum_{j=1}^{n_i} W_{ij}^w} \tag{11}$$

where subscripts $j = 1, 2, \ldots, m$ denote the plots managed by the i^{th} farmer, W_{ij}^w is the volume of withdrawn water (m^3) for plot j, P_{ij} is the seepage loss in the canal (m^3/s) for plot j and Q_{ij}^w is the withdrawn flow rate (m^3/s) for the plot j.

The seepage loss (P_{ij}) in the canal in m^3/s for plot j is calculated as follows:

$$P_{ij} = S_{ij} \times \lambda \tag{12}$$

where S_{ij} is the wetted area in the canal (m^2) for plot j and λ is a constant (0.12 m/h for soils with high filtration, 0.06 m/h for soils with medium filtration and 0.03 m/h for soils with low filtration).

The wetted area (S_{ij}) in the canal in m^2 for plot j is calculated as follows:

$$S_{ij} = L_{ij} \times \chi_{ij} \tag{13}$$

where L_{ij} is the length of the canal (m) for plot j and χ_{ij} is the canal wetted perimeter (m) for plot

j.

The canal wetted perimeter (χ_{ij}) in m for plot j is calculated as follows:

$$\chi_{ij} = b_{ij} + (2h_{ij}\sqrt{1 + m_{ij}^2}) \tag{14}$$

where b_{ij} is the canal bottom width (m) for plot j, h_{ij} is the water depth (m) for plot j and m_{ij} is the slope factor for plot j.

The canal flow rate (Q_{ij}) in m^3/s for plot j is calculated as follows:

$$Q_{ij} = A_{ij} \times V_{ij} \tag{15}$$

where A_{ij} is the cross sectional area of a trapezoidal canal (m^2) for plot j and V_{ij} is the average water velocity in the canal (m/s) for plot j.

The cross sectional area of a trapezoidal canal (A_{ij}) in m^2 for plot j is calculated as follows:

$$A_{ij} = (b_{ij} + h_{ij}m_{ij})h_{ij} \tag{16}$$

The average water velocity in the canal (V_{ij}) in m/s for plot j is calculated as follows:

$$V_{ij} = C_{ij}\sqrt{R_{ij} \times 0.001} \tag{17}$$

where R_{ij} is the hydraulic radius m in the canal for plot j and 0.001 is the assumed longitudinal slope of the canal.

The Chézy coefficient (C_{ij}) in $m^{0.5}/s$ is calculated as follows:

$$C_{ij} = \frac{1}{z_{ij}} \times R_{ij}^{\frac{1}{6}} \tag{18}$$

where z_{ij} is the canal bed roughness index for plot j which ranges between 0.020 to 0.030 for earth canals depending on soil.

The hydraulic radius (R_{ij}) in for plot j is calculated as follows:

$$R_{ij} = \frac{A_{ij}}{\chi_{ij}} \tag{19}$$

We calculate the weighted average relative management loss (ML_i) in $\%$ for the i^{th} as follows:

$$ML_i = \frac{\sum_{j=1}^{n_i} W_{ij}^w((Q_{ij}^w - P_{ij} - Q_{ij}^r)/(Q_{ij}^w)}{\sum_{j=1}^{n_i} W_{ij}^w} \tag{20}$$

where W_{ij}^w is the volume of withdrawn water (m^3) for plot j, Q_{ij}^w is the withdrawn flow rate (m^3/s) for the plot j which is not less than required water withdrawal rate 1 ha of crop, P_{ij} is the seepage loss in the canal (m^3/s) for plot j and Q_{ij}^r is the required flow rate (m^3/s) for plot j.

6.3 Appendix III: Results for the land-fragmentation indicator using the number of plots (NoP)

The LFI^{NoP} for the i^{th} farmer is defined as follows:

$$\text{LFI}_i^{NoP} = n_i \tag{21}$$

where subscripts $i = 1, 2, \ldots, 800$ denote the farmer and n_i is the number of plots for the i^{th} farmer.

To measure the land-fragmentation indicator, we additionally use the number of plots (NoP). Given that NoP is a nonnegative integer variable with a limited number of observations for each count, we select a Poisson-regression approach for analysis. In other words, NoP is assumed to follow a Poisson distribution conditional on a vector of some independent variables, $\mathbf{X}$, with the following specification:

$$\text{Prob}(\text{NoP}_i = h|\mathbf{X} = \mathbf{x}_j) = \exp[-\exp(\mathbf{x}_i\beta^{K\prime})][\exp(\mathbf{x}_i\beta^{K\prime})]^h/h!, \tag{22}$$

where $K = $ NoP, $h = 0, 1, \ldots, 13$ is the NoP the i^{th} farmer has, $\mathbf{x}_i = (1, x_{1i}, x_{2i}, \ldots, x_{\ell i})$ is

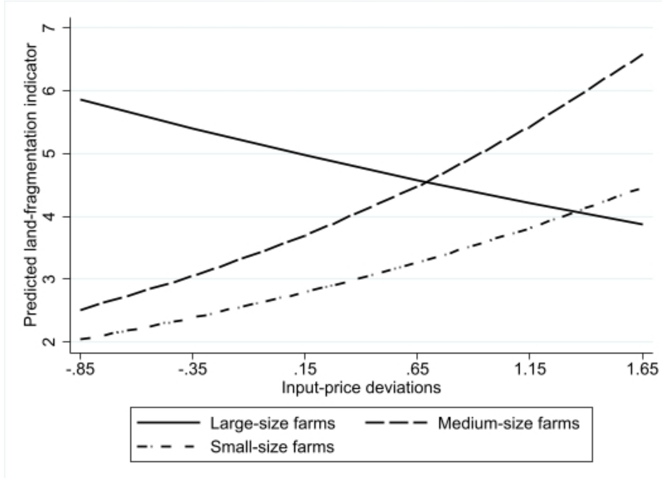


Figure 6: Predicted land-fragmentation indicator (NoP) over input-price deviations by farmers across farm sizes.

a vector of $\ell + 1$ independent variables consisting of intercept, farm-size, input-price deviations, cognitive and socioeconomic variables and the corresponding interaction terms, respectively. Finally, $\beta^K = (\beta_0^K, \beta_1^K, \ldots, \beta_\ell^K)$ is a vector of the coefficients associated with $\mathbf{x}_i$ to be estimated. The estimate for each coefficient is obtained through the quasi-maximum likelihood estimation method for the Poisson regression based on equation (22) (Wooldridge, 2019). We calculate the marginal effect of one independent variable on NoP from each estimated coefficient when the independent variable increases by one unit or from zero to one, holding other independent variables at their sample means.

Table 5: Estimated coefficients of the independent variables on the land-fragmentation indicator (number of plots) in the Poisson regression

	Model 1		Model 2		Model 3		Model 4	
	Coefficient	ME	Coefficient	ME	Coefficient	ME	Coefficient	ME
Farm-size variables								
Farm-size dummies								
(base group = Large-size farm)								
Medium-size farm	–0.22***	–0.96***	–0.20***	–0.89***	–0.21***	–0.92***	–0.38***	–0.94***
	(0.04)	(0.17)	(0.04)	(0.18)	(0.05)	(0.21)	(0.07)	(0.21)
Small-size farm	–0.47***	–1.84***	–0.46***	–1.77***	–0.50***	–1.91***	–0.65***	–1.93***
	(0.06)	(0.20)	(0.06)	(0.21)	(0.07)	(0.26)	(0.10)	(0.26)
Cognitive variables								
Input price deviations (IPDv)	0.27***	1.11***	0.22***	0.90***	0.19**	0.77**	–0.16	0.63*
	(0.07)	(0.29)	(0.07)	(0.29)	(0.08)	(0.35)	(0.14)	(0.35)
Climatic perceptions			0.01	0.06	0.01	0.05	0.01	0.05
			(0.01)	(0.04)	(0.01)	(0.04)	(0.01)	(0.04)
Farming experience			0.08***	0.31***	0.07***	0.29***	0.07***	0.27***
			(0.02)	(0.06)	(0.02)	(0.07)	(0.02)	(0.07)
Information access			–0.002	–0.01	–0.002	–0.01	–0.002	–0.01
			(0.01)	(0.02)	(0.01)	(0.03)	(0.006)	(0.03)
Education			0.01	0.04	0.03	0.12	0.03	0.11
			(0.02)	(0.09)	(0.02)	(0.10)	(0.02)	(0.10)
Socioeconomic variables								
Irrigation water availability (IWA)					0.02	0.08	0.02	0.08
					(0.02)	(0.07)	(0.02)	(0.08)
Equipment and services					0.01	0.04	0.01	0.06
					(0.01)	(0.06)	(0.01)	(0.06)
Primary income source (base group = non agriculture)					0.02	0.09	0.03	0.12
					(0.05)	(0.19)	(0.05)	(0.19)
Market distance					0.01	0.04	0.03	0.14
					(0.05)	(0.19)	(0.05)	(0.19)
Distance to plots					–0.01*	–0.06*	–0.02**	–0.07**
					(0.007)	(0.03)	(0.008)	(0.03)
River basin zone (base group = Kofarnihon)					–0.07	–0.27	–0.09*	–0.38*
					(0.05)	(0.23)	(0.05)	(0.23)
Family size					0.01***	0.05***	0.01***	0.05***
					(0.003)	(0.01)	(0.004)	(0.01)
Gender (base group = male)					0.15***	0.59***	0.15***	0.59***
					(0.05)	(0.20)	(0.05)	(0.20)
Interaction terms								
(base group = Large-size farm)								
Medium-size farm × IPDv							0.55***	
							(0.17)	
Small-size farm × IPDv							0.48**	
							(0.22)	
Constant	1.50***		1.05***		0.90***		1.00***	
Sample size	792		770		741		741	
Likelihood-Ratio	95.77***		123.30***		143.67***		154.57***	

*** significant at 1 % level
** significant at 5 % level
* significant at 10 % level
Standard errors are in parentheses

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