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W. Parker Wheatley
College of Saint Benedict/Saint John's University

Taznoore Khanam
Bangladesh Institute of Development Studies

Valerien O. Pede
International Rice Research Institute

Takashi Yamano
Asian Development Bank

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Weather risks, crop losses, and risk proneness: An examination of evolving risk preferences of rice farmers in Bangladesh

W. Parker Wheatley[a,*], Taznoore Khanam[b], Valerien O. Pede[c], Takashi Yamano[d]

[a] Department of Economics, College of Saint Benedict and Saint John's University, 37 South College Avenue, Saint Joseph, MN, USA 56374
[b] Bangladesh Institute of Development Studies, Dhaka, Bangladesh
[c] International Rice Research Institute, Los Baños, Philippines
[d] Asian Development Bank, National Capital Region, Philippines

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Changing climate poses significant challenges for smallholder rice farmers. Weather-related deviations from longer-term patterns and crop losses due to abiotic hazards can affect farmer risk preferences and drive adaptive responses. In addition, farmers' proneness to and past experiences with crop risks such as drought, submergence, and excess soil salinity can impact their baseline risk preferences and their response to changing risks. Using data for Bangladesh from two waves of the Rice Monitoring Survey, climate-related data (precipitation and temperature), farmer reports of crop losses, and measures of proneness to abiotic risks, this article estimates how weather deviations from longer-term trends, crop losses, and proneness to crop risks (submergence, drought, and soil salinity) affect elicited risk preferences over time. This research finds evidence in favor of the hypothesis that larger absolute seasonal deviations from past patterns of seasonal mean daily minimum temperature and seasonal total precipitation yield increased risk aversion. In addition, the research provides mixed evidence with respect to risk proneness and farmers' change in risk preferences over time. Contrary to our original hypothesis, individuals with land more prone to soil salinity become more risk averse rather than less, but, consistent with our hypothesis, those with land more prone to crop submergence become more risk preferring over time. Because of differences in crop experiences and degrees of proneness to risk, risk preferences for farmers in different regions are predicted to evolve along different pathways. This article contributes to the literature on risk preference formation by considering the possibility that less significant deviations than shocks might also contribute to evolving risk preferences. In addition, the article emphasizes the regional heterogeneity of changing preferences. An ancillary finding of this work suggests that risk preferences are only weakly related over time, contrary to other findings in the literature on the stability of risk preferences. Of policy relevance, the differential experiences in weather variability at the regional and local levels yield important differences in changes in preferences and should give rise to careful, regional-level policies to support adaptation to changing weather.

* Corresponding author.
E-mail addresses: pwheatley@csbsju.edu (W. Parker Wheatley), taznoore@bids.org.bd (T. Khanam), v.pede@irri.org (V.O. Pede), tyamano@adb.org (T. Yamano).

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1. Introduction

Extreme heat, prolonged droughts, and higher than normal precipitation can be attributed to climate change (National Academies of Sciences, Engineering, and Medicine, 2016). Farmers will need to adapt planting patterns, fertilizer choices, and crop choices to offset changes in net farm income arising from such challenges (Thomas et al., 2013), but if negative experiences lead farmers to adjust their risk preferences, that could change the speed or type of adaptation. Theory supports the idea that weather variability and other abiotic stresses are important determinants in the technology adoption process (Hiebert, 1974; Roumasset, 1976; Feder, Just, and Zilberman, 1985). Moreover, a significant body of research identifies how risk preferences affect risk management techniques, agricultural practices (modern versus traditional, perennial versus annual crops), adoption of climate-tolerant or pest-resistant crop varieties, fertilizer use, use of farm-related credit and insurance products, and adoption of post-harvest risk management technologies (Asravor, 2019; Brick & Visser, 2015; Channa et al., 2021; Feder, 1980; Holden & Quiggin, 2017; Isik & Khanna, 2003; Khor et al., 2018; Liu, 2013; Mehar et al., 2017; Ouattara et al., 2019; Visser et al., 2020). With the exception of post-harvest risk-reducing technologies, research finds that higher degrees of risk aversion decrease technology adoption and adaptation.

Given the salience of risk preferences to farmer adaptation, several researchers (Gloede et al., 2015; Sakha, 2019; Finger et al., 2022; Liebenehm, 2018; Liebenehm et al., 2023) have demonstrated that farmer risk preferences adjust to significant shocks, including major shocks in precipitation. However, with the exception of Di Falco and Vieider (2022), previous research made limited effort to capture the impact of modest deviations in precipitation, and no article has assessed the extent to which temperature deviations (either major shocks or minor deviations) impact risk preferences for farmers. Nguyen (2011) analyzes how individuals in risk-prone professions develop greater tolerance for risk, but prior research on the role of risk proneness in helping to shape risk preferences over time has considered only the context of disasters (Chantarat et al., 2019; Said et al., 2015), although Di Falco and Vieider (2022) do consider the importance of altitude. Our primary question is whether current season deviations in total precipitation and mean minimum daily temperatures from longer-term levels will yield changes in farmer risk preferences. We also ask whether current deviations in killing degree days[1] (KDD) as another metric of weather variability affect preferences. Although previously examined in Sakha (2019), we also re-consider whether reported crop losses impact risk preferences. Finally, we ask whether farmers' prior experiences with crop risks associated with precipitation and soil salinity will have an offsetting effect to such seasonal deviations in weather.

In formulating our hypotheses, we draw on the theoretical literature associated with the formation of risk preferences (Gollier and Pratt, 1996; Palacios-Huerta and Santos, 2004; Koszegi and Rabin, 2007) to argue that weather deviations from longer-term trends and crop losses will correspond with decreased willingness to bear risks and that proneness to crop risks will have an offsetting effect on the impact of weather deviations on risk preferences. Data employed in this study are derived from the household-level Rice Monitoring Surveys of 2013–2014 (Yamano, 2017) and 2016–2017 (unpublished), asset valuation data from Ahmed (2013) and IFPRI (2016), salinity data from Dasgupta et al. (2015), and weather data from Funk et al. (2014). We estimate the extent to which weather deviations from longer-term trends, crop losses, and proneness to crop risks (submergence, drought, and soil salinity) impact elicited risk preferences over time. Identification of the impacts of weather deviations and crop losses depends on whether deviations in weather patterns are exogenous to farmer locations, and we contend that this is reasonable given the samples considered. We find evidence in favor of the hypothesis that larger absolute seasonal deviations from past patterns of seasonal mean daily minimum temperature and seasonal total precipitation yield increased risk aversion. These results are both statistically significant and of sufficient magnitude to have a bearing on farmer behavior. In addition, we find mixed evidence with respect to risk proneness and farmers' changes in risk preferences over time. Contrary to the original hypothesis, individuals with land more prone to soil salinity are more risk averse rather than less, but consistent with our hypothesis, farmers who are more prone to crop submergence are more risk preferring. Because of differences in crop experiences and degrees of proneness to risk, risk preferences for farmers in different regions are predicted to evolve along different pathways.

We contribute to this literature in three ways. First, aside from Di Falco and Vieider (2022), no other studies consider the impact of continuous deviations in precipitation on risk preferences, and no other studies have included temperature and killing degree days as potential determinants. We therefore expand the scope of possible weather-related variables. Second, this research acknowledges that past exposure to crop risks as measured by proneness to such risks might offset the impact of more recent deviations in experiences. Said et al. (2015) control for previous flood experience, but our approach differs in that it captures multiple proneness metrics that allow for modest environmental variability and not necessarily proneness to extreme damage. Third, this research further examines more directly how differences in experiences across regions can yield divergences in preferences across a country and permit policy formulations according to different experiences, and although not novel, this further supports the care needed in formulating policies across different populations. Finally, although not an initial purpose of the study, we identify risk preferences over time that, contrary to previous literature on the stability of preferences, indicate greater instability and less relationship in elicited risk preferences over time.

In the subsequent sections of this article, we first review the literature associated with risk preference elicitation and the impacts of production and weather-related shocks on farmer risk preferences. Subsequently, we review the data obtained to better understand how measured risk preferences evolved over the study periods. Grounded in the theoretical and empirical literature, we present our arguments relative to the hypotheses formulated about how weather experiences and self-reported crop losses impact willingness to bear risk. We then explain our econometric approach and results, followed by an examination of the robustness of our findings. We

[1] Killing degree days are days when daily mean temperatures reach a level sufficiently high so as to significantly stress rice plants.

conclude with a consideration of the importance of our findings for the broader literature as well as for policy implications.

2. Literature review

Aside from the concern about how farmers might adapt to changing climate, this study is motivated by the substantial literature that examines the stability of risk preferences and the impact of environmental conditions on the evolution of risk preferences. Relevant to the formation of hypotheses around the impacts of changing weather experiences, perceptions of risk, and experienced loss is the theoretical literature on the formation of risk preferences (Gollier and Pratt, 1996; Palacios-Huerta and Santos, 2004; Koszegi and Rabin. 2007). Gollier and Pratt's theory implies that increases (decreases) in unfair background risk will cause risk-averse individuals to behave in a more (less) risk-averse manner, where unfair background risk corresponds with changes in risk with a non-positive expectation (i.e., implying a worsening outcome on average). Guiso and Paiella (2008) as well as Liebenehm et al. (2023) find support for a positive relationship between increased background risk and increased risk aversion. Palacios-Huerta and Santos (2004) move away from fixity of preferences and identify economic, social, legal, and cultural structures as affecting the formation and expression of preferences across all domains, including risk preferences. Their model predicts that there will be an endogenous relationship between risk attitudes and market structures. To the extent that economic institutions such as credit markets are well-functioning, then lower risk aversion prevails given that individuals can insure against risk by accessing credit markets; however, if macro shocks occur that undermine such mechanisms, risk aversion can increase. Their empirical evidence provides support for their hypotheses on the interactions of shocks and institutions. Koszegi and Rabin (2007) argue that risk preferences are dependent on a reference point (i.e., past risk exposure) such that individuals with greater past exposure to risk would be less risk averse and less reactive to negative or positive experiences. Nguyen (2011) expands this approach in his proposition that individuals with a higher risk endowment based on their career experiences will be more willing to bear risk.

In addition, the substantial literature on the stability of preferences informs this study and the empirical methods chosen. The literature on the stability of risk preferences addresses potential challenges to obtaining valid measures of preferences, identifies potential contextual reasons for instability of measured risk preferences, and entertains the possibility that exogenous factors might play a role in the evolution of risk measures. Schildberg-Hoerisch (2018) identifies the broad theoretical and empirical concerns in this context, and Chuang and Schechter (2015) review the limitations of preference elicitation in developing countries, including some potential biases due to lower education or the impact of poverty on a subject's attentional resources that might have cognitive impacts and thus yield biases or inconsistent results. In addition, they note that some research suggests that survey measures outperform experimental measures of risk preferences in terms of the external validity of the findings (Dohmen et al., 2011; Lönnqvist et al., 2015). A broad literature demonstrates and examines the causes of instability of preferences across elicitation procedures (Anderson and Mellor, 2009; Berg et al., 2005; Hey et al., 2009; Holzmeister & Stafan, 2021; Isaac and James, 2000; Pedroni et al., 2017). Theories that explain variation in results include Pedroni et al.'s argument that preferences are constructed during the elicitation process and Weber et al.'s (2002) contention that a given measure of preferences can be dependent on the context or domain of the decision-making environment (e.g., financial versus health, etc.). At the same time, Dohmen et al. (2011) note that, although measured preferences might differ, they are correlated across time.

There are also contextual reasons for preference changes that require reference back to the underlying theories on the possibility of evolving preferences. Several scholars have examined the impact of natural disasters (earthquakes, floods, and hurricanes), and some results appear contradictory. Some researchers (Hanaoka et al., 2018; Kahsay and Osberghaus, 2018; Eckel et al., 2009; Page et al., 2014) find that severe shocks yield increases in risk-loving behavior in some sectors of the population, with Eckel et al. (2009) finding that time since a shock attenuates the risk-loving impact. Callen (2015), Cameron and Shah (2015), Cassar et al. (2017), and Chantarat et al. (2019) consider the impacts of disasters on risk preferences in developing countries. Cameron and Shah (2015), Cassar et al. (2017), and Chantarat et al. (2019) find increasing risk aversion as a result of disasters or shocks. The studies that reveal increased willingness to bear risk after shocks use data from developed countries while those studies finding increased risk aversion use developing-country data, and as Liebenehm (2018) finds, the context and institutional structures in different countries can mediate the effects of shocks and thus yield different impacts on risk preferences.

Further support relative to experience-driven evolution of risk preferences is the literature that examines adverse events in the agricultural context (Gloede et al., 2015; Sakha, 2019; Finger et al., 2022; Di Falco and Vieider, 2022; Liebenehm et al., 2023). Reflecting the developed-country and developing-country divide of the disaster research noted above, Finger et al. (2022) find an increased risk tolerance for those who experience negative weather and pest-related events for individuals in a developed country (Switzerland); whereas, in developing-country contexts, Gloede et al. (2015) (agricultural shocks in Thailand), Di Falco and Vieider (2022) (rainfall in Ethiopia), Liebenehm et al. (2023) (rainfall shocks in Thailand), and Sakha (2019) (agricultural shocks in Thailand) all find that adverse agricultural shocks yield increased risk aversion. Theory suggests that individual preferences will adjust as a result of changing contexts and environments, and although a variety of individual-level factors unrelated to exogenous events might explain some variability, the empirical literature in the agricultural context provides support for the role of negative events in the risk preferences of farmers.

3. Data

This research uses two primary data sources: (i) individual and household data from Bangladesh collected as part of the Rice Monitoring Survey (RMS) of the International Rice Research Institute (IRRI) and (ii) precipitation and temperature data from the Climate Hazards Group Precipitation with Stations at the 0.05 arc degree level (Funk et al., 2014). We obtain supplementary asset valuation data from the International Food Policy Research Institute's (IFPRI) Bangladesh Integrated Household Survey (BIHS) (Ahmed, 2013; IFPRI, 2016), and we obtain measures of soil salinity from Dasgupta et al. (2015).

3.1. Rice marketing survey

3.1.1. Economic and demographic features

IRRI began conducting the RMS in 2013–2014, with a subsequent round occurring in 2016–2017, with broad coverage of rice-producing regions in Bangladesh, India, and Nepal. For Bangladesh, surveys were conducted in rural villages in six of the seven divisions of Bangladesh (Barisal, Chittagong, Dhaka, Khulna, Rajshahi, and Rangpur). The original sample in 2013–2014 contained 1,500 households. A stratified sample was taken, with samples of 10 households drawn from each of 150 villages across these regions. Samples were drawn from 18 to 20 villages in Chittagong, Dhaka, Khulna, and Rangpur. Samples were drawn from a larger number of villages in Barisal (44) and Rajshahi (30). By 2016–2017, the total sample decreased to 1,486 households. One village in Rajshahi Division was omitted for logistical reasons in the second round of the survey (accounting for 10 units of this decrease) and four households had either migrated or it was not possible to arrange surveys with an appropriate respondent in the second round. Households were surveyed on a broad range of individual, household, and village-level characteristics. This research will focus only on those households where the same individuals served as respondents in each round of the survey and whether a household planted during the Aman season[2]; therefore, the sample size decreases to 827 households. Changes in respondents at the household level arose because the original respondent was not at home when the enumerators were conducting the surveys either because they were in town or working away from home at the time. As Liebenehm et al. (2023) note, this approach will diminish potential bias arising from obtaining preference data from different household members over time but will necessarily decrease the sample size. In Table 1, we present the summary statistics of key variables. In a later section on attrition and robustness, we will consider the extent to which the included samples differ from the excluded samples in a statistical sense.

The key household and farm-level variables included in Table 1 are age, sex, education, the number of adults in the household, the number of children in the household, kilometers from the input market, the value of household assets, the value of household animals, the number of acres owned, the value of land owned, the share of farmed land that is reported to be on low-lying (submergence-prone) land, the share of farmed land that is reported to be on high (more drought-prone) land, the share of land planted in rice, the amount of rice output reported, the amount of output lost in the most recent season due to abiotic stressors, and the share of planted acreage that is irrigated. Value of assets, value of animals, and value of land were calculated using asset, animal, and land totals from the RMS and prices or values from the BIHS. In addition, total loss was imputed based on farmer reports of shares lost due to various sources of abiotic stress (drought, salinity, or submergence). The salinity index from Dasgupta et al. (2015) at the upazila level[3] is used, and it represents the level of soil salinity that farmers must confront in their growing operations, with no salinity corresponding to an index value of 0 and extreme salinity corresponding to an index value of 7.

3.1.2. Measurement of risk preferences

For this study, the primary element of interest was the measurement of risk preferences. As noted above, Chuang and Schechter (2015) stress the limitations of preference elicitation in developing countries, and there are ongoing debates on the external validity of experimental measures relative to survey measures (Dohmen et al., 2011; Lönnqvist et al., 2015; Burks et al., 2012). Liebenehm et al. (2023) review this literature further, weighing the costs and benefits of different metrics, and from that, it is clear that there is no full consensus on the proper metrics as of yet. However, we know that simple elicitation approaches would be preferred to more complex ones, particularly in the developing-country context. It is also clear that one should be cautious in the use of some precise parametric measure of preferences. In that context, risk preferences for this study were elicited using a gamble choice game based on Binswanger (1980), following the example of several studies that have used similar procedures in a developing-country context (Barr and Genicot, 2008; Cardenas and Carpenter 2013; Cameron and Shah, 2015; Said et al., 2015; Chantarat et al., 2019). The script of the elicitation procedure is provided in Appendix 1. Such games are simple and easily understood by less educated populations. Individuals were given an oral presentation of five gamble options that were ordered from least risky to most risky. Subjects were informed that, although the gambles were hypothetical, they should pretend that there were real cash payments associated with the gambles and should consider the choice carefully. Cameron and Shah (2015) report findings that, although hypothetical games will yield lower degrees of risk aversion, the impacts of external events remained consistent with those from non-hypothetical games. Camerer and Hogarth (1999) identify no uniform direction of the impact on risk aversion in hypothetical gamble choice games, but Binswanger (1980) notes greater dispersion of risk aversion metrics when choices are not incentivized. This represents an acknowledged limitation

[2] Bangladesh has three planting seasons – Aman, Boro, and Aus. Aman is the most important season for rice production; therefore, we include data only from that season in this study. This is also a practical necessity because rain and temperature are highly correlated across seasons even if the means differ widely across seasons.

[3] An upazila (formerly known as thana) is a political division corresponding to a county-level geographic distribution.

Table 1
Sample Summary Statistics of Survey Respondents.

Variable	Mean	Standard Deviation	Min	Max
Age (years)	50.04	12.33	21	93
Sex (female)	0.05			
Education (years)	5.95	4.23	0	16
# of Adults in Household	3.99	1.94	1	18
# of Children in Household	1.69	1.42	0	11
km from Input Market	1.84	1.75	0	12
Asset Value (BDT)[1]	12,063.91	23,045.16	0	200,466.20
Animal Value (BDT)[1]	37,138.52	49,776.38	0	544,236.20
Acres Owned	1.8	1.96	0	18.2
Land Value (BDT)[1]	3,487,598.00	3,156,506.00	0	39,100,000.00
Share Planted in Rice	0.91	0.19	0.08	1
Aman Rice Output (kg)	2,598.65	2,442.43	0	21,360
Aman Loss Output (kg)	580.46	1,790.49	0	24,800
Salinity Index (0 to 7)	0.93	1.64	0	7
Low Land Share[2]	0.46	0.42	0	1
High Land Share[2]	0.15	0.26	0	1
Share Irrigated[2]	0.30	0.44	0	1

[1] Asset values, animal values, and land values are quoted in Bangladeshi Taka (BDT).
[2] Share of land that is low lying (Low Land Share), sitting on high land (High Land Share), or irrigated (Share Irrigated).

of this study.

Risk preference experiments were conducted in both rounds of the survey. Subjects were informed that their hypothetical payment was contingent on the role of a six-sided die. A value of 1, 3, or 5 would correspond to a low payoff and a value of 2, 4, or 6 would yield a high payoff. Although no payments were made, subjects were informed that the die-rolling exercise would occur so that they could see what they would have won had there been actual payments. With respect to risk preferences, this question asked individuals to choose a certain payment or one of four other riskier prospects. Individuals who chose the certain payment (Option 1) would be the most risk-averse individuals and those who chose the riskiest option would be the least risk averse (Option 5). As with other studies, these choices permitted a definition of the boundaries of a person's coefficient of relative risk aversion, assuming a CRRA utility function ($U = x^{(1-\gamma)}/(1-\gamma)$). Although we will not exploit these CRRA measures directly in this study, Table 2 provides the hypothetical payments, expected values, riskiness, and implied boundaries on the coefficient of relative risk aversion associated with each choice. Note that the average daily rural wage was 291 Bangladeshi Taka in 2014 and 364 in 2017 (Bangladesh Bureau of Statistics, 2015; Bangladesh Bureau of Statistics, 2018); therefore, the hypothetical payments are appropriately salient for the subjects at between 18 percent (in 2013–2014) and 14 percent (in 2016–2017) of the daily rural wage.

Recognizing that the specific preference measure might be less important than the general category of risk identified by the selected option, Table 3 allows us to consider the distribution of preferred choices and the extent of change in aggregate between the two periods. Over a third of the respondents in both periods chose the zero-risk option (Option 1), but this value declined modestly for the households in the latter survey. The share of individuals selecting Option 2 is similar at approximately 14 % in both the first and second rounds of the survey. The share selecting Option 3 approximately doubles from 8.71 % to 17.29 % for the sample. The share selecting Option 4 grows modestly between the two survey rounds, and the share selecting Option 5 falls substantially for the sample. A simple chi-square test of homogeneity is conducted to determine whether the samples are drawn from the same distribution across time, and with a chi-square statistic of 51.98 and 4 degrees of freedom, we reject the null hypothesis of no differences in proportions in each group across the two sample years at the 0.05 significance level.

Fig. 1 summarizes the changes in the risk option chosen from the first round to the second round of the survey for those individuals included in the sample analyzed. Nearly a quarter of the respondents had no change in preferences from the first round to the second round, and similar percentages of the sample became less risk averse versus more risk averse. A positive (negative) difference implies that a respondent is more (less) willing to bear risk (i.e., their CRRA is declining (increasing)). Approximately 23 percent of the sample changed their preferred option by two or more values in the direction of risk aversion and approximately 28 percent changed their preferred option by two or more in the direction of less risk aversion.

Finally, we analyze the extent to which risk preferences in the sample are correlated over time. Spearman and polychoric correlations reveal statistically significant correlation coefficients of −0.073 and −0.06, respectively, suggesting very modest negative relationships. Moreover, a cross-tabulation in Table 4 shows a high degree of variability in transitions from one risk category to another over the two periods. Based on a chi-square test of association between choices made in 2014 and choices made in 2017, we are unable to state that the two responses are unrelated. Therefore, although the earlier test seemed to suggest that the overall samples come from different distributions and the above correlation metrics indicate different aggregate distributions over time and little correlation at the

Table 2
Choice game, expected values, and risk aversion ranges.

	Low Payoff	High Payoff	Expected Value	Standard Deviation	CRRA Risk Preference (γ)
Option 1	52	52	52	0	> 1.92
Option 2	39	77	58	19	1.92 to 0.68
Option 3	26	103	64.5	38.5	0.68 to 0.40
Option 4	13	130	71.5	58.5	0.40 to 0.19
Option 5	0	155	77.5	77.5	<0.19

Payoffs quoted in Bangladeshi Taka (BDT).

Table 3
Choices Made Across Years.

	2014	2017	Diff.
Option 1	316	297	−19
	38.21	35.91	−2.30
Option 2	115	123	8
	13.91	14.87	0.96
Option 3	72	143	71
	8.71	17.29	8.58
Option 4	124	152	28
	14.99	18.38	3.39
Option 5	200	112	−88
	24.18	13.54	−10.64

Note 1: For each option, the first row represents the total number of respondents choosing that option and the second row is the percentage of respondents in the corresponding year who chose that option.
Note 2: The last column shows the difference in raw numbers and percentage points between 2017 and 2014.

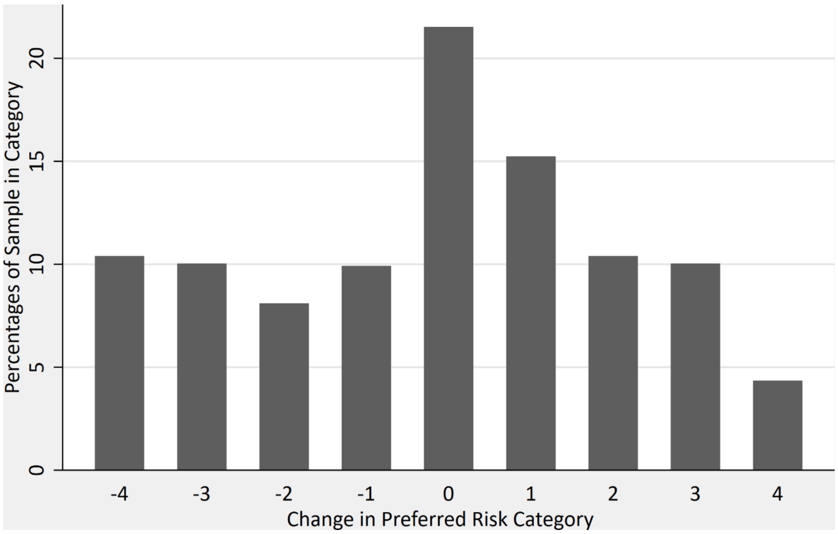

Fig. 1. The distribution of the sample of changes in preferred risk category between the 2013–2014 and 2016–2017 survey rounds. Columns display share of sample corresponding with each category.

individual level, there is some evidence of association between choices made in 2014 and choices made in 2017. In both periods, the highest density of responses is for the Option 1 and Option 2 categories. Although the number of individuals whose preferences evolve over time is quite large, approximately 23 percent express no change in preferences from one period to the next, with an additional 23 percent shifting their preferred option by only one category in either direction of their original choice.

Based on the literature, some of this change in preferences might well arise from changes in context from the perspective of farmers – wealth, age, and agricultural conditions – in the first period relative to the latter period. However, Dohmen et al. (2011) and Di Falco and Vieider (2022) observe correlation of preferences over time, and our results suggest a weaker relationship that merits further study to determine the source of such differences and weakening of relationships in preferences over time.

Table 4
Cross-Tabulation of Risk Choices from 2014 to 2017.

		2017 Response				
		Option 1	Option 2	Option 3	Option 4	Option 5
2014 Response	Option1	13.13	6.80	7.54	8.48	5.52
	Option2	4.44	2.56	2.15	2.42	2.29
	Option3	2.49	0.94	2.22	1.75	1.01
	Option4	6.20	1.21	1.41	2.15	2.42
	Option5	9.36	2.83	3.91	3.43	3.30

Note 1: Chi-square (16) = 43.62, p = 0.000. These are the chi-square statistics corresponding to a test of association between participant responses in 2014 and participant responses in 2017.
Note 2: Each cell provides the share of individuals choosing Option X in 2014 that chose Option Y in 2017.

3.2. Weather data

Changing weather represents an important experience of farmers as they consider their decisions and options. To identify relationships between risk preferences and changing weather conditions, we collected daily precipitation, maximum temperature, and minimum temperature data for the ten planting seasons immediately preceding the second round of the Rice Monitoring Survey (2007 through 2016).[4] These data were matched to each household based on GPS data collected at the time of the household surveys. Given that 97 % of the farmers from the larger data set engage in rice farming during the Aman season and that this season remains the most important productive season, we use the Aman season statistics. Note that the start and end of the planting season varies widely by area in Bangladesh; therefore, we adopted the widest bounds in our seasonal calculations, with the Aman season being from July to December.

The literature considers a variety of precipitation and temperature metrics (Arslan et al., 2017; Asfaw et al., 2016; Rahman et al., 2016). We calculate seasonal total precipitation, daily mean temperature, and daily mean minimum temperature for each of the ten years. The use of seasonal total rainfall is consistent with Arslan et al. (2017). We use daily mean temperature to calculate the sum of killing degree days (KDD) for rice (i.e., days with mean temperatures in excess of 35 °C) given that the agronomic literature finds that these days cause significant harm to rice growth and production (Wang et al., 2014; Ding et al., 2020). Also, Peng et al. (2004) find that high evening temperatures negatively affect rice yields. Consequently, we use daily minimum temperature to capture the impact of temperatures during what would be expected to be evening periods. Using those data, we construct measures of deviations from a longer-term average weather experience (i.e., weather variability) by taking the difference between the current-year weather metric and the mean of that metric for the previous nine years.

Given the above explanation, Table 5 provides the summary statistics for this set of data. As seen, the mean number of killing degree days across regions is 2.08, with a fairly broad range of outcomes from 0 days to 11 days. For the 2016 season, the mean deviation of KDD from the longer-term average over the 2007 to 2015 period is −0.69. The mean minimum daily temperature for the Aman season of 2016 was 23.93, with a range of 22.45 to 27.05, and this value is on average 0.4 degree higher than the longer-term average, suggesting warmer than average temperatures for 2016. Finally, the mean total precipitation for the 2016–2017 season was 1,439 mm, with a range from 808.04 mm to 2,521.81 mm. This seasonal mean is 112.64 mm higher than the longer-term average, suggesting a rainier season on average. However, the experiences of farmers ranged widely: from a decline of −99.37 mm to an increase of 837.13 mm.

In order to highlight the regional disparities in experiences in the 2016 season relative to historical patterns, we provide the following two figures. Fig. 2 shows the differences in experiences in terms of KDD and daily minimum temperatures. Farmers in the Khulna and Rajshahi regions saw their number of KDD fall most significantly at between 1.50 and 1.75 days. At the same time, all six regions saw their mean daily minimum temperature rise by less than 1 °C.

As shown in Fig. 3, precipitation experiences varied widely. Farmers in Barisal, Dhaka, and Khulna regions experienced deviations of fewer than 100 mm; farmers in Chittagong saw their precipitation increase by 250 mm to 300 mm. Finally, farmers in Rajshahi experienced a modest decline in precipitation from longer-term averages, and farmers in Rangpur, on average, had a substantial positive annual deviation of nearly 500 mm.

For subsequent work and consistent with Di Falco and Vieider (2022), we take the absolute values of the temperature and precipitation deviations to reflect the notion that deviations from the average in either direction could have negative impacts as they deviate from expectations; however, this approach has a limitation in the sense that lower than mean seasonal precipitation might be preferred in some regions that are more prone to crop submergence and higher than mean precipitation might be preferred in other more drought-prone regions. However, the impact of such limitations would yield an understatement of the impact of deviations on preferences in the final estimates of impacts. The approach taken in this project is different from the shock measures proposed in Liebenehm et al. (2023), which identified shocks as a one standard deviation from the historical average. Few households in this data

[4] Note: The literature suggests that a longer time horizon of data would be preferred in order to identify longer-term climate-related changes. These data represent the total number of years that could be employed given the resources available at the time of data collection. However, the data are still sufficiently long that a one-year deviation from the previous nine years should be adequate in terms of the impact on farmer perceptions.

Table 5
Summary of Key Weather Metrics.

	Mean	Std. Dev.	Min	Max
Killing Degree Days (KDD)	2.08	3.08	0.00	11.00
KDD Deviation from Long-Term Average (in days)	−0.69	1.06	−5.22	1.67
Mean Seasonal Daily Minimum Temperature (°C)	23.93	0.78	22.45	27.05
Min Temp Deviation from Long-Term Average (°C)	0.40	0.23	0.58	0.87
Total Precipitation in 2016–2017 Season (mm)	1,439.75	462.48	808.04	2,521.81
Precipitation Deviation from Long-Term Average (mm)	112.64	198.38	−99.37	837.13

Observations: 827

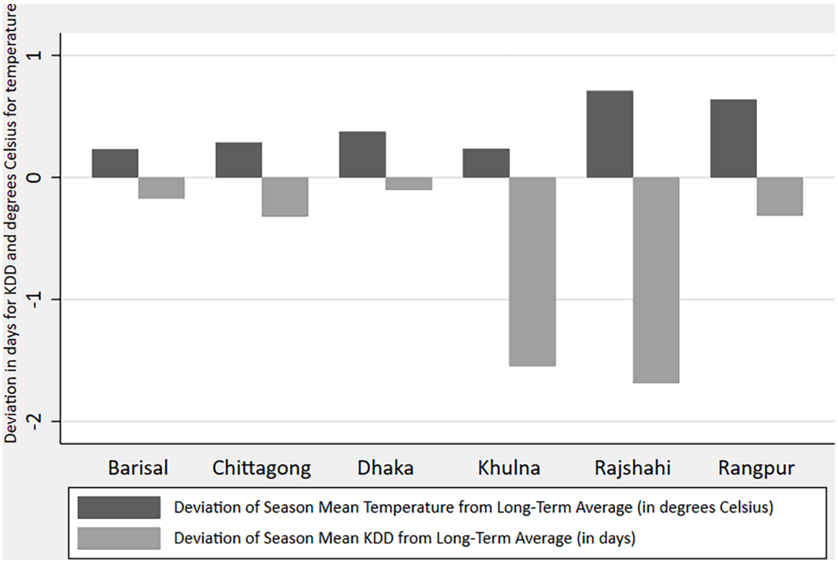

Fig. 2. Deviations in the 2016 KDD and mean daily minimum temperatures from the previous nine-year average of each variable by government division.

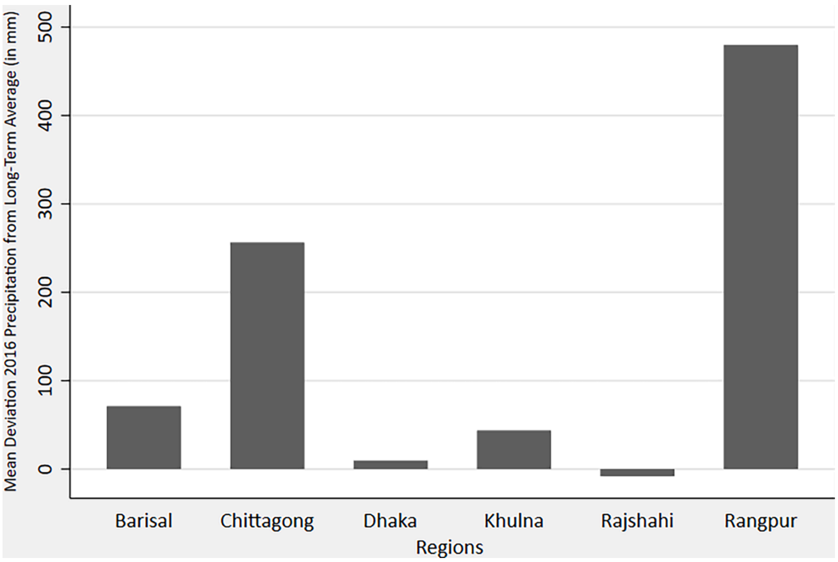

Fig. 3. Deviations in the 2016 total precipitation for the Aman season from the previous nine-year average by government division.

set experienced such shocks; therefore, we would have inadequate shocks in the data to identify such effects. This difference will allow us to test whether less extreme deviations are relevant to farmer preferences, and this represents a contribution of this article.

4. Hypothesis formation

Four related variables represent different forms of weather experiences that should affect risk preferences based on the theoretical literature. These are the imputed loss reported by farmers and the deviations of each of the following from the average of the previous nine years of data: KDD in 2016, the mean daily minimum temperature in 2016, and seasonal total precipitation in 2016. In addition, some variables capture a household's prior experience with various forms of risk. Specifically, salinity levels, proneness to submergence, and proneness to dry conditions represent environments that farmers must experience and contend with on a yearly basis. The share of land farmed that lies on low land represents a measure of likelihood of or proneness to submergence, which is harmful for rice growth, and the share of land farmed that lies on high land represents a measure of proneness to dry conditions. Both provide measures of proneness to these two risks and a measure of past experiences with them. Based on the theoretical literature, the following are the two key hypotheses that we examine.

H.1. Positive deviations in killing degree days, absolute deviations in mean seasonal daily minimum temperature, and absolute deviations in total precipitation from longer-term averages as well as reported crop losses will yield increasing risk aversion.

The mechanisms of these effects are twofold: (1) perception of increased background risk and (2) incomplete institutions (e.g., credit markets). Gollier and Pratt (1996) find that increases in background risk yield increases in risk-averse behavior, with decreases in background risk having the opposite impact, and support for this is found in Liebenehm et al. (2023) and Guiso and Paiella (2008). Farmers' experiences with crop losses, more than usual killing degree days, larger absolute deviations of daily minimum temperatures, or larger absolute deviations in precipitation, are treated as negative events that could be construed to represent increased risk from the perspective of farmers on average. Secondarily, as identified by Palacios-Huerta and Santos (2004), for environments such as rural Bangladesh where institutions cannot or do not permit insurance against negative experiences arising from weather deviations, for example, individuals will also exhibit increased risk aversion upon experiencing such deviations.

H.2. Past exposure to and experience of risks should yield a higher willingness to bear risk.

Three factors correlate with a farmer's prior experience with risk. Specifically, each farmer engages in agriculture in more or less salinity-prone areas as indicated by the salinity index in their particular upazila. In addition, each farmer has an endowment of high land and low land. Farmers with low-lying land are more likely to experience submergence on their plots than farmers who identify their land as high land or neither. At the same time, farmers having a larger share of their land on high land are likely to experience more drying when rains are inadequate and thus have more experience with drought conditions. In each of these, the reference point literature (Koszegi and Rabin, 2007) suggests that farmers with more experience with such challenges will display lower levels of risk aversion. One caution or caveat for this hypothesis relates to the empirical literature. Specifically, the empirical evidence for such situations lies in Nguyen's (2011) article, which finds that individuals in high-risk professions have built up a higher risk endowment. The difference here is that, for the most part, individuals in this sample do not choose their location as freely as individuals might choose their profession.

5. Econometric methods

We have constructed our dependent variable as the change in the most preferred risk choice. This is a novel approach relative to other studies that examine the impact of events on preferences. All previous studies have examined the current period's chosen risk preference (however measured) as a function of the other variables. In terms of methods used, Chantarat et al. (2019) and Said et al. (2015) examined risk preferences in the context of rare events such as disasters and elicited preferences in a manner similar to Binswanger (1980). In order to estimate the impacts of events on the risk option chosen, they both employed an ordered probit technique to identify the event effects, and Chantarat et al. (2019) also compared their ordered probit results with those from OLS. Cameron and Shah (2015) performed similar preference elicitations, and, instead of an ordered probit regression, they engaged in two processes: (1) a probit regression where the dependent variable takes a value of 1 for individuals who prefer the riskier options presented and 0 for individuals who prefer the less risky options and (2) an interval regression on the range of possible coefficients of relative risk aversion. Finally, Liebenehm et al. (2023), unlike others, used Dohmen et al.'s (2011) survey-based measure where respondents were asked to rate themselves on an 11-point Likert scale ranging from a value of 0 as being "unwilling to take risks" to 10 corresponding to "fully prepared to take risks," and they converted the scale so that the least risk averse individuals would have a value of −10 associated with them, with the most risk averse individuals having a value of 0 associated with them, so that positive coefficients on a covariate would imply that the covariate caused individuals to become more risk averse.

Notwithstanding the limited dependent variable, we chose to use ordinary least squares in estimating the determinants of the respondent's change in risk preferences over time, and the specification is shown in equation (1) below. Although the econometric method chosen is simple in nature, it permits an easily interpretable finding and consideration of the hypotheses proposed. Equation (1) presents the empirical model:

$$\Delta RA_i = \beta_o + \beta_{KDD} Dev_{iKDD} + \beta_{Precip} Dev_{iPrecip} + \beta_{Min} Dev_{iMinTemp} + \beta_{Loss} Loss_i + \sum_{j \in P} \gamma_j Prone_{ij} + \sum_{k \in K} \lambda_k Dem_{ik} + \sum_{m=2}^{6} \delta_m Div_{im} + \varepsilon_i \quad (1)$$

In this equation, the following are the variables: ΔRA_i corresponds to change in risk aversion category for household i; Dev_{iKDD}

represents the deviation in killing degree days; $Dev_{iPrecip}$ represents the absolute value of the deviation in precipitation; $Dev_{iMinTemp}$ represents the absolute value of the deviation in minimum daily temperature; and $Loss_i$ represents the imputed loss based on farmer reports of loss due to crop stressors. These variables are those that provide the opportunity to test hypothesis 1 as they represent potentially negative outcomes for farmers. Next, $Prone_{ij}$ corresponds to all j of the P proneness measures (i.e., measures of salinity, share of low land, share of high land, and share of irrigation). These values allow us to examine hypothesis 2. Whether a farmer has an irrigation system can act as insurance against risk and it allows a longer cropping time horizon, and although farmers with a greater degree of risk aversion might be more likely to purchase the equipment necessary for irrigation, having an irrigation system itself might change a farmer's willingness to bear risk in the future. Dem_{ik} represents the k demographic measures, including age, sex, education, number of adults in the household, and marital status. Most of these are common controls for individual difference, but some also correspond to greater or lesser ability to manage risk (e.g., distance from output markets or changes in wealth over time). Proximity to output markets should also correspond to easier access to supplementary supplies, credit, and other resources should farmers have shortfalls in crops because of problematic changes in weather, and this provides access to alternative income sources. Finally, Div_{im} represents the dummy variables for the different high-level administrative divisions (excluding the Barisal region, which will serve as the baseline).

In considering the hypotheses posed, we used five specifications based on equation (1), with increasing controls for other covariates and factors that might influence farmer preferences. Specification 1 considers only the relationship between the predictors associated with hypothesis 1 and specification 2 includes only those variables associated with hypotheses 1 and 2 (i.e., measures of deviations of key weather and loss variables and measures of proneness to risk). In specification 3, all variables from the previous two specifications are included along with all relevant household and demographic variables. Finally, specifications 4 and 5 are identical in that they both

Table 6
Econometric Findings.

	(1)	(2)	(3)	(4)	(5)
Deviations					
KDD Deviation (in days)	−0.310***	−0.304***	−0.282***	0.127	0.127
	0.000	0.000	0.001	0.195	0.218
Min Temp Deviation (^oC)	1.484***	−0.759	−0.680	−4.778***	−4.778***
	0.000	0.142	0.196	0.000	0.000
Precipitation Deviation (mm)	0.000	−0.001	−0.001*	−0.003***	−0.003**
	0.360	0.104	0.054	0.000	0.015
Rice Crop Loss (in kg)	−0.00003	−0.00001	−0.00002	−0.00012	−0.00012
	0.769	0.913	0.846	0.277	0.259
Proneness to Risk					
Salinity Index (0 to 7)		−0.307***	−0.346***	−0.362***	−0.362***
		0.000	0.000	0.000	0.001
Share Low Land		0.458**	0.347*	0.730***	0.730***
		0.025	0.095	0.000	0.008
Share High Land		0.499	0.476	0.157	0.157
		0.135	0.156	0.628	0.670
Share Irrigation		0.891***	0.923***	−0.075	−0.075
		0.000	0.000	0.780	0.740
Individual and Household Characteristics					
Female			0.783**	0.194	0.194
			0.050	0.607	0.672
Age (years)			0.003	0.003	0.003
			0.663	0.673	0.675
Married			−0.416	−0.438	−0.438
			0.399	0.343	0.387
Education (years)			−0.0004	−0.0017	−0.0017
			0.984	0.925	0.923
# of Adults			0.096**	0.102***	0.102***
			0.021	0.009	0.005
# of Children			−0.015	0.043	0.043
			0.785	0.406	0.427
km from Input Market			0.013	−0.054	−0.054
			0.763	0.191	0.261
Land Owned (acres)			−0.042	−0.074	−0.074
			0.332	0.075	0.064
Change in Wealth (BDT)			−0.00000004*	−0.00000004**	−0.00000004**
			0.071	0.046	0.039
Constant	−0.889	−0.213	−0.175	0.359	0.359
	0.000	0.441	0.791	0.574	0.640
Clustered s.e.'s (village)	No	No	No	No	Yes
Regional FE	No	No	No	Yes	Yes
# of Observations	827	827	827	827	827
R-squared	0.058	0.127	0.124	0.254	0.254

Note 1: Values below coefficients are p-values. *, **, and *** correspond to the 0.1, 0.05, and 0.01 levels of significance.

further add dummy variables for unobserved regional differences, but the latter specification also incorporates cluster-corrected standard errors at the village level.

6. Results and interpretation

Table 6 presents the results from each of the specifications considered. The results on the deviations in KDD are statistically significant and consistent with hypothesis 1 for specifications 1 through 3 but no longer display such consistency once regional dummy variables are incorporated. Larger deviations in the minimum daily temperature from the longer-term average imply increased risk aversion in all specifications, with the impact being statistically significant for specifications 1, 3, 4, and 5. This result supports the hypothesis that deviations in seasonal mean daily minimum temperature from past experience correspond to increased aversion to risk. Finally, with the exception of specification 1, larger deviations in seasonal precipitation from the longer-term average correspond to increased risk aversion (i.e., a more negative change in preferred option), and this value is statistically significant to varying degrees in specifications 3 through 5. Again, this result provides further support for hypothesis 1 and is consistent with Liebenehm et al.'s (2023) finding that precipitation shocks correspond to declining willingness to bear risk as well as Di Falco and Vieider's (2022) finding of decreased risk tolerance with higher deviations of precipitation. The strongest statistical evidence in favor of hypothesis 1 appears to be in the analysis of daily temperature and in seasonal precipitation. The weakest evidence for hypothesis 1 appears to be in the farmer's self-reported crop losses. Although the coefficient on crop losses is uniformly negative, suggesting that increased reported losses imply greater risk aversion, the finding is not statistically significant. Although not specific to weather, the above findings, in a context of potentially marginal changes in condition, are consistent with Sakha's (2019) finding that more agricultural shocks increase the risk aversion of farmers.

The evidence for hypothesis 2 is less promising depending on the variable considered. Three risk proneness measures were used: (1) Salinity Index, (2) Share Low Land, and (3) Share High Land. One factor that mitigates some drying risk was also included: Share Irrigation. The original hypothesis expected that greater risk proneness and therefore experience of risk would correspond to lower degrees of risk aversion and therefore a positive coefficient signifying lowered risk aversion across time as farmers experience greater risk over time. In this context and across all specifications, the coefficient on Salinity Index is negative and statistically significant and therefore corresponds to an increased risk aversion across time. At the same time, all specifications indicate that farmers with larger shares of land on low land have lower levels of risk aversion between the two periods, which is consistent with hypothesis 2. The sign on Share High Land is as hypothesized but is not statistically significant. Although not a measure of risk proneness, Share Irrigation is included in the discussion because it represents a risk mitigation tool, and although ownership of irrigation tools is itself endogenous to an individual's risk preferences, once a farmer has irrigation tools, it changes the farmer's working environment and thus could affect the future evolution of risk. However, because the use of irrigation is so strongly associated with farming in the dryer Rangpur and Rajshahi divisions, we are unable to identify the role of irrigation in the fullest specifications.

The result corresponding to salinity proneness merits further consideration because of the challenges of mitigating salinity risk, and the problem of soil salinity is its non-variable and likely worsening nature over time as storm surges and rising sea levels result in increased salinity intrusion into groundwater and river water (Dasgupta et al., 2015). The options for mitigating or adapting to such risks are limited, including migration or changing crop type (if possible) (Chen and Meuller, 2018); so, unlike the difficult but more manageable ongoing risks of rainfall variability or changing temperature stresses, this risk has impacts that require avoidance and thus might explain some of the differences in outcomes between the temperature and rainfall proneness measures relative to the salinity proneness measure. More study would be needed to better understand those differences.

We will not discuss the other covariates further but include them for completeness. Notably, however, specification 2, which includes only the deviation and proneness metrics, provides about half of the total predictive capacity of the full model and even more than is provided by the addition of the several other demographic determinants.

Given the statistical evidence, we now examine the economic importance of two deviation measures (Min Temp Deviation and

Table 7
Total Effects of Actual Annual Deviations in Temperature and Precipitation and Risk Proneness on the Change in Risk Preferences.

	Barisal	Chittagong	Dhaka	Khulna	Rajshahi	Rangpur
Weather Variability Effects						
Temp Deviation Effect	−1.10	−1.37	−1.78	−1.12	−3.39	−3.05
Precipitation Deviation Effect	−0.27	−0.77	−0.21	−0.15	−0.08	−1.45
Total Deviation Effect	−1.36	−2.13	−2.00	−1.27	−3.46	−4.50
Risk Proneness Effects						
Salinity Index Effect	−0.59	−0.24	0.00	−0.95	0.00	0.00
Share Low Land Effect	0.43	0.57	0.54	0.14	0.18	0.21
Total Proneness Effect	−0.16	0.33	0.54	−0.81	0.18	0.21
Total versus Actual Effects						
Deviation and Proneness Total	−1.53	−1.81	−1.46	−2.08	−3.28	−4.29
Actual Average Change	−1.05	−0.46	0.62	0.71	0.96	0.15

Note 1. This table presents the weather variability effects associated with temperature and precipitation deviations, and the effects of proneness to risk for salinity and low land, and provides a comparison of total estimated effects versus actual changes in preferences.
Note 2. The values in each cell correspond to the measured change in risk category. A value of −1 would imply a shift of one risk category in the direction of greater risk aversion (i.e., in the negative direction).

Precipitation Deviation) and two proneness measures (Salinity and Share Low Land). We focus on these impacts across regions in order to consider their importance at a more disaggregated level. Table 7 presents the total effects of temperature deviation and precipitation deviation on risk preferences as well as the two proneness measures. To obtain these values, we took the average of each of the variables at the divisional level and multiplied them by their respective coefficients as derived from specification 5. We added the two deviation effects to get the total impact of seasonal deviations from long-term averages on risk preferences, and we also added the two proneness effects to get the total impact of risk proneness on risk preferences. These impacts are most substantial for deviations in mean daily minimum temperature, with the smallest effect being for the Barisal region, with a change of −1.10, which signifies an individual selecting the risk option that was one step less risky from the earlier period to the next. The largest impacts were for Rajshahi and

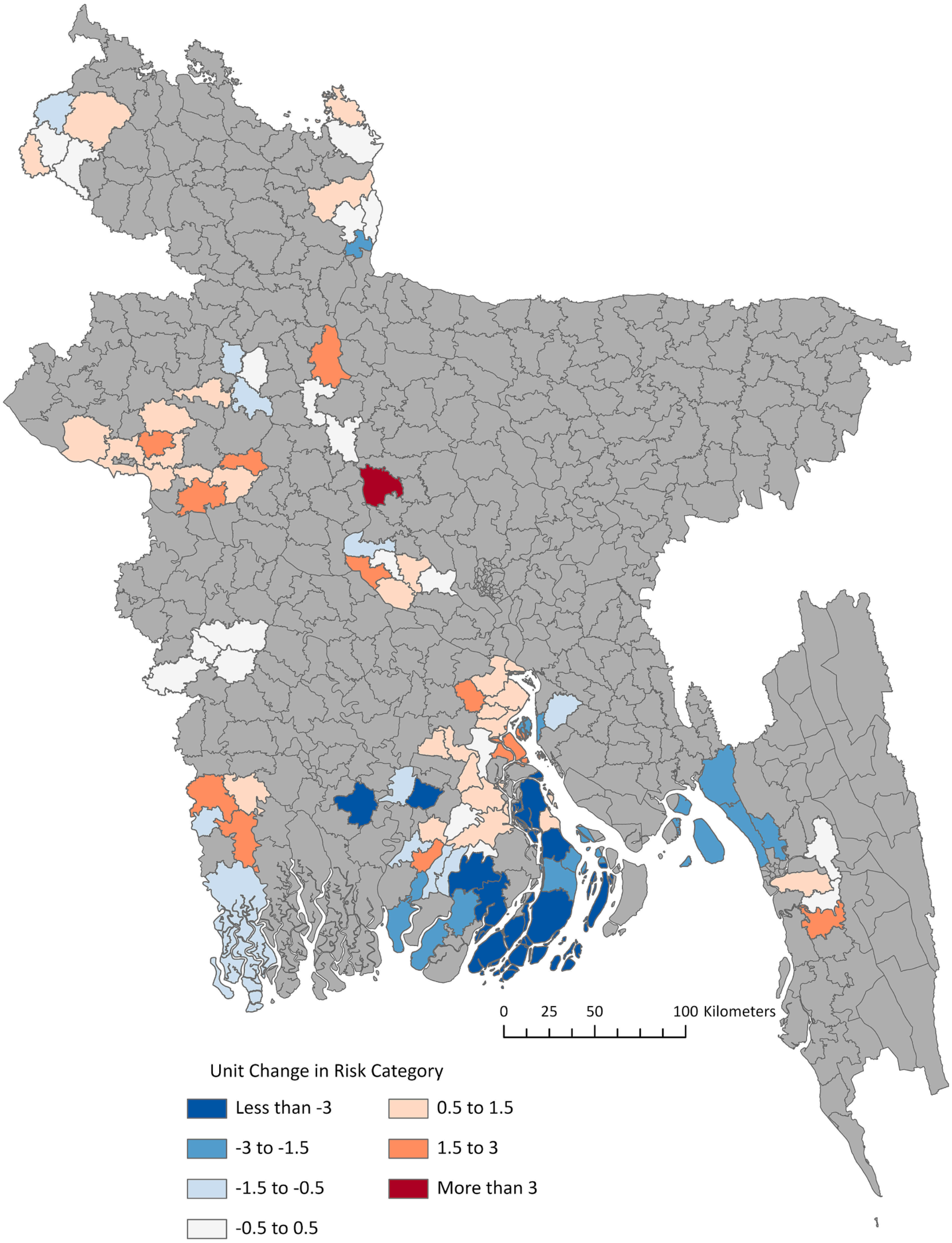

Fig. 4. Regional distribution of mean change in preferred risk category at the upazila level. Category scales between −4 and 4.

Rangpur at −3.39 and −3.05, respectively, as these two regions saw their daily mean minimum temperature rise by greater than 0.5 °C in 2016 relative to the previous nine-year average. The impacts of changes in precipitation are more modest, but are still substantial for the regions of Chittagong and Rangpur, which experienced the largest deviations in seasonal precipitation, and these respondents, on average, would be predicted to choose a risk category on the order of one category less risky (with an effect of −0.77 and −1.45, respectively). The total effects of deviations are notable across all regions, with the greatest impacts in Rajshahi and Rangpur. The impacts of proneness on the change in risk category choice are smaller than that of the deviation measures, but Salinity Index has a moderate impact for both the Barisal and Khulna regions – two regions with high salinity. The impact of proneness to submergence as

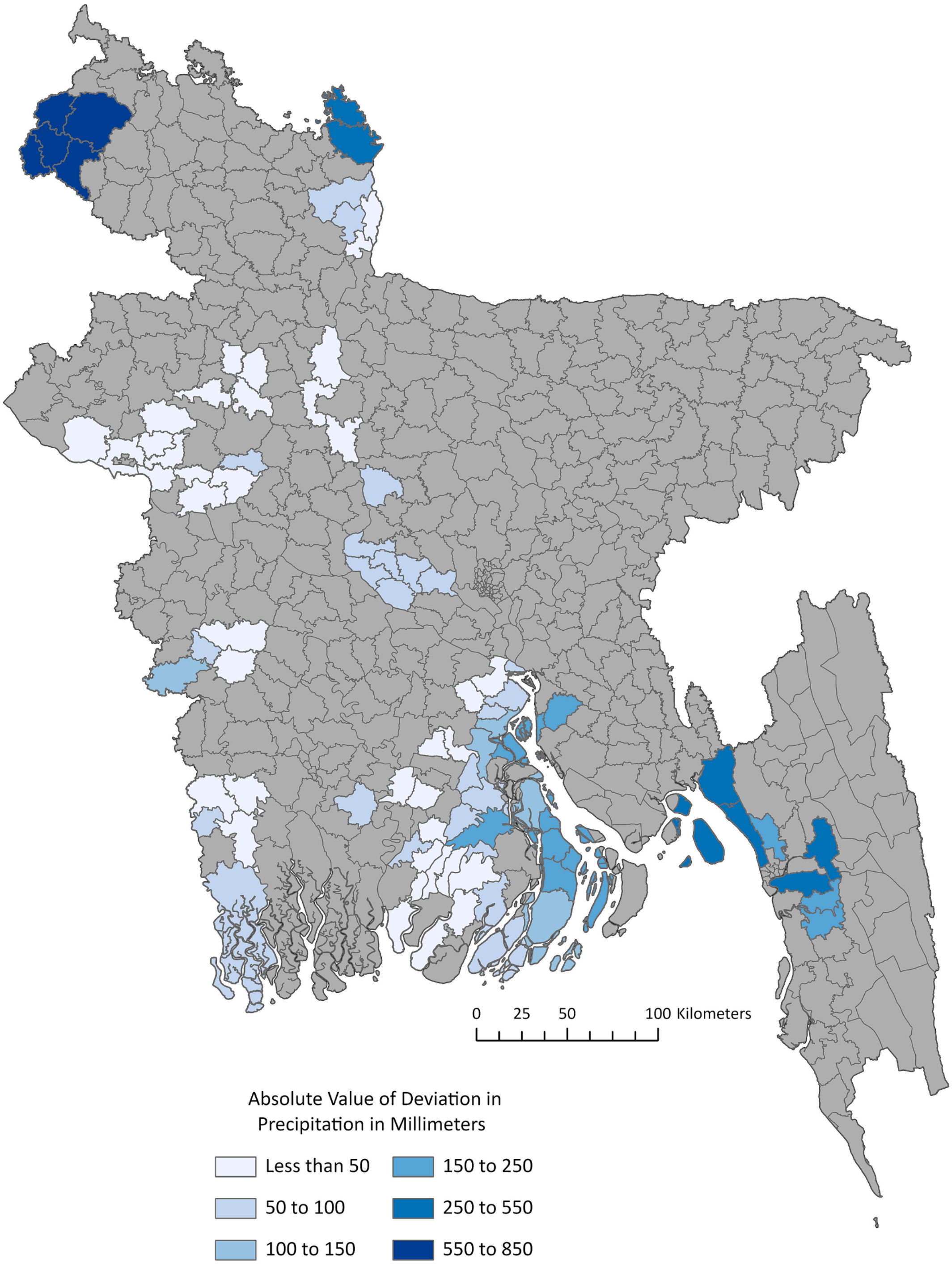

Fig. 5. Regional distribution of the absolute value of deviation in precipitation (in mm) from long-term averages at the upazila level.

measured by the Share Low Land variable is also limited, with the impact being greatest for the lowest-lying divisions: Barisal, Chittagong, and Dhaka. The net impact of all proneness measures is modest, with only Khulna seeing an effect coming close to a 1-unit reduction, on average, of preferred risk category – suggesting modestly higher risk aversion. The total effects across both deviation effects and proneness effects are moderate to large impacts of changes in preferred risk category chosen. The actual mean change in preferred risk category across the regions was −0.14, with this value ranging at the regional level from −1.05 in Barisal to 0.96 in Rajshahi. Although other factors are quite important in determining changes in preferred risk category preferences over time, the overall impacts of the events in one planting year relative to the longer-term average appear to have a depressing value on farmer willingness to bear risk, and these impacts are quite different across regions – suggesting that some care is needed in designing

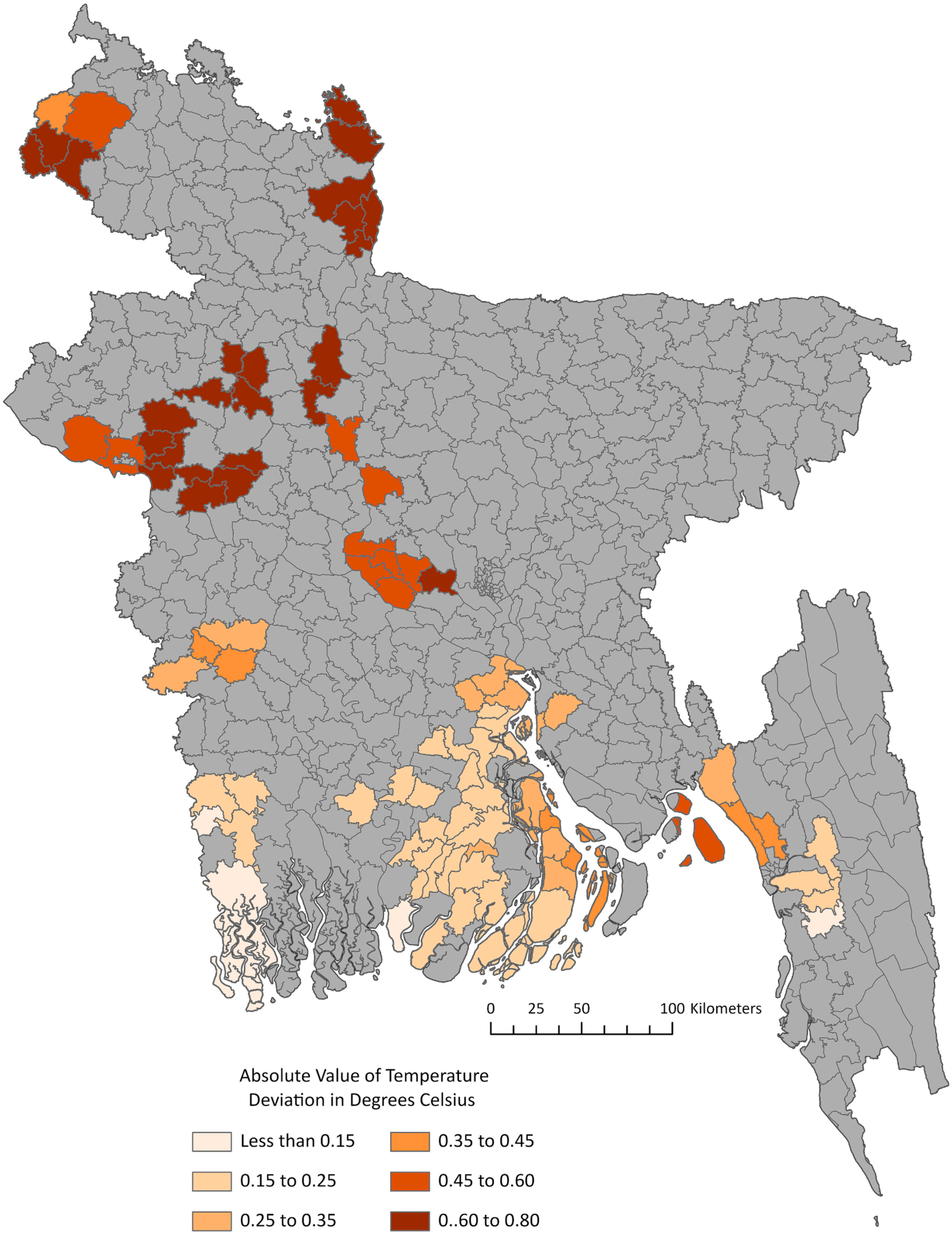

Fig. 6. Regional distribution of the absolute value of deviation in temperature (in degrees Celsius) from long-term averages at the upazila level.

programs that encourage adaptive strategies as such programs must reflect the broad differences in experiences across the country.

To provide an even more disaggregated image of the changes in preferred risk category, the changes in weather, and the estimated impacts of such weather deviations on the dependent variable, we provide the following figures. Fig. 4 provides the actual mean change in preferred risk category at the upazila level. Farmers in the coastal regions had the biggest decline in preferred risk category and therefore became more risk averse, with farmers to the north and west demonstrating greater willingness to bear risk but with broad diversity in changes. Figs. 5 and 6 display maps of the mean absolute deviations in precipitation and temperature across regions.

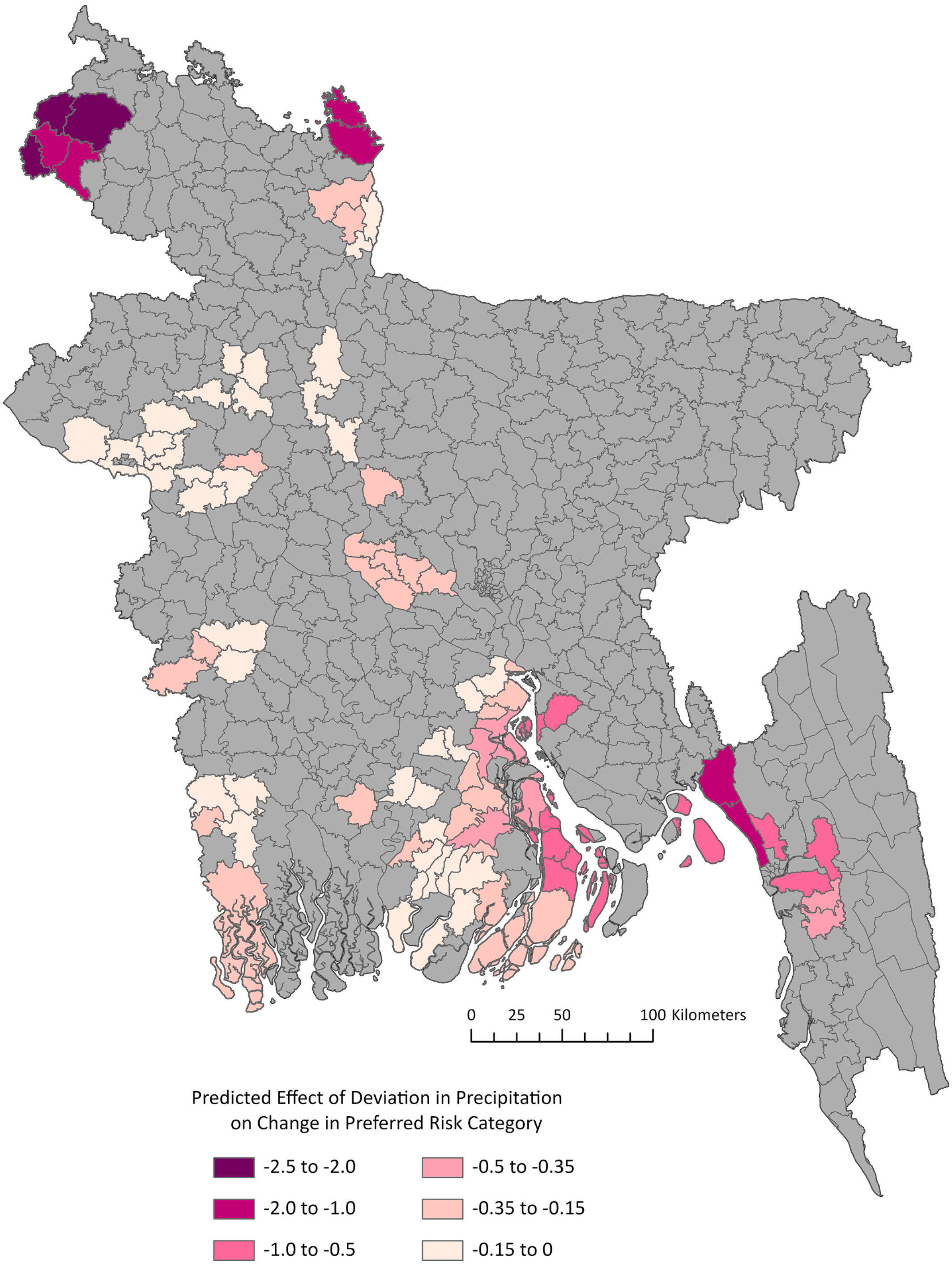

Fig. 7. Regional distribution of the predicted impact of deviations in precipitation (in mm) from long-term averages on the extent of change in preferred risk category between the 2013–2014 survey round and the 2016–2017 survey round at the upazila level.

In terms of the geographic diversity of weather experience, the far northwestern regions and far southeastern regions saw significant deviations in precipitation from their long-term averages, with regions closer to the mouth of the Meghina River in the south also experiencing more pronounced deviations in precipitation. Other regions saw more modest deviations in precipitation. The more northerly regions experienced higher mean daily minimum temperatures than the southern regions, with a few exceptions. Figs. 7 and 8 show the predicted impact of deviations in precipitation and temperature across regions. In Fig. 7, we observe in the northwest and far southeast that some but not all upazilas are predicted to experience an increase in risk aversion (i.e., as measured by larger negative

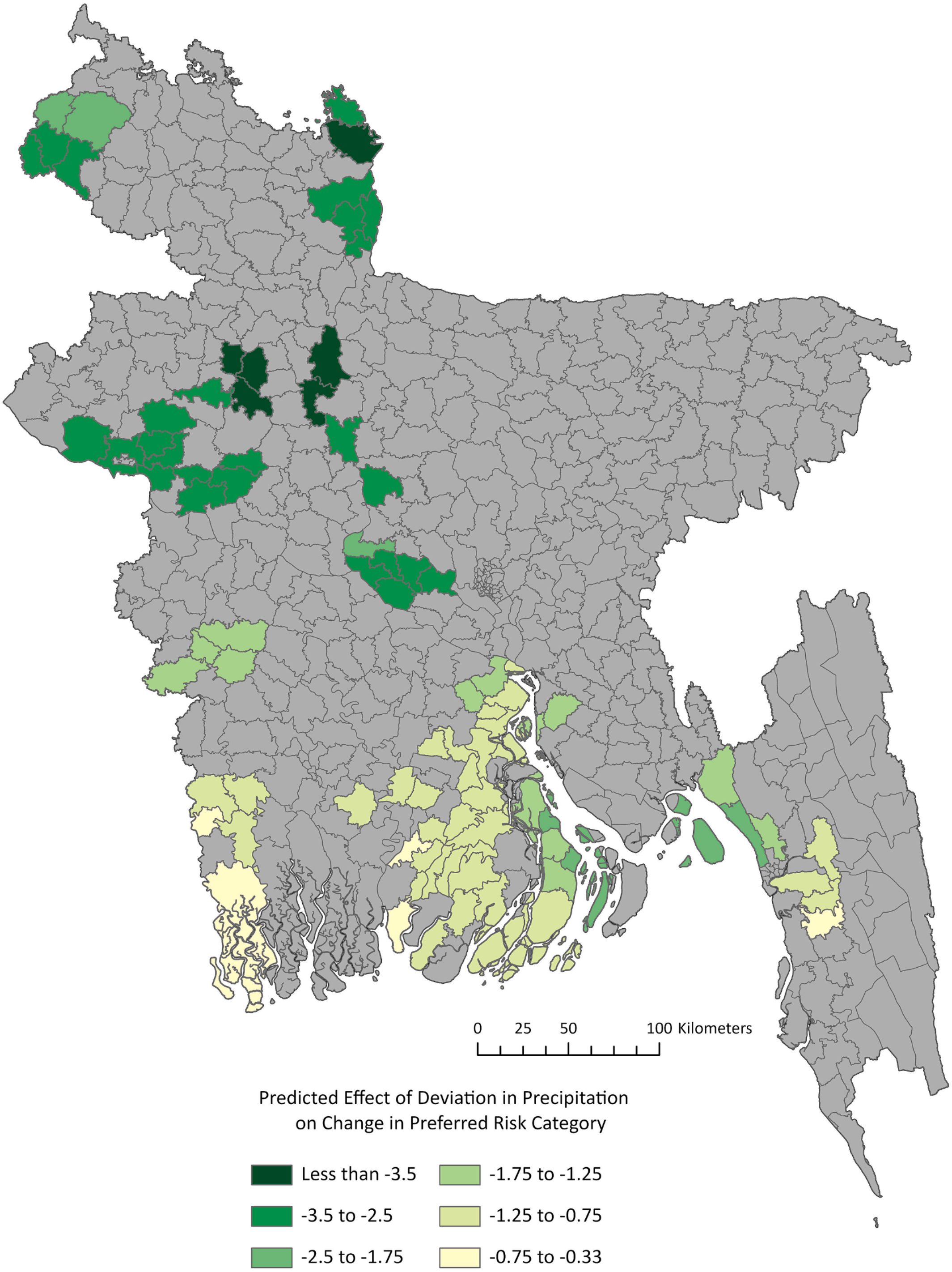

Fig. 8. Regional distribution of the predicted impact of deviations in mean daily minimum temperature (in degrees Celsius) from long-term averages on the extent of change in preferred risk category between the 2013–2014 survey round and the 2016–2017 survey round at the upazila level.

values), and these predictions correspond to the larger deviations in precipitation for these same regions in Fig. 5. These regions also experience large deviations in temperature, which further compounds the change in risk preferences. However, when comparing these predictions with actual changes in preferences, we note that only the far southeast upazilas have results fully consistent with predictions. As seen in Fig. 4, farmers in the far south saw the greatest increase in risk aversion, and the predicted changes shown in Fig. 7 and Fig. 8 explain these actual changes for upazilas closest to the Meghina River in the south. Improving models of the evolution of risk preferences could support more refined structuring of incentives across regions to reflect the average experiences of these farmers.

7. Robustness considerations

7.1. Comparison of OLS and ordered probit findings

Our use of OLS given the nature of the dependent variable could give rise to some concerns about specification. In Table 8, we compare the OLS parameter estimates and those of the ordered probit for specification 5. For completeness, all specifications were estimated using ordered probit, and those results can be inspected in Appendix 1. In reviewing the estimates, the signs and significances are consistent for all variables as expected.

Although they are more difficult to interpret, we include the marginal effects along with the implied total effects across regions in Table 9, which can be compared with those in Table 7. Columns 1 through 9 correspond to the different changes in preferred risk category. Column 1 corresponds to an individual who switched from the riskiest option to the least risky option, and all other columns can be interpreted similarly. In the section of this table corresponding to the rows labeled Min Temp Deviation to Share Low Land, the marginal effect of a change in the variable on the probability of changing the preferred risk catory by a particular extent is noted. For example, in column 1 corresponding to the Min Temp Deviation, a 1-degree deviation in the mean minimum daily temperature would increase the probability of switching from the most risk-preferring option to the least risk-preferring option by 0.39, a substantial increase. With the exception of the 0 unit change in preferred risk category, all of these marginal effects are statistically significant at the 0.01 significance level or better. The marginal effect of a precipitation deviation appears small, but this is a scale effect since a 1-unit deviation in precipitation would be only 1 mm. Larger deviations such as 100 mm would imply increases in the probability of changing one's preferred option by −4 units to −1 units on the order of 0.02 and 0.01. To provide some correspondence to the regional disaggregation in Table 7, we calculate the cumulative effects across both weather deviation variables (Min Temp Deviation and Precipitation Deviation) and stress proneness variables (Salinity Index and Share Low Land) for each region. We see that the cumulative effects vary. For example, the experiences in Barisal increased the probability by 0.119 that an individual would change their preferred option by −4 units and decreased the probability by 0.0698 of changing the preferred option by 4 . At the same time, experiences in Rangpur, on average, would cause those individuals to increase the probability by 0.34 of changing their preferred option by −4, with a corresponding decrease of −0.1995 in probability of changing their preferred option by 4. Again, although less easy to interpret, these results correspond well to those calculations performed to create Table 7.

7.2. Considering selection and attrition

As noted earlier, although 1,486 households appeared in both rounds of the survey, only 827 households were examined because they both had the same respondent in each round and were planting in Aman season in the second round. As discussed, the sample decreased to limit potential bias in the dependent variable arising from a change in respondent over time (although not a change in household). Although this change is not the typical sort of attrition because all of the 1,486 households were in both rounds of the survey (i.e., they had not moved), it represents an attrition of sorts because the respondent changed over time, and this impinges on the data that can be used if comparing risk preferences over time. To address potential concerns about whether our findings are robust to such sample reduction, we perform several checks. We first compare means of the data in the included and excluded samples, and we then test whether the distribution of the dependent variable is unrelated to whether the data came from the included sample or the excluded sample. We then follow Fitzgerald et al. (1998) in running a probit regression to determine whether exclusion from the sample was a function of household characteristics. Finally, we run the regression for the whole sample to determine whether the results were affected to any significant degree by the sample reduction.

We first check the extent to which the individuals included in the sample analyzed in the latter round are statistically similar to those who are excluded in that round. Table 10 presents the differences in means and confidence intervals on those differences. We find that many variables have no statistical difference in the sample means of the observations included and excluded from the statistical analysis. However, we cannot reject the null of no systematic differences because that is not true for all variables. The data suggest that the respondents in the included sample are 5.64 years older on average, have a smaller share of female respondents, had values on animal assets about 20 percent higher, and had output about 12 percent higher than those in the excluded sample. These data suggest some modest differences in the samples, and they should be considered in evaluating statistical findings.

Next, Table 11 provides the distributions in percentage terms of the dependent variable for the included and excluded samples along with the result of a chi-square measure of association to determine whether distribution of the change in preferred risk category is associated with whether we are considering the included sample or the excluded sample. The chi-square test leads us to reject the hypothesis that the distribution is not related to the sample. Visually, these differences appear small, but the included sample appears to have a marginally larger share of individuals shifting toward greater risk aversion. Although the difference is not large, it is present.

Then, we estimate whether exclusion from the sample is a function of household characteristics in 2014, and the marginal effects from this probit regression appear in Table 12. The only modifications were that we used total wealth in 2014 instead of the change in

Table 8
A Comparison of OLS and Ordered Probit Parameter Estimates.

	OLS	Ordered Probit
Deviations		
KDD Deviation (in days)	0.127	0.0738
	0.218	0.16
Min Temp Deviation (°C)	−4.778***	−2.6428***
	0.000	0.000
Precipitation Deviation (mm)	−0.003**	−0.0015***
	0.015	0.008
Rice Crop Loss (in kg)	−0.00012	−0.0001
	0.259	0.238
Proneness to Risk		
Salinity Index (0 to 7)	−0.362***	−0.1785***
	0.001	0.002
Share Low Land	0.730***	0.3874
	0.008	0.007*
Share High Land	0.157	0.0683
	0.670	0.709
Share Irrigation	−0.075	−0.0505
	0.740	0.668
Individual and Household Characteristics		
Female	0.194	0.1028
	0.672	0.666
Age (years)	0.003	0.0012
	0.675	0.705
Married	−0.438	−0.259
	0.387	0.301
Education (in years)	−0.0017	−0.0009
	0.923	0.920
# of Adults	0.102***	0.0526***
	0.005	0.005
# of Children	0.043	0.0187
	0.427	0.490
km from Input Market	−0.054	−0.0307
	0.261	0.237
Land Owned (acres)	−0.074	−0.0265
	0.064	0.185
Change in Wealth (BDT)	0.000**	0.000**
	0.039	0.046
Clustered s.e.'s (village)	Yes	Yes
Regional Dummy Variables	Yes	Yes
# of Observations	827	827
R-squared/pseudo-R-squared	0.254	0.0662

Note 1: Values below coefficients are p-values. *, **, and *** correspond to the 0.1, 0.05, and 0.01 levels of significance.

Table 9
Marginal Effects for Key Variables Across Categories and Total Implied Effect by Region.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Risk Change Category	−4	−3	−2	−1	0	1	2	3	4
Variable	dp/dx								
Min Temp Deviation	0.3900	0.2380	0.1360	0.1020	0.0183	−0.1560	−0.1980	−0.3010	−0.2290
Precipitation Deviation	0.0002	0.0001	0.0001	0.0001	0.0000	−0.0001	−0.0001	−0.0002	−0.0001
Salinity Index	0.0264	0.0160	0.0092	0.0069	0.0012	−0.0106	−0.0134	−0.0203	−0.0154
Share Low Land	−0.0572	−0.0348	−0.0199	−0.0150	−0.0027	0.0229	0.0290	0.0441	0.0335
Region	Total Effect Across Key Variables								
Barisal	0.1190	0.0725	0.0414	0.0311	0.0056	−0.0477	−0.0605	−0.0917	−0.0698
Chittagong	0.1413	0.0861	0.0492	0.0369	0.0066	−0.0565	−0.0718	−0.1089	−0.0829
Dhaka	0.1189	0.0726	0.0415	0.0311	0.0056	−0.0476	−0.0604	−0.0918	−0.0699
Khulna	0.1606	0.0977	0.0559	0.0420	0.0075	−0.0643	−0.0815	−0.1237	−0.0940
Rajshahi	0.2681	0.1636	0.0935	0.0701	0.0126	−0.1072	−0.1361	−0.2069	−0.1574
Rangpur	0.3400	0.2073	0.1184	0.0889	0.0159	−0.1361	−0.1728	−0.2623	−0.1995

Note 1: The values corresponding to dp/dx are the marginal effects associated with each statistically significant weather variability metric or risk proneness metric.
Note 2: The values corresponding to Total Effect Across Key Variables provide the product of the corresponding marginal effects with the actual weather variability and proneness metrics.

Table 10
Differences in Means of Included and Excluded Data.

Variable	Difference in Means	95 % Confidence Interval
Age (years)	5.64	(6.94, 4.34)**
Sex (female)	−0.16	(−0.13, −0.20)**
Education (years)	−0.13	(0.31, −0.58)
# of Adults	0.00	(0.20, −0.20)
# of Children	−0.10	(0.05, −0.24)
km from Input Market	0.00	(0.17, −0.17)
Asset Values (BDT)	1,494.97	(3,699.69, −709.75)
Animal Value (BDT)	7,457.67	(11,670.91, 3,244.43)**
Acres Owned	0.24	(0.44, 0.04)
Land Value (BDT)	242,103.00	(557,138.96, −72,932.96)
Share Planted in Rice	−0.01	(0.02, −0.04)
Aman Rice Output (kg)	283.90	(537.51, 30.30)**
Aman Loss Output (kg)	7.96	(172.95, −157.03)
Salinity Index (0 to 7)	0.24	(0.39, 0.09)
Low Land Share	−0.04	(0.01, −0.09)
High Land Share	0.01	(0.04, −0.03)
Share Irrigated	0.03	(0.08, −0.01)

Note 1: *, **, and *** correspond to the 0.1, 0.05, and 0.01 levels of significance of difference in intervals.

Table 11
Distribution of Data in Each Risk Change Category.

Risk Change Category	Included	Excluded
−4	5.79	3.57
−3	5.59	3.43
−2	4.51	3.10
−1	5.52	4.71
0	11.99	11.38
1	8.48	4.65
2	5.79	5.19
3	5.59	5.19
4	2.42	3.10
# of Observations	827	658
% of Total	55.69	44.31

Note 1: Risk change category represents the change between the risk option chosen in 2014 and the risk option chosen in 2017.
Note 2: The Included and Excluded columns correspond to the share of respondents from each sample that changed their category preference by the corresponding risk change category extent.
Note 3: Chi-square (8) = 20.19, p = 0.010. These statistics correspond to a chi-square statistic of association between a household's risk category and whether it was in the Included or Excluded sample.

Table 12
Marginal Effects of Probit Estimation of Probability of Exit from Sample.

Variable	dy/dx	P>z
Salinity Index (0 to 7)	−0.0486	0.000
Female 2014	0.4701	0.000
Married 2014	−0.2678	0.000
Adults 2014	0.0274	0.001
Age 2014	−0.0033	0.010
Land Owned 2014	−0.0214	0.013
Share High Land 2014	0.1227	0.087
Children 2014	0.0109	0.310
Total Wealth 2014 (BDT)	0.0000	0.322
Share Irrigation 2014	0.0261	0.454
Education 2014 (in years)	−0.0019	0.500
Share Low Land 2014	0.0241	0.553
km from Input Market	0.0030	0.729

Note 1: Values are sorted by p-value.
Note 2: Column dy/dx provides the marginal effect of each variable on probability of exclusion from the second-round survey.

wealth, and we did not include weather changes.

We find that five variables were significant (Salinity Index, Female 2014, Adults 2014, Married 2014, Age 2014, and Land Owned 2014). A 1-unit increase in Salinity Index yields a reduction in probability of being out of the sample in the latter period. Note that about 94 percent of the sample has a Salinity Index value of 3 or lower, so it is possible that this picks up some small sample properties of the individuals in high-salinity areas. Consistent with Sakha (2019), we see that each year of age corresponds to a lower probability of being out of the sample of −0.022 per year, and the greater the number of adults in the household in 2014 implied a higher probability of being out of the sample. Given the larger numbers of adults in a household, it is plausible to suggest that the person at home when enumerators arrive would be more highly variable. The female variable is not as surprising as it might seem. The RMS is focused on data relative to rice production activities, and since male heads of household were the primary target, a female might have been surveyed in the first round because the head of the household was out of the home at the time, but when the second round arrived, the female was not surveyed because the male head of the household was present. The marriage dummy variable corresponds to a 0.2678 lower probability of being out of the sample. Only about 5 percent of the sample was unmarried, so this impact on the results should be quite small. Finally, the amount of land owned decreased the likelihood of being out of the sample. However, 95 % of the sample owned 5 or fewer acres; so, even at 5 acres, that would imply only a 0.1 reduction in probability of being excluded. Although some factors are of note, many of the effects are marginal or only impact a small share of the overall sample.

As a final check, we ran specification 5 when using the whole sample for which all variables were available even if the respondents changed over time. Note that the sample is modestly smaller than the full data set of 1,486 at 1,387 observations. Most of this reduction is accounted for because, of the total, 1,389 households produced in the Aman season in 2016. We still excluded the non-Aman producers because they would not have experienced weather relevant to their economic experience. An additional two observation reduction arise from those households not having data for all variables. Appendix 1 presents the results from this regression, and we note that coefficient signs and significance remain similar to those displayed in Table 6. This might seem surprising, but Kimball et al. (2009) find a high degree of intra-household correlation in risk preferences. They argue that correlation in spousal preferences arises from assortative mating and similarity of life experiences.

8. Limitations and future research

Some limitations of the current study are the following. First, although our survey environment includes the exact same households from one period to the next, the respondents differ across time. As a result, in an effort to ensure that we are examining how individual preferences evolve as a result of their experiences, we were limited to a smaller subset of the data. In examining that smaller subset relative to those excluded from the sample under study, we found that the two groups were largely similar but with some significant differences, especially in the age of the respondent, and we found that some factors such as salinity of land, whether the initial respondent was female, respondent age, whether a person was married, and the number of household members all affected the probability of having the same respondent in both periods. Our weather data are at the 0.05 arc degree level, and this results in some loss of granularity and assumes a uniformity of weather experience that might differ from the exact experience of specific farms. Other factors that might explain some of the directional change of preferences but that are not captured in this study include macro factors such as political or national economics events not otherwise captured by changes in assets. In our choice to consider the actual change in risk category over time, we limited the ability to introduce such controls by reducing the study to what is a cross-sectional study.

In terms of future work, because we test how several factors might simultaneously affect farmer responses, we are able to identify multiple impacts. Further research might arrive at an appropriate joint metric that captures how these factors jointly combine to affect farm productivity (e.g., higher temperatures increase the moisture-holding capacity of air). Further study is also needed to infer whether these changes in risk preferences affect actual farmer behavior (i.e., external validity). In addition, the contradictory findings on submergence proneness and salinity proneness suggest an opportunity to better understand how farmers perceive different persistent, unavoidable, but potentially mitigatable risks to explain why such factors are affecting risk preferences differentially. Finally, we have chosen a weather variability metric (i.e., a one-year deviation from a longer-term trend), so we identify only how weather variability affects preferences; therefore, further research on the role of weather variability and climate change on preferences should be performed with a longer time series of weather-related data.

9. Concluding observations

We contribute to the existing literature that examines the impact of events on risk aversion, but instead of examining major changes in precipitation or temperature, we consider any deviations as possibly having an impact on farmer risk preferences. By examining deviations from longer-term weather patterns as well as farm-level, time-invariant proneness to different abiotic crop stressors, we are able to identify the importance of short-term deviations in growing environment experience in farmers' risk preferences. Our findings that deviations in temperature and precipitation yield a change in a respondent's willingness to accept riskier options aligns with the findings demonstrated in other literature that focus on the impacts of catastrophes (Callen, 2015; Cameron and Shah, 2015, Cassar et al., 2017; Chantarat et al., 2019) or shocks (Di Falco and Vieider, 2022; Sakha, 2019; Liebenehm et al., 2023) on risk preferences in the developing-country context. Our approach differs from previous panel-based studies that examine how weather experiences or other shocks affect current levels of measured risk preference in that we explore how such deviations affect the change in elicited preference from one survey round to the next. Rather than focusing on a single factor that might affect farmer experience, we consider multiple weather and experience factors that might simultaneously affect the preferences of farmers – sometimes in potentially contradictory ways. Aside from Di Falco and Vieider (2022), no other studies consider the impact of continuous deviations in precipitation on risk preferences, and no other studies have included temperature and killing degree days as potential determinants. Moreover, unlike previous studies, we tested whether general farm-level proneness to crop stressors affects the rate at which a farmer's preferences evolve. We found that farmers with submergence-prone land seem to be more willing to take on risk, consistent with our hypothesis, but farmers with salinity-prone land were less willing to bear risk. An incidental but broadly relevant implication of this study contributes to the literature on stability in risk preferences. We found that preferences were only weakly related over time, contrary to previous studies.

Additional analysis of the data makes clear the regional heterogeneity of outcomes due to differences in regional experience. These differences are of some note in that the impacts of weather variability and proneness to risk vary widely across regions at both the higher level of divisions as well as the less aggregated level of the upazila. As policymakers consider the development of policies to incentivize adaptation and resilience to weather variability, careful note should be taken to incorporate how weather variability affects farmer preferences and therefore the extent of incentives needed to generate the necessary adaptation.

CRediT authorship contribution statement

W. Parker Wheatley: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization, Visualization. **Taznoore Khanam:** Writing – original draft, Visualization, Investigation, Data curation, Conceptualization. **Valerien O. Pede:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Formal analysis. **Takashi Yamano:** Writing – review & editing, Supervision, Resources, Project administration, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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Appendix 1. Risk preference elicitation script

The full text of the survey is not included here; but, to support consideration of the risk preference elicitation method, below is the script of the elicitation process.

As the last question in the survey, we'd like to offer you a choice among the following payment options. Although this is a hypothetical question, please pretend that I am giving you the cash and please think carefully about your choice.

- You may make one choice among the five options after I read all of the options to you.
- After you make that choice, I will throw a six-sided die to determine what payment you would earn hypothetically.

Option 1. You receive a certain payment of BDT 52.
Option 2. If an odd number is rolled (1, 3, or 5), you receive BDT 39.
If an even number is rolled (2, 4, or 6), you receive BDT 77.
Option 3. If an odd number is rolled (1, 3, or 5), you receive BDT 26.
If an even number is rolled (2, 4, or 6), you receive BDT 103.
Option 4. If an odd number is rolled (1, 3, or 5), you receive BDT 13.
If an even number is rolled (2, 4, or 6), you receive BDT 130.
Option 5. If an odd number is rolled (1, 3, or 5), you receive BDT 0.
If an even number is rolled (2, 4, or 6), you receive BDT 155.

Appendix Table 1
Ordered Probit Findings.

	(1)	(2)	(3)	(4)	(5)
Deviations					
KDD Deviation (in days)	−0.1396***	−0.1410***	−0.1332***	0.0738	0.0738
	0.0000	0.0010	0.0010	0.1420	0.1600
Min Temp Deviation (^{o}C)	0.6271***	−0.3883	−0.3756	−2.6428***	−2.6428***
	0.0000	0.1170	0.1380	0.0000	0.0000
Precipitation Deviation (mm)	−0.0002	−0.0004	−0.0004*	−0.0015***	−0.0015***
	0.3730	0.1080	0.0550	0.0000	0.0080
Rice Crop Loss (in kg)	0.0000	0.0000	0.0000	−0.0001	−0.0001
	0.7670	0.9200	0.8720	0.2610	0.2380
Proneness to Risk					
Salinity Index (0 to 7)		−0.1367***	−0.1569***	−0.1785***	−0.1785***
		0.0000	0.0000	0.0000	0.0020
Share Low Land		0.2187**	0.1704*	0.3874***	0.3874***
		0.0260	0.0890	0.0000	0.0070
Share High Land		0.2358	0.2205	0.0683	0.0683
		0.1400	0.1720	0.6840	0.7090
Share Irrigation		0.4347***	0.4483***	−0.0505	−0.0505
		0.0000	0.0000	0.7150	0.6680
Individual and Household Characteristics					
Female			0.3735*	0.1028	0.1028
			0.0540	0.6020	0.6660
Age (years)			0.0014	0.0012	0.0012
			0.6740	0.7060	0.7050
Married			−0.2282	−0.2590	−0.2590
			0.3330	0.2740	0.3010
Education (years)			−0.0002	−0.0009	−0.0009
			0.9870	0.9210	0.9200
# of Adults			0.0464**	0.0526**	0.0526***
			0.0200	0.0100	0.0050
# of Children			−0.0082	0.0187	0.0187
			0.7540	0.4800	0.4900
km from Input Markets			0.0038	−0.0307	−0.0307
			0.8550	0.1570	0.2370
Land Owned (acres)			−0.0103	−0.0265	−0.0265
			0.6200	0.2120	0.1850
Change in Wealth (BDT)			0.0000*	0.0000*	0.0000**
			0.0800	0.0580	0.0460
Cut 1: Constant	−0.9871	−1.3308	−1.3855	−1.8253	−1.8253
Cut 2: Constant	−0.5329	−0.8603	−0.9126	−1.2985	−1.2985
Cut 3: Constant	−0.2602	−0.5742	−0.6247	−0.9792	−0.9792
Cut 4: Constant	0.0250	−0.2750	−0.3236	−0.6536	−0.6536
Cut 5: Constant	0.5911	0.3198	0.2772	−0.0134	−0.0134
Cut 6: Constant	1.0276	0.7765	0.7397	0.4777	0.4777
Cut 7: Constant	1.4109	1.1710	1.1395	0.8987	0.8987
Cut 8: Constant	2.0596	1.8238	1.7976	1.5943	1.5943
Clustered s.e.'s (village)	No	No	No	No	Yes
Regional Dummy Variables	No	No	No	Yes	Yes
# of Observations	827	827	827	827	827
Pseudo R-squared	0.0126	0.0291	0.0329	0.0662	0.0662

Note 1: Values below coefficients are p-values. *, **, and *** correspond to the 0.1, 0.05, and 0.01 levels of significance.

Appendix Table 2
Deviations, Proneness, and Changing Risk Aversion – Whole Sample.

Deviations	
KDD Deviation (in days)	0.155*
	0.074
Min Temp Deviation (^{o}C)	−4.940***
	0.000
Precipitation Deviation (mm)	−0.002**
	0.028
Loss (in kg)	0.000
	0.178
Proneness to Risk	

(*continued on next page*)

Appendix Table 2 (*continued*)

Salinity Index	−0.364***
	0.000
Share Low Land	0.745***
	0.002
Share High Land	0.110
	0.712
Share Irrigation	−0.347*
	0.066
Individual and Household Characteristics	
Female	0.075
	0.691
Age (years)	−0.005
	0.357
Married	−0.161
	0.560
Education (in years)	0.007
	0.631
# of Adults	0.062**
	0.036
# of Children	0.030
	0.474
km from Input Markets	−0.050
	0.243
Land Owned	−0.044
	0.210
Change in Wealth	−0.0000001**
	0.013
Constant	0.597
	0.278
Clustered s.e.'s (village)	Yes
Regional Dummy Variables	Yes
# of Observations	1387
R-squared	0.223

Note 1: Values below coefficients are p-values. *, **, and *** correspond to the 0.1, 0.05, and 0.01 levels of significance.

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