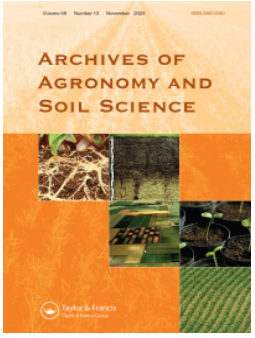


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# Determinants of minimal soil disturbance adoption over time and in the face of climate vulnerability

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**ABSTRACT**

Minimal soil disturbance (MSD) can reduce soil degradation and ensure agricultural sustainability. This study examines MSD adoption status (i.e. long-term non-adoption, dis-adoption, late-adoption and long-term adoption) and their determinants. Datasets of 1,659 Bangladeshi rice-farm households were utilized from the Bangladesh Integrated Household Surveys of 2013, 2016 and 2020. Long-term non-adopters (58%) are those who did not practice MSD in any survey years, dis-adopters (23%) are the households who abandoned MSD after practicing in a given period of time, late-adopters (13%) are the households who adopted later than their peer, and long-term adopters are the households (6%) who practiced MSD for three survey years. We used an ordered logit model to find out the determinants of four types of adoption. Heavy rainfall ($p < 0.05$) and storm vulnerability ($p \le 0.01$) decrease the likelihood of long-term adoption of MSD. Farmers are more likely to be long-term adopters with increasing salinity vulnerability and improving soil organic matter (SOM) level in farm-fields ($p \le 0.01$). Larger farm-size ($p \le 0.1$) and higher education years of female household members also increase long-term adoption, implying that strengthening farm-households' socio-economic status is the driver of MSD adoption. This study suggests designing and implementing policies, tailored based on different climate hazards vulnerability to improve MSD adoption.

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**KEYWORDS**
Minimal soil disturbance; climate hazards; soil degradation; order logit model

## Introduction

Intensive agriculture has led to one-third of the world's soil being degraded (FAO 2015). This degradation negatively impacts agricultural productivity, profitability and sustainability which exacerbates food insecurity, poverty and vulnerability to climate hazards (Maraseni and Cockfield 2011a; FAO 2015; Barbier and Hochard 2018; Yang et al. 2022). The World Commission on Environment and Development pointed a 'vicious cycle' between poverty and soil degradation. Poor people largely depend on agriculture and over-exploit natural resources for survival, which again leads to low productivity and poverty (Stockdale 1990). Increasing the level and stability of agricultural returns in a sustainable manner is a central challenge to reduce global poverty and conserve environmental resources (FAO 2023).

Conservation agriculture (CA) has become a hegemonic paradigm over the past decades for ensuring sustainable agricultural development. Numerous development projects, research and policy institutes were dedicated in researching and promoting CA (McCarthy et al. 2011; FAO

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2015). At the same time, questions and controversies have emerged regarding the universal applicability of CA in the context of diverse and small farms (Guto et al. 2012; Kirkegaard et al. 2014). Three main principles of CA are – (1) minimal soil disturbance (MSD), (2) permanent soil cover and (3) crop rotation/diversification (Busari et al. 2015; Entz et al. 2022). The first component, MSD, refers to farm-practices where disruption to soil is intentionally minimized during soil preparation, planting and cultivation, such as, no tillage and reduced tillage (Entz et al. 2022). MSD practices aim to preserve soil structure, composition and beneficial organisms and maintain long-term soil health, productivity and environmental sustainability (Maraseni and Cockfield 2011b; Busari et al. 2015; Wang et al. 2020; Graham et al. 2021; Tang et al. 2021). Substantial research has demonstrated benefits of MSD over intensive tillage for cost and labor savings, yield and profit increases, and soil quality improvement in long-term with reduced greenhouse gas emissions (Ngwira et al. 2013; TerAvest et al. 2015; Bell et al. 2018; Si et al. 2018; Haque et al. 2023; Paye et al. 2023). It is nonetheless acknowledged that MSD uptake at farm-level along with other CA practices has been slow and low and varies greatly among different environmental contexts (Derpsch et al. 2010; Erenstein et al. 2012; Teklewold et al. 2013; Ngongo 2016; Kumar et al. 2021; Ogieriakhi and Woodward 2022; Sharna et al. 2022). Assertion of exponential uptake in some areas is juxtaposed with evidence of dis-adoption and limited uptake elsewhere (Andersson and D'Souza 2014; Sharna et al. 2023).

Understanding the decision-making process and drivers behind CA technology adoption is still limited (Maraseni et al. 2021; Begho et al. 2022; Sharna et al. 2023) because decision-making is context-specific and time-variant particularly under changing climate (Hisali et al. 2011). Existing literature noted that various socio-economic, demographic, farm, infrastructural and institutional factors influence CA adoption either positively or negatively across different geographic contexts (Amusa et al. 2016; Tesfahunegn 2019; Kwadzo and Quayson 2021; Oduniyi et al. 2022; Sharna et al. 2024). Sharna et al. (2022) reported that drought severity reduces the adoption likelihood of zero tillage, while salinity increases the adoption probability of the practice. Some authors identified insufficient recognition of soil erosion risk, lack of training and incentive as reasons for abandoning previously adopted sustainable land management technologies (Alemu et al. 2022, 2023). Lack of actual information and technology demonstration, less supportive policies, traditional believes and climatic factors hinder dissemination of CA technologies (Chatterjee and Acharya 2021). Determinants of continued adoption of CA strategies have been reported as binary choices, though adoption tends to be partial and incremental (Umar et al. 2011). Many of the reported studies were carried out under promotional projects that provide input support, subsidies and respondent selection; consequently, findings are project-biased (Andersson and D'Souza 2014). These studies are not comprehensive and predominantly focused on MSD adoption within specific agro-ecological regions and for a single year or crop season. Hence, there are knowledge gaps on drivers of MSD adoption across wide geographical area encompassing diverse climate hazard vulnerability (Sharna et al. 2023). Exploring multidimensional adoption over time is important (Tesfahunegn 2019; Deines et al. 2019; Pannell and Claassen 2020; Sharna et al. 2023). Some farmers may discontinue after initial adoption, while others may adopt later than others.

The aim of this study is to address these gaps by examining the multidimensional nature of MSD adoption over time with long-term perspective, considering climate hazards vulnerability. The specific objectives are as follows: (1) to estimate the MSD adoption status over time (i.e. long-term non-adoption, dis-adoption, late-adoption and long-term adoption); (2) to evaluate the differences among households in these four adoption groups in terms of demographic and socio-economic context, farm characteristics, institutional factors and climate hazards vulnerability; (3) to identify the determinants of long-term non-adoption, dis-adoption, late-adoption and long-term adoption of MSD. To achieve these objectives, we considered Bangladesh as a case study due to available data which is statistically representative of the whole country. Besides, Bangladesh is moving forward to adoption of conservation agriculture from the intensive green revolution (Faroque et al. 2011; Pingali 2023). We analyzed the data through descriptive statistics along with using an ordered logit model.

## Methodology

### *Study area*

Bangladesh is selected as a case study due to its heavy reliance on agriculture, which contributes 11.50% to its gross domestic product (MoF 2023). However, the availability of arable land has been decreasing, from 65.05% in 2010 to 58.19% in 2020 with an annual rate of 0.68% because of land use changes (SRDI 2020). It is experiencing severe soil degradation (SRDI 2020). The depletion of soil organic matter (SOM) poses a significant constraint to achieving higher crop production in Bangladesh. Approximately 35% of the land has low to very low SOM levels (≤1.7), while around 60% falls under the medium SOM category (1.71 < SOM < 3.4). Only a small percentage, 4.58%, has a high SOM level (3.41 < SOM < 5.5), and merely 1.40% falls under the very high SOM category (SOM >5.5). About 27% of the land is affected by soil nutrient depletion due to intensified farming practices (SRDI 2020). The major factors contributing to SOM depletion in the country are intensive tillage, puddling, soil erosion, soil salinity and acidity, deforestation, nutrient leaching and limited application of manure (Alam et al. 2017; Hasan et al. 2020). Bangladesh is the seventh most vulnerable country to climate change, indicated by the Global Climate Risk Index-2021 (Eckstein et al. 2021). This susceptibility to climate change could result in a 33% yield loss by the next century (Karim et al. 2012). Bangladeshi rice farmers were chosen as the sample population for this study, given that rice is one of the most extensively cultivated crops in the country. Moreover, rice is the primary staple crop in Bangladesh, occupying 75% of the total cropped area (BRRI 2020).

### *Dependent variables*

This study utilized open data available from the Bangladesh Integrated Household Survey conducted by the International Food Policy Research Institute (IFPRI). The surveys were conducted in 2013, 2016 and 2020. All three surveys cover statistically representative sites of the whole Bangladesh. BIHS-2013, BIHS-2016 and BIHS-2020, respectively, collected data from 6500, 6500 and 5604 rural households covering the same households (IFPRI 2013, 2016, 2020). These datasets on rural households not only represent the farming households but also other non-farming occupied households (i.e. wage labor, salaried worker, self-employment, trader, etc.). These surveys include detailed data on household demographics, socio-economic conditions, dietary intake, agricultural production and practices. As the present study is based on rice-farmers, we filtered out the datasets to include only rice-cultivating households. 2988, 3082 and 2681 rice-cultivating households were, respectively, retained from the BIHS rounds in 2013, 2016 and 2020. As the whole survey covers both farming and non-farming households, it is reasonable that the number of rice-farming households does not represent 75% of the total number of sample households, though rice-cultivated area covers 75% of the total cropped area of the country (BRRI 2020). A next filtering was conducted by matching household IDs that are surveyed constantly in all three years and cultivated rice in all three survey years. A total of 1659 rice-farming households were retained. This 'Matched sample' (Figure 1) was analyzed to determine the adoption status of MSD over time through using the three-year data of MSD adoption and non-adoption status. MSD considered and reported were zero tillage, intercropping and hand weeding. Information on these practices was available in all three rounds of BIHS. For each survey years, the number of adopters and non-adopters of MSD was calculated. Adoption refers to commencing of practicing a new technology (Tiwari et al. 2008). However, we defined adopters as households who practiced any one of the mentioned MSDs or a combination of those due to information unavailability regarding who practiced MSD for the first time. Non-adopter refers to households who did not practice any of those MSDs. Yearly-adoption status means the number of adopters and non-adopters in each survey year within the matched sample. To identify the status of MSD adoption over time among the matched sample, we categorized the dependent variables based on adoption characteristics (Figure 1):

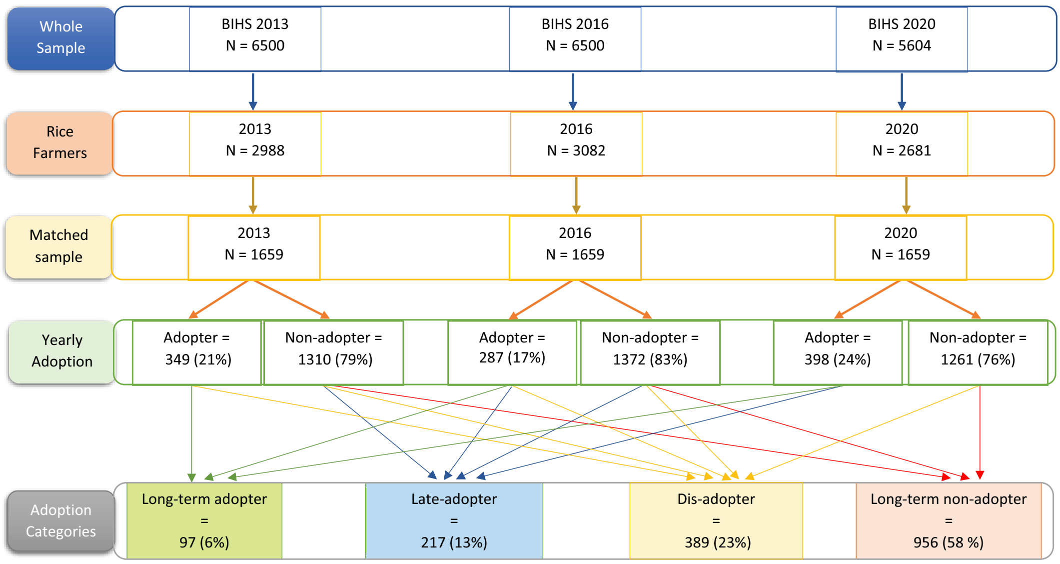


**Figure 1.** Detail steps of dependent variable organization, including long-term adopter, late-adopter, dis-adopter and long-term adopter of minimal soil disturbance (MSD).

- Long-term adopter: who continuously adopted MSD over three survey years.
- Late-adopter: who did not adopt MSD in early survey years but adopted later (i.e. did not adopt BIHS-2013 but adopted in BIHS-2016 and BIHS-2020/did not adopt in BIHS-2013 and BIHS-2016 but adopted in BIHS-2020).
- Dis-adopter: who adopted MSD in early years but did not adopt later (i.e. adopted in BIHS-2013 and did not practice both in BIHS-2016 and BIHS-2020/adopted in BIHS-2013 and BIHS-2016 and dis-adopted in BIHS-2020/did not practice in BIHS-2013 but adopted in BIHS-2016 and again dis-adopted in BIHS-2020).
- Long-term non-adopter: who did not adopt any MSD in all three survey years.

Figure 2 illustrates the spatial distribution of the matched samples' location along with the location of the sample of four groups of MSD adopters.

## *Explanatory variables*

We conducted an extensive literature review from Scopus, Web of Science, Science Direct and Google Scholar using the search string ('adoption') AND ('determinants' OR 'drivers') AND ('minimal soil disturbance' OR 'minimum soil disturbance' OR 'soil management') AND ('farming' OR 'agriculture') in the title-abstract-keywords to identify the explanatory variables. The literature provided various factors that significantly influence sustainable farm-practices adoption, both positively and negatively, in different contexts (Belachew et al. 2020; Sharna et al. 2020; Kwadzo and Quayson 2021; Mponela et al. 2021; Oyetunde-Usman et al. 2021; Anik et al. 2022; Begho et al. 2022; Chuma et al. 2022; Singana Tapia and Satama Bermeo 2022; Yifru et al. 2022; Alemu et al. 2023; Fentahun et al. 2023; Ngaiwi et al. 2023). These factors include demographic and socio-economic characteristics (e.g. age, gender of household head, household size, education, assets, income, off-farm income, women's empowerment and food insecurity status), farm characteristics (e.g. farm size, livestock, irrigation facilities, tenure and production shocks), cognitive factors (perception of soil erosion, soil degradation and climate change) and institutional and infrastructural access (e.g. market distance, road access, extension services, training, risk attitude, group membership and credit access). Some

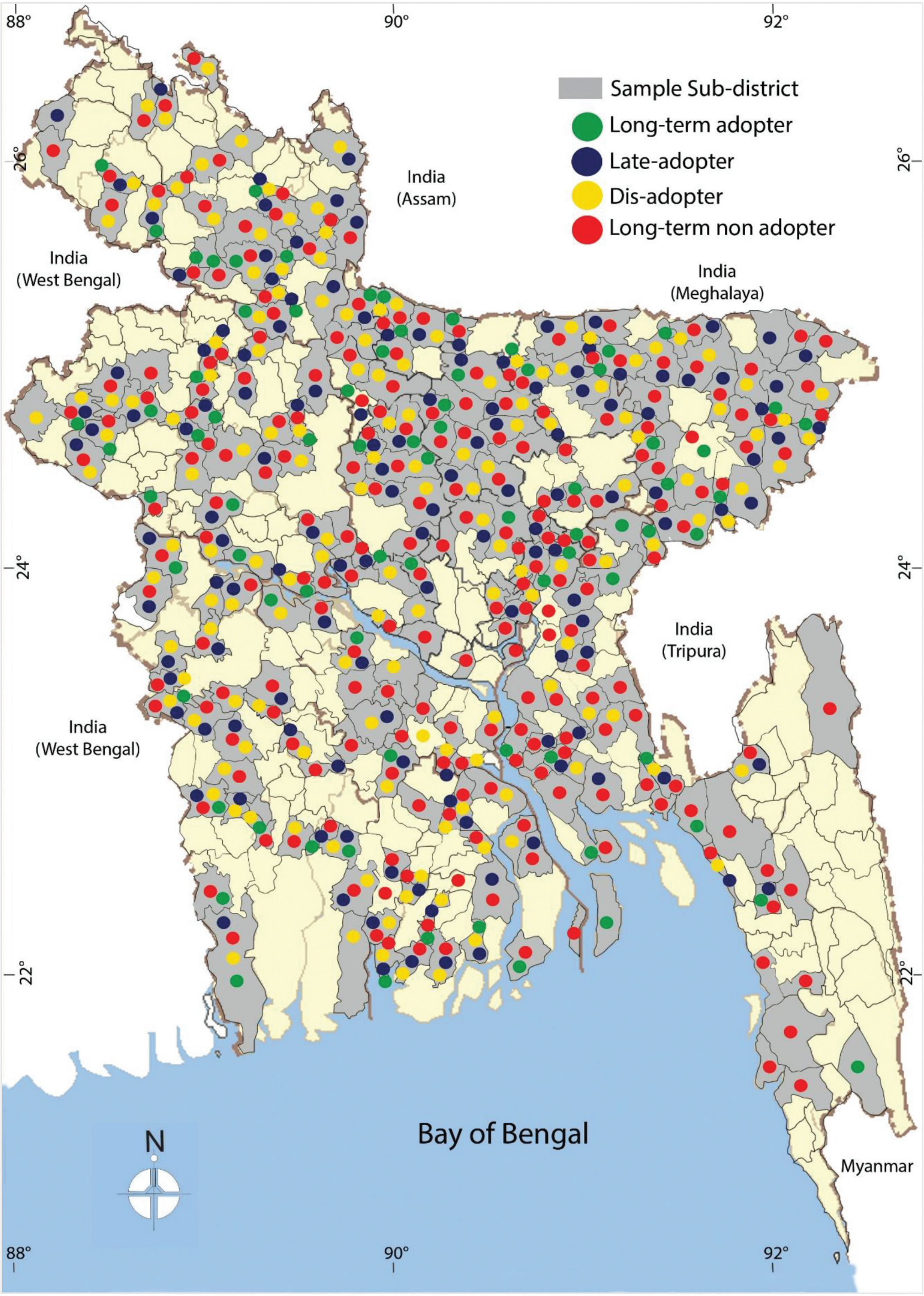


**Figure 2.** Spatial distributions of matched sample location (i.e. sub-district) in the Bangladesh Integrative Household Surveys (BIHS in 2013, 2016 and 2020) (IFPRI 2013, 2016, 2020).

literature also considered the impact of biophysical factors such as drought, soil fertility, slope, temperature change, average rainfall, flood, salinity and cyclones on adoption (Anik et al. 2022; Mairura et al. 2022; Singana Tapia and Satama Bermeo 2022; Fentahun et al. 2023).

The list of factors as explanatory variables we considered includes the households' demographic, socio-economic and farm characteristics, institutional and infrastructural access (e.g. age and gender of household head, dependency-ratio, household size, household heads' and female members' education, asset, off-farm income, economic shock, farm-size, livestock value, irrigation facilities, tenure, distance to nearest town, road access, subsidy card, extension service, NGO assistance, training, credit access, social assistance, agricultural facilities) along biophysical factors (e.g. flood depth, river erosion) that were available in BIHS-2020 (IFPRI 2020). Information on vulnerability to other climate hazards (e.g. salinity, storm, cyclone and heavy rainfall) was organized from the Bangladesh Agro-Meteorological Information Portal (Department of Agricultural Extension 2020). Furthermore, information regarding SOM level was collected from the Soil Resource Development Institute (SRDI) (SRDI 2021). Information from the Bangladesh Agro-Meteorological Information Portal and SRDI is based on sub-district level. All these datasets were collated with BIHS dataset by households' sub-district information using STATA 16 (StataCorp 2023). Multicollinearity among these variables was tested using the variance inflation factor (VIF). VIF reflects multicollinearity through quantifying the extent to which the behavior (variance) of an independent variable is influenced by its correlation with other independent variables. VIF values range from 1 to infinity meaning increase in correlation with increase in numbers. VIF = 1 reflects the total absence of collinearity, VIF > 2.5 indicates considerable collinearity, VIF > 5 is moderate collinearity, and VIF > 10 indicates a serious collinearity problem (Thompson et al. 2017; Johnston et al. 2018). Variables with a VIF greater than 5 were excluded for avoiding multicollinearity (McCormick and Salcedo 2017). The mean VIF for the remaining variables is 1.43, and VIF ranges from 1.04 to 2.33 for all retained variables ensuring almost no correlation (Table A1). Table 1 presents the description and sources of all the considered explanatory variables.

## *Econometric analyses*

Since the dependent variable is ordinal, an ordered logit model was used to find out the drivers and their magnitude of different adoption status of MSD. Using latent variable, the model can be expressed as follows:

$$\lambda_i^*(Adoption^*) = \sum_{i=1}^{n} X_i\beta + \varepsilon_i$$

where *Adoption*$^*$ reflects the adoption status taking values 0 to *k*-categories. The dependent variable is categorized into 'four-point scale' ranges from 0 to 3 according to adoption status:

$\lambda_0 = 0 if \lambda_i^* < \emptyset_0$, refers to Long-term non-adopter
$\lambda_1 = 1 if \lambda_i^* < \emptyset_1$, refers to Dis-adopter
$\lambda_2 = 2 if \lambda_i^* < \emptyset_2$, refers to Late-adopter
$\lambda_3 = 3 if \lambda_i^* < \emptyset_3$, refers to Long-term adopter

Here, $\lambda_i^*$ is the latent variable (or unobserved) adoption status, $X$ is a vector of explanatory variables, $\beta$ is a vector of parameters denoting the relationship between adoption status and explanatory variables $X$, and $\varepsilon$ is an identically distributed error term with variance 1 and mean 0. The threshold parameters $\emptyset_j$ are the cut-off points between adjacent values of the observed dependent variable. The probability associated with a farmer's adoption status can be written as follows:

**Table 1.** Description and summary statistics of explanatory variables for the whole matched sample ($N = 1659$). Means are reported with standard deviations, while mean refers to the average, calculated by dividing the sum of all values by $N$ for a specific explanatory variable. Frequency describes the number and percentage among total $N$ under a particular category.

| Variable | Description | Mean ± SD | Frequency *n* | Frequency % | Source |
|---|---|---|---|---|---|
| Household head education | Formal schooling completed by the household head (years) | 3.55 ± 4.16 | | | IFPRI 2020 |
| Women education | Formal schooling completed by the woman, mostly household head's spouse (years) | 3.31 ± 3.51 | | | |
| Age | Age of the household head (years) | 49.15 ± 12.18 | | | |
| Dependency-ratio | Ratio of economically inactive household members to total household members (ratio) | 0.73 ± 0.13 | | | |
| Asset | Market value of all agricultural and non-agricultural productive assets (excluding land) owned by the household ('00USD/per capita) | 2.98 ± 2.86 | | | |
| Social assistance | Dummy; households' access to social assistance | | | | |
| | Received = 1 | | 749 | 45.15 | |
| | Didn't receive = 0 | | 910 | 54.85 | |
| NGO membership | Dummy; households' status of having NGO membership | | | | |
| | Had = 1 | | 140 | 8.44 | |
| | Didn't have = 0 | | 1,519 | 91.56 | |
| Concrete road | Dummy; access of concrete road from house | | | | |
| | Had = 1 | | 1,565 | 94.33 | |
| | Didn't have = 0 | | 94 | 5.67 | |
| Subsidy card | Dummy; households' access to agricultural input subsidy card | | | | |
| | Had = 1 | | 354 | 21.34 | |
| | Otherwise = 0 | | 1,305 | 78.66 | |
| Extension | Dummy; households' status of receiving soil and/or fertilizer-related extension service from government/NGOs officials | | | | |
| | Received = 1 | | 327 | 19.71 | |
| | Otherwise = 0 | | 1,332 | 80.29 | |
| Farm size | Total area planted under different crops (ha) | 0.56 ± 0.55 | | | |
| Agricultural facilities | Average distance from house to the closest agricultural extension office, seed dealer, fertilizer dealer, pesticide dealer, input market/factory (km) | 1.80 ± 1.78 | | | |
| Livestock | The market value of owned livestock by the households ('00USD) | 5.75 ± 6.62 | | | |
| Soil texture | The most kind of soil type in farm | | | | |
| | Clay = 1 | | 86 | 5 | |
| | Loam = 2 | | 257 | 15 | |
| | Sandy = 3 | | 165 | 10 | |
| | Clay-loam = 4 | | 727 | 44 | |
| | Sandy-loam = 5 | | 424 | 26 | |
| Flood depth | The usual flood depth during monsoon/flood season, in case of multiple plots the plot with maximum depth was reported (0 if not flooded) (feet) | 3.29 ± 3.54 | | | |

(*Continued*)

**Table 1.** (Continued).

| Variable | Description | Mean ± SD | Frequency *n* | Frequency % | Source |
|---|---|---|---|---|---|
| Salinity | Dummy; whether household live in salinity affected area | | | | DAE |
| | Affected = 1 | | 398 | 23.99 | 2020 |
| | Non-affected = 0 | | 1,261 | 76.01 | |
| Storm | Category; whether household live in storm risk area | | | | |
| | Very high risk = 5 | | 30 | 1.81 | |
| | High risk = 4 | | 48 | 2.89 | |
| | Moderate risk = 3 | | 82 | 4.94 | |
| | Low risk = 2 | | 69 | 4.16 | |
| | Very low risk = 1 | | 109 | 6.57 | |
| | No risk = 0 | | 1,321 | 79.63 | |
| Cyclone | Category; whether household live in cyclone risk area | | | | |
| | Very high risk = 5 | | 21 | 1.27 | |
| | High risk = 4 | | 116 | 6.99 | |
| | Moderate risk = 3 | | 111 | 6.69 | |
| | Low risk = 2 | | 327 | 19.71 | |
| | Very low risk = 1 | | 450 | 27.12 | |
| | No risk = 0 | | 634 | 38.22 | |
| Rainfall | Category; whether household live in rainfall (i.e. one-day maximum rainfall in mm) risk region | | | | |
| | Very high risk = 5 | | 31 | 1.87 | |
| | High risk = 4 | | 207 | 12.48 | |
| | Moderate risk = 3 | | 432 | 26.04 | |
| | Low risk = 2 | | 417 | 25.14 | |
| | Very low risk = 1 | | 484 | 29.17 | |
| | No risk = 0 | | 88 | 5.30 | |
| SOM level | Category; soil organic matter status in households' location. | | | | SRDI |
| | Very high (SOM >5.5) and forest area = 5 | | 72 | 4.34 | 2021 |
| | High (3.41 < SOM < 5.5) = 4 | | 103 | 6.21 | |
| | Medium (1.71 < SOM < 3.4) = 3 | | 943 | 56.84 | |
| | Low (1.00 < SOM < 1.7) = 2 | | 431 | 25.98 | |
| | Very low (SOM ≤1.0) = 1 | | 110 | 6.63 | |

Mean and standard deviation (SD±) are calculated for continuous variables, while frequency (*n* and %) is estimated for categorical variables.

$$\pi\left(\lambda_i \leq \frac{j}{X_i}\right) = \Delta\left(\gamma_j - X_i'\beta\right) - \Delta\left(\gamma_{j-1} - X_i'\beta\right);$$

Here, $j$ is the observed variable, and $\gamma$ is the threshold parameter. The formal ordered logistic regression model is:

$$Logit(Y_i) = Log_e\left(\frac{\pi}{1-\pi}\right) = \beta_0 + \beta_i X_i + \varepsilon$$

Here, $Y_i$ is the dependent variable reflecting MSD adoption status, and $X_i$ represents the determining explanatory factors (Williams 2018; Kabir et al. 2023). The data analyses of the ordered logit model were carried out in STATA 16.00 to identify the determinants of long-term adoption, late-adoption, dis-adoption and long-term non-adoption. This model was conducted with the available command 'ologit $ylist $xlist' in STATA. After that, we utilized the command 'margins' to calculate the separate marginal effects of the explanatory variables on four types of adoption. As we have four different groups, we calculated marginal effects for those four groups with different coded equations (i.e. margins, dydx(*) atmeans predict(outcome(0)); margins, dydx(*) atmeans predict(outcome(1)); margins, dydx(*) atmeans predict(outcome(2)); margins, dydx(*) atmeans predict(outcome(3))) (Stata 2023). Descriptive statistical analyses, namely, ANOVA and chi-square tests were conducted in STATA 16 (StataCorp 2023) to assess statistically significant differences among the groups, respectively, for continuous and categorical variables (Hamilton 2012). For the continuous explanatory variables, we have performed the normality test including Skewness/Kurtosis tests and the Shapiro–Wilk *W* test. All explanatory variables are normally distributed only except 'household head education' and 'women education'. Those variables indicate the formal year of education, which ranges from 0 to 16. As many of the rural households' head and female member have zero year of formal education, these two variables are skewed. Since the main priority of the manuscript is the order logit model, which doesn't have the criteria of a normality test, we performed ANOVA test as all other variables are normally distributed.

## Results

### *Adoption status of minimal soil disturbance over time*

Long-term non-adopter stands out among the four groups consisting of around 58% of the sample households (Figure 1). They never adopted MSD in all three survey years (BIHS-2013, BIHS-2016 and BIHS-2020). Dis-adopter encompasses 23% of the sample who abandoned MSD after initial adoption, followed by late-adopter (13%). In contrast, only 6% of the sample adopted MSD for the long-term meaning practicing MSD in all survey years (Figure 1).

### *Differences for descriptive characteristics among the four adoption groups*

Differences in climate hazards vulnerability and socio-economic characteristics were found among long-term non-adopters, dis-adopters, late-adopters and long-term adopters. Statistically significant differences were observed among these four groups for vulnerability to storm, cyclone and heavy rainfall ($p \leq 0.01$) (Table 2). Only 4% of long-term non-adopters lived in storm-risk regions while 40–50% of dis-adopters, late-adopters and long-term adopters lived in storm-risk regions. Farm-field SOM level as well significantly differs among the four adopter groups. About 65% of long-term non-adopters lived in medium SOM-level areas, while 36–49% of long-term adopters, late-adopters and dis-adopters lived in medium SOM-level areas. However, farm-fields' SOM level ranged from medium to low among the four groups suggesting variability among groups in addition of within groups (Table 2). A higher percentage of long-term adopters received social assistance compared to late-adopters, dis-adopters and long-term non-adopters ($p \leq 0.10$). The average farm size of the whole sample is 0.56 ha (Table 1), while long-term adopters owned on average 0.81 ha which is more than the other three groups ($p \leq 0.05$) (Table 2).

**Table 2.** Descriptive statistics of explanatory variables for four adoption groups of minimal soil disturbance (MSD) including long-term non-adopter, dis-adopter, late-adopter and long-term adopter. Mean refers to the average calculated by dividing the sum of all values by *N* for a specific explanatory variable. Frequency with number and percentage among total *N* under a particular category is also shown. *F* and chi-square value were reported with star marks representing statistical significance levels for differences among the four groups.

| | Long-term non-adopter | | | Dis-adopter | | | Late-adopter | | | Long-term adopter | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean ± SD | Frequency | | Mean ± SD | Frequency | | Mean ± SD | Frequency | | Mean ± SD | Frequency | | |
| Variables | | *n* | % | | *n* | % | | *n* | % | | *n* | % | *F*/chi-square† |
| Household head education | 3.51 ± 4.02 | | | 3.53 ± 4.23 | | | 3.72 ± 4.10 | | | 3.81 ± 5.13 | | | 0.36 |
| Women education | 3.16 ± 3.43 | | | 3.38 ± 3.65 | | | 3.54 ± 3.35 | | | 3.75 ± 4.12 | | | 2.26 |
| Age | 48.47 ± 12.57 | | | 47.23 ± 12.13 | | | 49.43 ± 11.91 | | | 47.43 ± 11.23 | | | 1.73 |
| Dependency-ratio | 0.71 ± 0.11 | | | 0.73 ± 0.12 | | | 0.74 ± 0.15 | | | 0.69 ± 0.16 | | | 1.67 |
| Asset | 2.92 ± 2.14 | | | 2.95 ± 2.69 | | | 3.04 ± 2.72 | | | 3.53 ± 1.72 | | | 0.12 |
| Social assistance | | | | | | | | | | | | | 6.45* |
| Received | | 401 | 42 | | 190 | 49 | | 102 | 47 | | 56 | 58 | |
| Otherwise | | 555 | 58 | | 199 | 51 | | 115 | 53 | | 41 | 42 | |
| NGO membership | | | | | | | | | | | | | 3.58 |
| Had | | 24 | 3 | | 75 | 19 | | 29 | 13 | | 12 | 12 | |
| Didn't have | | 932 | 97 | | 314 | 81 | | 188 | 87 | | 85 | 88 | |
| Concrete road | | | | | | | | | | | | | 1.23 |
| Had | | 949 | 99 | | 348 | 89 | | 191 | 88 | | 77 | 79 | |
| Didn't have | | 7 | 1 | | 41 | 11 | | 26 | 12 | | 20 | 21 | |
| Subsidy card | | | | | | | | | | | | | 23.64 |
| Had | | 124 | 13 | | 119 | 31 | | 80 | 37 | | 31 | 32 | |
| Didn't have | | 832 | 87 | | 270 | 69 | | 137 | 63 | | 66 | 68 | |
| Extension | | | | | | | | | | | | | 3.28 |
| Received | | 150 | 16 | | 97 | 25 | | 59 | 27 | | 21 | 22 | |
| Otherwise | | 806 | 84 | | 292 | 75 | | 158 | 73 | | 76 | 78 | |
| Farm size | 0.56 ± 0.52 | | | 0.59 ± 0.61 | | | 0.61 ± 0.53 | | | 0.81 ± 0.71 | | | 3.23** |
| Agricultural facilities | 1.76 ± 1.31 | | | 1.59 ± 1.79 | | | 1.84 ± 1.81 | | | 0.98 ± 0.85 | | | 2.29* |
| Livestock | 6.37 ± 5.39 | | | 5.39 ± 5.23 | | | 7.46 ± 9.34 | | | 8.05 ± 4.14 | | | 6.41 |
| Soil texture | | | | | | | | | | | | | 27.75*** |
| Clay | | 30 | 3 | | 21 | 5 | | 19 | 9 | | 16 | 16 | |
| Loam | | 155 | 16 | | 56 | 14 | | 35 | 16 | | 11 | 11 | |
| Sandy | | 98 | 10 | | 35 | 9 | | 23 | 11 | | 9 | 9 | |
| Clay-loam | | 461 | 48 | | 167 | 43 | | 64 | 29 | | 35 | 36 | |
| Sandy-loam | | 212 | 22 | | 110 | 28 | | 76 | 35 | | 26 | 27 | |
| Flood depth | 3.35 ± 3.63 | | | 3.01 ± 3.24 | | | 3.36 ± 3.64 | | | 3.01 ± 2.71 | | | 1.46 |
| Salinity | | | | | | | | | | | | | 3.72 |
| Affected | | 214 | 22 | | 98 | 25 | | 55 | 25 | | 31 | 32 | |
| Non-affected | | 742 | 78 | | 291 | 75 | | 162 | 75 | | 66 | 68 | |
| Storm | | | | | | | | | | | | | 41.82*** |

(*Continued*)

**Table 2.** (Continued).

| | Long-term non-adopter | | | Dis-adopter | | | Late-adopter | | | Long-term adopter | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean ± SD | Frequency | | Mean ± SD | Frequency | | Mean ± SD | Frequency | | Mean ± SD | Frequency | | |
| Variables | | *n* | % | | *n* | % | | *n* | % | | *n* | % | *F*/chi-square† |
| Very high risk | | 8 | 1 | | 14 | 4 | | 5 | 2 | | 3 | 3 | |
| High risk | | 6 | 1 | | 19 | 5 | | 14 | 6 | | 9 | 9 | |
| Moderate risk | | 17 | 2 | | 35 | 9 | | 19 | 9 | | 11 | 11 | |
| Low risk | | 0 | 0 | | 43 | 11 | | 12 | 6 | | 14 | 14 | |
| Very low risk | | 9 | 1 | | 51 | 13 | | 42 | 19 | | 7 | 7 | |
| No risk | | 916 | 96 | | 227 | 58 | | 125 | 58 | | 53 | 55 | |
| Cyclone | | | | | | | | | | | | | 59.05*** |
| Very high risk | | 3 | 0 | | 3 | 1 | | 10 | 5 | | 5 | 5 | |
| High risk | | 82 | 9 | | 10 | 3 | | 13 | 6 | | 11 | 11 | |
| Moderate risk | | 58 | 6 | | 27 | 7 | | 17 | 8 | | 9 | 9 | |
| Low risk | | 245 | 26 | | 49 | 13 | | 21 | 10 | | 12 | 12 | |
| Very low risk | | 243 | 25 | | 130 | 33 | | 60 | 28 | | 17 | 18 | |
| No risk | | 325 | 34 | | 170 | 44 | | 96 | 44 | | 43 | 44 | |
| Rainfall | | | | | | | | | | | | | 97.33*** |
| Very high risk | | 1 | 0 | | 18 | 5 | | 8 | 4 | | 4 | 4 | |
| High risk | | 152 | 16 | | 33 | 8 | | 17 | 8 | | 5 | 5 | |
| Moderate risk | | 280 | 29 | | 84 | 22 | | 55 | 25 | | 13 | 13 | |
| Low risk | | 236 | 25 | | 99 | 25 | | 47 | 22 | | 35 | 36 | |
| Very low risk | | 278 | 29 | | 124 | 32 | | 63 | 29 | | 19 | 20 | |
| No risk | | 9 | 1 | | 31 | 8 | | 27 | 12 | | 21 | 22 | |
| SOM level | | | | | | | | | | | | | 201.96*** |
| Very high | | 25 | 3 | | 29 | 7 | | 13 | 6 | | 5 | 5 | |
| High | | 34 | 4 | | 47 | 12 | | 16 | 7 | | 6 | 6 | |
| Medium | | 623 | 65 | | 189 | 49 | | 96 | 44 | | 35 | 36 | |
| Low | | 270 | 28 | | 85 | 22 | | 54 | 25 | | 22 | 23 | |
| Very low | | 4 | 0 | | 39 | 10 | | 38 | 18 | | 29 | 30 | |
| *N* | 956 | | | 389 | | | 217 | | | 97 | | | |

Mean is calculated for continuous variables, while frequency (*n* and %) is estimated for categorical variables. † *F* and chi-square value were derived from ANOVA and Pearson chi-square test, respectively. *, ** and *** refer to significance levels of 10% ($p \le 0.1$), 5% ($p \le 0.05$) and 1% ($p \le 0.01$).

### Determinants of adoption

Tables 3 and 4, respectively, illustrate the coefficients and marginal effects of explanatory variables on four kinds of adoption from an ordered logistic regression model. The threshold estimates $\varnothing_j$ are equivalent to the intercept of the regression model. Those represent the cut-off points between two consecutive categories of dependent variables (Williams 2018). For instance, the third cut-off value, 4.75, is the estimated threshold point on the underlying variable that distinguishes between 'late-adopter' and 'long-term adopter' of MSD when all predictor variables are set to 0. The log likelihood-ratio test shows strong significance, indicating a good fit for the model. Additionally, the pseudo-$R$-square reflects the model's explanatory capacity (Table 3).

Long-term adoption of MSD is highly constrained by storm and heavy rainfall vulnerability. Higher storm-risk decreases the likelihood of long-term adoption by 0.4% while increasing long-term non-adoption probability by 12% (Table 4). Likewise, heavy rainfall vulnerability decreases long-term adoption and late-adoption probability of MSD. In contrast, living in salinity affected region facilitates the probability of being long-term adopter and late-adopter by 1% and 4%, while reducing the probability of being long-term non-adopter and dis-adopter by 15% and 10% (Table 4). It is worth noting that soil characteristics including soil texture and SOM level at the farm presented a significant effect on the likelihood of households' behavior of MSD adoption. Having clay-loam soil at farm increases the likelihood of long-term non-adoption by 14% and dis-adoption by 9% while decreasing

**Table 3.** Determinants of long-term non-adopter, dis-adopter, late-adopter and long-term adopter of minimal soil disturbance. Results are calculated from the matched sample by conducting an ordinal logistic regression model in STATA 16.00.

| Variables | Co-efficient | St. Er. | *P*-value |
|---|---|---|---|
| Household head education | −0.01 | 0.01 | 0.80 |
| Women education | 0.05** | 0.02 | 0.03 |
| Age | −0.01 | 0.01 | 0.39 |
| Dependency-ratio | −0.62 | 0.43 | 0.14 |
| Asset | −0.10*** | 0.03 | 0.00 |
| Social assistance | 0.14 | 0.11 | 0.27 |
| NGO membership | −0.35* | 0.19 | 0.06 |
| Concrete road | −0.48* | 0.23 | 0.06 |
| Subsidy card | 0.44 | 0.11 | 0.00 |
| Extension | −0.18 | 0.14 | 0.19 |
| Farm size | 0.08* | 0.09 | 0.30 |
| Agricultural facilities | −0.05 | 0.03 | 0.08 |
| Livestock | 0.05 | 0.01 | 0.00 |
| Soil texture (Base = Clay) | | | |
| Loam | 0.25 | 0.26 | 0.33 |
| Sandy | −0.05 | 0.27 | 0.82 |
| Clay-loam | −0.68*** | 0.23 | 0.00 |
| Sandy-loam | −0.47* | 0.24 | 0.06 |
| Flood depth | −0.02 | 0.01 | 0.31 |
| Salinity | 0.75*** | 0.22 | 0.00 |
| Storm | −0.53*** | 0.07 | 0.00 |
| Cyclone | 0.24 | 0.09 | 0.00 |
| Rainfall | −0.13** | 0.05 | 0.02 |
| SOM level | 0.24*** | 0.05 | 0.00 |
| Threshold values | | | |
| Threshold 1 ($\varnothing_1$) | 0.89 | 0.55 | |
| Threshold 2 ($\varnothing_2$) | 2.53 | 0.56 | |
| Threshold 3 ($\varnothing_3$) | 4.75 | 0.60 | |
| Model diagnostic | | | |
| Log likelihood | −1,322.57 | | |
| LR chi2(24) | 186.11 | | |
| Prob > chi2 | 0.00 | | |
| Pseudo R2 (Cox-Snell/ML) | 0.18 | | |
| Number of obs. | 1,659 | | |

*, ** and *** refer to significance levels of 10% ($p \leq 0.1$), 5% ($p \leq 0.05$) and 1% ($p \leq 0.01$).

**Table 4.** Marginal effect estimates for explanatory variables on four adoption groups of minimal soil disturbance adoption including long-term non-adopter, dis-adopter, late-adopter and long-term adopter. Marginal effect values are estimated from the coefficient results of the ordinal logistic regression model in STATA 16.00.

| Variable | Long-term non-adopter | Dis-adopter | Late-adopter | Long-term adopter |
|---|---|---|---|---|
| Household head education | 0.001 | −0.001 | −0.0003 | −0.0001 |
| Women education | −0.01** | −0.01** | 0.002** | 0.001* |
| Age | 0.001 | −0.001 | −0.0002 | −0.0001 |
| Dependency-ratio | 0.13 | −0.08 | −0.03 | −0.005 |
| Asset | 0.02*** | 0.01*** | −0.01** | −0.001* |
| Social assistance | −0.03 | 0.02 | 0.01 | 0.001 |
| NGO membership | 0.06* | 0.05* | −0.02* | −0.005* |
| Concrete road | 0.09* | 0.07* | −0.03* | −0.004* |
| Subsidy card | −0.08 | 0.06 | 0.03 | 0.01 |
| Extension | 0.03 | −0.02 | −0.01 | −0.001 |
| Farm size | −0.01* | −0.01* | 0.02* | 0.001* |
| Agricultural facilities | 0.01 | −0.01 | −0.002 | −0.0004 |
| Livestock | −0.01 | 0.01 | 0.003 | 0.0005 |
| Soil texture (Base = Clay) | | | | |
| Loam | −0.05 | −0.037 | 0.01 | 0.002 |
| Sandy | 0.01 | −0.01 | −0.004 | −0.001 |
| Clay-loam | 0.14*** | 0.09*** | −0.04** | −0.006** |
| Sandy-loam | 0.10* | 0.06* | −0.03* | −0.004 |
| Flood depth | 0.003 | −0.002 | −0.001 | −0.0001 |
| Salinity | −0.16*** | −0.11*** | 0.04*** | 0.01*** |
| Storm | 0.12*** | 0.08*** | −0.04*** | −0.004*** |
| Cyclone | −0.05 | 0.03 | 0.01 | 0.001 |
| Rainfall | 0.04** | 0.02** | −0.01** | −0.001** |
| SOM level | −0.05*** | −0.03*** | 0.01*** | 0.01*** |

*, ** and *** refer to significance levels of 10% ($p \le 0.1$), 5% ($p \le 0.05$) and 1% ($p \le 0.01$).

the probability of long-term adoption and late-adoption. Likewise, sandy-loam soil at farm also increases the likelihood of long-term non-adoption by 10% and dis-adoption by 6%. With higher SOM level at farm, farmer is 5% and 3% less likely to be long-term non-adopter and dis-adopter. Improving SOM level increases the probability of long-term adoption and late-adoption (Table 4).

MSD adoption over time is also influenced by household female member education, asset ownership, farm-size and access to concrete road. Households with one year more educated female member have 1% less probability of long-term non-adoption and dis-adoption, while they have 0.2% and 0.1% higher probability of late-adoption and long-term adoption (Table 4). Owning USD100/capita more assets increases the probability of being long-term non-adopter by 2% and dis-adopter by 1% while decreasing the probability of being long-term adopter and late-adopter. With increasing farm size by one hectare, households are 1% less probable to be long-term non-adopters and dis-adopters, while they are more probable to be long-term adopters and late-adopters. Households having access to concrete road have a 9% higher probability of being long-term non-adopters. Likewise, having NGOs membership positively affects long-term non-adoption and dis-adoption while negatively affecting long-term adoption and late-adoption (Table 4).

## Discussion

### *Long-term adoption and dis-adoption of MSD*

In this study, the least number of farmers are long-term adopters (6%), while 58% and 23% of the farmers are long-term non-adopters and dis-adopters of MSD. Previous literature confirmed low adoption and dis-adoption of MSD in different contexts, for instance, as reported for Zambia between 2004 and 2008 (Arslan et al. 2014). Low adoption of MSD was also reported in central India due to farmers' less interests, mindset about prevailing tillage practices, requirement of heavy investment and non-involvement of the government and NGOs (Kumar et al. 2021). Around 80% of arable land in Bangladesh is under mechanized tillage

(Biggs et al. 2011). The country strongly promoted agricultural machineries to address the shortage of farm power (i.e. draft oxen used in tillage), in the aftermath of floods and cyclones during the late 1980s (Biggs et al. 2011). Bangladesh has seen a massive investment and utilization on intensive tillage tools, 2-wheel tractors (Mottaleb et al. 2016; Jaleta et al. 2019) due to their versatile and mobile nature, lower operating costs and operational capability in small and fragmented plots (Kahan et al. 2018). Farmers also firmly believe intensive tillage as must-to-do farming operation (Chatterjee and Acharya 2021). In already mechanized systems like Bangladesh, reduced tillage may require additional types of machineries whose availability and accessibility should be considered. Furthermore, technical training may be required to improve farmers' operational skills as well as their mindset and conventional beliefs regarding the role and impact of tillage operations.

### Climate hazards, soil characteristics and MSD adoption

The results from the ordered logit model show that heavy rainfall vulnerability supports long-term non-adoption and dis-adoption of MSD and hinders both long-term adoption and late-adoption. MSD was recommended among conservation practices with advantage in soil water conservation (Hobbs et al. 2008). It is likely that in regions with high rainfall, technologies conserving water, like MSD have limited relevance. Singana Tapia and Satama Bermeo (2022) also confirmed that average rainfall contributes negatively to the adoption of MSD. Furthermore, longer delays in the onset of the rainy season positively affect MSD adoption probability since MSD potentially provides adaptation to rainfall delays (Arslan et al. 2014). Given the annual rainfall fluctuation both in terms of low and heavy rainfall, this is an important criterion for assessing MSD suitability for different types of farmers in different agro-ecological zones (Andersson and D'Souza 2014).

Increase in storm vulnerability increases the probability of being long-term non-adopter by 12% (Table 4). Storms have a severe impact on agriculture, especially on paddy production in coastal areas, therefore recognized as one of the most devastating natural disasters in Bangladesh (Bangladesh Bureau of Statistics 2016). This kind of uncertain disaster has a short time span but has rapid onset effects, and pre-season forecasts are not available. Thus, farmers may be motivated to compensate the temporary loss of a given season through intensification practices and might discourage farmers to implement conservation agriculture, such as MSD. The results also report that increase in salinity vulnerability decreases the probability of long-term non-adoption and dis-adoption while increasing the probability of long-term adoption and late-adoption. Salinity is a climate hazard, which detrimentally affects soil and production (Dewi et al. 2022). In saline-prone areas, farmers might try various adaptation practices to ensure production (Gaydon et al. 2021) and also invest on MSD for minimizing exposure to risk. This can explain the positive coefficients associated with the salinity vulnerability on MSD adoption (Tables 3 and 4). Sharna et al. (2022) also suggested a positive correlation between salinity vulnerability and zero-tillage adoption. These urge timely climate hazards forecast and tailored policy design based on specific climate hazards; hence, farmers can plan about the preferable practices and implementation time. Besides, specific technical assistance is necessary in the promotion of MSD adoption and adaptation to different climate vulnerable areas.

Soil characteristics such as soil texture, slope, soil depth, level of gravel in the topsoil and fertility level are important factors for describing soil management related technologies (Dai et al. 2015; Belachew et al. 2020; Begho et al. 2022; Mairura et al. 2022). Farms with clay-loam and sandy-loam soil have a low probability of adoption over time including long-term adoption and late-adoption. Dai et al. (2015) found the soil texture affects adoption of water-saving irrigation technologies in China. Improvement in SOM level positively affects adoption over time including long-term adoption and late-adoption. Mairura et al. (2022) reported that good soil fertility status promotes adoption of soil nutrient and water management practices. The application of MSD, particularly with residue retention enhanced soil organic carbon under intensive rice-based cropping systems in Bangladesh (Alam et al. 2018; Maraseni et al. 2018). Farmers may try to focus on environment-friendly measures when the soil is already of higher quality. Arslan et al. (2014) reported that households who face moderate soil constraint are less likely to adopt MSD and likely to devote a significantly smaller share of land to MSD compared to households with no nutrient constraint. These prove that improvements in soil health support MSD adoption, which drives for policy design focusing on improving soil quality.

### *Effects of socio-economic characteristics and institutional factors on MSD adoption*

The results illustrate that women education has an important contribution in MSD adoption over time. Increase in years of female household's member education increases the likelihood of being a long-term adopter and late-adopter while decreasing the likelihood of being a long-term non-adopter and dis-adopter (Table 4). Education increases farmers' knowledge acceptance, awareness toward opportunities and information (Betela and Wolka 2021; Mairura et al. 2022; Yifru et al. 2022). This development of knowledge-seeking behavior initiates the technology adoption process (Roy et al. 2017; Chatterjee and Acharya 2021). Farm-households with higher education levels, especially with educated female members, have higher awareness about soil degradation than households with lower levels of education (Tesfahunegn 2019), which increases MSD adoption likelihood. Similar results were reported by previous literature (Tsegaye et al. 2017; Abera et al. 2020; Xu et al. 2022). Positive relationship was found between women-managed farms and the number of implemented soil conservation practices (Singana Tapia and Satama Bermeo 2022). Thus, increasing women's access to education is a multi-benefits strategy in policy design for the betterment of society, environment and global sustainable growth.

Households with higher asset ownership have a higher probability of being long-term non-adopter s and dis-adopters (Table 4). Households with more assets have the capability to spend on available intensive mechanized tillage. Since MSD is generally perceived as low-input systems and MSD tools are not widely available in Bangladesh (Kahan et al. 2018), farmers with higher assets do not have incentives to follow MSD. These results highlight the gaps in the perception of MSD benefits, which is a key in formulating incentives and MSD dissemination strategies at different farm scales.

Access to NGOs and concrete road decreases the likelihood of late-adoption and long-term adoption of MSD while increasing long-term non-adoption and dis-adoption. Concrete road accessibility from households makes it easier to access market, intensive tillage machineries, improved seeds, open new venues for sales and participate in non-farm activities, hence less likely to put effort on sustainable technologies (Arslan et al. 2014). Better access to market increases the demand for more products thus incentivizing more intensified production system. Alemu et al. (2023) reported that market access reduces the possibility of continued adoption of CA as it increases non-farm opportunities. Sharna et al. (2022) found that households who have concrete road accessibility are less likely to practice zero-tillage. In contrast, Darkwah et al. (2019) found a positive influence of road infrastructure investment on soil conservation practices, including crop rotation, zero-tillage, intercropping, the application of manure and compost. In developing countries, NGOs act as a great information and credit source for farmers as well provide hands-on training on various technologies (Hartmann et al. 2019). The resources and financial support from NGOs and the government motivate them to adopt soil and water conservation measures. However, they lose interest in practicing those when incentives are removed (Alemu et al. 2023). All of these may increase the likelihood of being long-term non-adopter and dis-adopter of MSD. As these kinds of government and non-governmental supports lower the implementation of MSD, this opens the debate on the importance of soil conservation in policy design (Barbayiannis et al. 2011; Singana Tapia and Satama Bermeo 2022). These suggest designing other external support to improve MSD adoption along with other conservation farm practices at the same time of providing the mentioned institutional assistance. Supports are required for heavy investment on MSD implementation in response to the financial conditions of majority farmers with engagement of the government and private sector for out-scaling of MSD.

## Conclusion and recommendation

MSD can be an effective solution to preserve soil quality along with ensuring sustainable food production. We estimated MSD adoption status over time, including long-term non-adoption, dis-adoption, late-adoption and long-term adoption and their drivers among Bangladesh rice-farmers in the face of climate vulnerability. Long-term adoption of MSD is extremely low (6%) while around 58% of the sample never adopted MSD in all survey years. Storm and heavy rainfall vulnerability reduce the likelihood of long-term adoption and late-adoption and provoke long-term non-adoption and dis-adoption probability of MSD, while salinity vulnerability promotes long-term adoption of MSD and decreases the probability of long-term non-adoption. Higher SOM levels, more women's education and larger farms promote long-term adoption of MSD while decreasing the probability of long-term non-adoption. Alternatively, households with more assets, concrete road accessibility and institutional support are less likely to be long-term adopters and late-adopters but more likely to be long-term non-adopters and dis-adopters of MSD.

This study provides new insights for policymakers to promote long-term adoption of MSD. Policy design and implementation should be tailored based on different climate hazards in vulnerable regions rather than common policies for all vulnerable regions to improve MSD adoption. Development of easily operational and suitable for diverse soil and climatic conditions MSD tools is necessary. Availability of appropriate MSD machineries with lower resource requirement than current intensive tillage tools can ensure initial adoption and continuation of practicing MSD. Financial support from the government and private sector is also needed to initiate the adoption process. Extensive training is required with demonstration of MSD benefits to change farmers' mindset and conventional beliefs regarding tillage as shifting from intensive to MSD is difficult and takes time. The policy implications suggest the importance of women's education and empowerment around agriculture since women's education significantly raises MSD long-term adoption. Increasing knowledge and skills of farmers and female household members through providing technical and resource supports could help MSD adoption.

Further comprehensive research is required with farmers' perceptions and experiences on MSD machineries and how to introduce them to farmers for ensuring long-term adoption. Revealing farmers' experience on adoption impact can also provide thorough reasons for non-adoption, dis-adoption and late-adoption. This would assist policy makers to design suitable policies to reduce dis-adoption and non-adoption.

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## Disclosure statement

No potential conflict of interest was reported by the author(s).

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## Data availability statement

All the data used in this research are available online (IFPRI 2013; MoDMR 2016; IFPRI 2016, 2020; DAE 2020; SRDI 2021).

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## Appendix. Multi-collinearity test among the explanatory variables (VIF = Variance Inflation Factor)

**Table A1.** Multi-collinearity test among the explanatory variables (VIF = variance inflation factor).

| Variable | VIF | 1/VIF |
|---|---|---|
| Head education | 1.40 | 0.71 |
| Women education | 1.45 | 0.68 |
| Age | 1.20 | 0.83 |
| Dependency-ratio | 1.11 | 0.90 |
| Asset | 1.84 | 0.54 |
| Social assistance | 1.06 | 0.939 |
| NGO membership | 1.04 | 0.95 |
| Concrete road | 1.08 | 0.92 |
| Subsidy card | 1.12 | 0.89 |
| Extension | 1.08 | 0.92 |
| Farm size | 1.18 | 0.84 |
| Agricultural facilities | 1.06 | 0.94 |
| Livestock | 1.71 | 0.58 |
| Soil type | 1.05 | 0.95 |
| Flood depth | 1.09 | 0.92 |
| Salinity | 2.33 | 0.38 |
| Storm | 2.28 | 0.37 |
| Cyclone | 2.34 | 0.42 |
| Rainfall | 1.29 | 0.77 |
| SOM level | 1.07 | 0.93 |
| Mean VIF | 1.41 | |