

## Original Research Article

### **Exploring Perceived Weather Uncertainty Among Indian Farmers: Insights from Micro-Level Analysis and Interpretations**

**Comment [p1]:** Perception on weather risk among Indian farmers: A micro analysis

#### **ABSTRACT**

India's economy relies heavily on farming, crucial for growth, jobs, and survival. But weather uncertainties like droughts, floods, and heatwaves make farming challenging. These uncertainties lower crop yield and quality, causing financial problems for farmers. Despite farmers' efforts, unpredictable weather still hurts crop management. Understanding how farmers feel about these uncertainties is vital for adapting to climate change and reducing risks. The present study was conducted in three villages: Bhomrapara, Mitrapur, and Maniktala of Haringhata block of Nadia district of West Bengal, India, from 2021 to 2022. Nadia district was purposively selected as it comes under the new alluvial zone (NAZ), which has decent productivity in terms of agriculture. A hundred farmers with good farming experiences were identified from the sampling frame, and responses were collected through a structured interview schedule. The study explores the diverse perspectives of Indian farmers on climate-related uncertainty, revealing that factors such as age, education, and landholding size significantly influence these views. Experienced farmers and those with more extensive landholdings perceive more significant uncertainty, with irrigation practices, crop yield, and cultivation costs playing crucial roles. The study emphasizes the urgency of proactive risk reduction and resilience enhancement to avoid severe implications for agriculture and food security.

**Comment [p2]:** Risks instead of uncertainty

#### **INTRODUCTION**

Indian economy predominantly depends on the agricultural sector as almost two-thirds of the nation directly or indirectly depends upon it (Srivastava et al., 2016). A significant percentage of the population receives employment, financial support, and nourishment from it (Saxena, 2018; Gillespie et al., 2019), and also makes a significant contribution to trade, economic and social growth of the community (Bisht et al., 2020; Hinz et al., 2020). Even though the irrigated system depends on monsoon rainfall (Lutz et al., 2022) and the majority of agricultural lands are rainfed (Kumar et al., 2022), the sector is very vulnerable to the hazards associated with climate change, particularly to drought (Roy et al., 2022). Flooding is also a considerable issue in many regions of the nation, particularly in the east, where floods occur frequently (Merz et al., 2021). Furthermore, heat waves in the middle and northern regions, cyclones along the eastern coast, and frost in the northwest equally wreak chaos. Recently, the incidence of these climatic extremes has increased due to the rising air temperature, increasing the possibility of significant losses in crop production (Beillouin et al., 2020). Both direct and indirect effects of climate change on crops, soils, livestock, and pests can impact agriculture (Hatfield et al., 2018). Increased atmospheric carbon dioxide affects agricultural fertility in several ways, including crop length, respiration rates, photosynthesis, evapotranspiration, and fertilizer use efficiency (Kingra&Misra, 2021). Successful farming relies on weather, land quality, irrigation, and crop management(Lal, 2009. Even with farmers doing their best, there are things beyond their control. These unpredictable factors, which can affect farming and make it hard to foresee income or outcomes, are called uncertainty(Reilly &Willenbockel, 2010). Weather uncertainty is the most significant uncertainty in agriculture among all categories. Climatic events like droughts, floods, and extremely high or low temperatures are examples of unpredictable weather patterns that can majorly impact livestock production and crop harvests, underscoring the importance of weather in agriculture(Das, 2005). Weather conditions play a crucial role in determining the quality of

crop output as it gets moved from the field to storage and then to the market(Hoogenboom, 2000). Adverse weather conditions can harm the quality of crops, whether they are left outside, stored indoors, or transported(Miraglia et al., 2009), which can ultimately damage the viability and strength of seeds and planting materials when stored(Long et al., 2014). Farmers generally want to mitigate unfavorable weather conditions, as they can result in substantial financial losses. However, achieving flawless coordination between crop production and meteorological circumstances is enormous. Weather patterns exhibit inherent unpredictability and can demonstrate significant year-to-year variability(Tonkin et al., 2017). Although farmers make diligent attempts to strategize and minimize risks, they cannot exert complete control or accurately forecast the weather(Elias et al., 2019). The absence of predictability in agricultural operations creates uncertainty, which hinders the consistent adjustment of crop quality and production(Hammer et al., 2001). The present study investigates the factors influencing farmers' perceptions of weather-related uncertainty and their contributions and interconnections. This study provides vital insights into how farmers manage the difficulties caused by uncertainty and adjust their methods in response to changing environmental circumstances. The study aims to illuminate the complexities of decision-making in agricultural environments by examining the nuances of farmers' perceptions and the underlying causes that influence them. Gaining a comprehensive understanding of these processes is essential for formulating efficient strategies and interventions to assist farmers in reducing risks and enhancing their ability to withstand unpredictable weather patterns and broader patterns related to climate change.

## METHODOLOGY

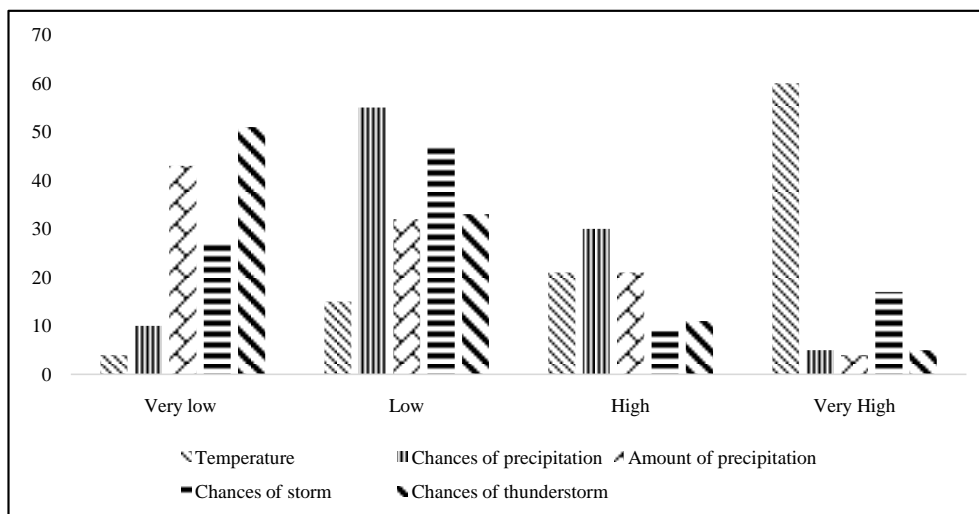
The present study envisages the relationship between the critical factors of **uncertainty** in farming and the socio-ecological variables. An *ex-post facto* research design (Ray & Mondal, 2014) was followed to conduct the study. The study was conducted by randomly

selecting three villages, namely Bhomrapara, Mitrapur, and Maniktala, of the Haringhata block of Nadia district in West Bengal. Nadia district of West Bengal comes under the New Alluvial Zone (NAZ), characterized by highly fertile, productive land and high cropping intensity (Chatterjee et al., 2015; Gangopadhyay et al., 2022). Despite that, the farmers are not facing easy farming due to uncertainty. A score of 100 respondents has been selected through a random sampling method. Data are collected between August 2021 and May 2022 through a structured interview schedule using face-to-face interactions. The data were collected in terms of independent and dependent variables. Twenty-three socio-ecological variables are identified as independent variables based on the review of literature and pilot study for the study. For assessing uncertainty in agriculture, the dependent variable, i.e., weather uncertainty (WU), is considered the prime factor of uncertainty. This variable is quantified using a ten-point rating scale.

$$WU = \frac{(WUS_1 + WUS_2 + WUS_3 + WUS_4 + WUS_5)}{5} \text{ Where } WUS = \text{weather uncertainty statement}$$

A score of ten defines the highest perception value, and a score defines the lowest perception value, respectively, with five statements. The collected data are analyzed through both descriptive and multivariate analysis. Statistical Package for the Social Science v23.0 (SPSS) of IBM and online statistical tool OPSTAT (Sheoran et al., 1998) are used for analyzing the coefficient of correlation, stepwise regression, and path analysis.

## **RESULT AND DISCUSSION**



*Fig 1. Perceived uncertainty of different climate events*

Figure 1 presents the selected farmers' perceived uncertainty of different climate events. The study shows that 60 per cent of farmers had perceived very high uncertainty about the temperature, 55 per cent of farmers had perceived low uncertainty about chances of precipitation, and 47 per cent about chances of the storm. At the same time, 51 per cent and 43 per cent of farmers had perceived very low uncertainty about the chances of thunderstorms and the amount of precipitation, respectively. The study suggests that the farmers have a broad understanding of the uncertainty of different climate events, ranging from very low to very high. A similar study also reveals that the participant has a good appreciation of the uncertainty of weather forecasts. However, they tend to avoid forecasts based on low probabilities for their decisions (Kox et al., 2015).

#### **Relation between perceived weather uncertainty and selected socio-ecological variables**

Weather uncertainty is a condition where an uncertain weather event can be seen that directly impacts farming. Farmers can perceive uncertain weather conditions by achieving some socio-ecological attributes. Table 1 envisages the association between the dependent

variable, perceived weather uncertainty, and selected socio-ecological variables using Pearson's multiple correlation coefficients. It has been found that variables age (x1), education (x2), dependency ratio (x6), cultivated land (x7), landholding(x9), irrigated land (x11), crop diversity index (x13), yield of crop (x14), cost of cultivation (x15), information seeking behavior (x21) have recorded significant correlation with the dependent variable perceived weather uncertainty. among them, the following variables age (x1), landholding (x9), and cost of cultivation (x15) have recorded positive correlations, whereas education (x2), dependency ratio (x6), cultivated land (x7), irrigated land (x11), crop diversity index (x13), yield of crop(x14), information seeking behavior (x21) have recorded negative correlation with perceived weather uncertainty.

**Table 1: Coefficient of Correlation: Weather uncertainty (y) and 23 independent variables (x1-x23)**

Sl. No.	Independent Variables	'r' value	Remarks
1	Age(x1)	0.253	*
2	Education (x2)	-0.266	**
3	Family size (x3)	-0.053	
4	Sex ratio (x4)	-0.061	
5	Cost of energy consumption (x5)	0.083	
6	Dependency ratio (x6)	-0.426	**
7	Cultivated land (x7)	-0.206	*
8	Homestead land (x8)	0.039	
9	Landholding(x9)	0.482	**
10	Number of fragments (x10)	-0.156	
11	Irrigated land (x11)	-0.393	**
12	Cropping intensity (x12)	-0.059	

13	Crop diversity index (x13)	-0.389	**
14	Yield of crop (x14)	-0.292	**
15	Cost of cultivation (x15)	0.342	**
16	On-farm income (x16)	-0.134	
17	Off farm income (x17)	0.011	
18	Income per year (x18)	-0.120	
19	Training received (x19)	-0.166	
20	Farming experience (x20)	0.133	
21	Information seeking behaviour (x21)	-0.406	**
22	Health status (x22)	0.110	
23	Stress (x23)	-0.070	

*N.B. \*\*Correlation is significant at the 0.01 level; \*Correlation is significant at the 0.05 level*

The study reveals that older farmers have a heightened perception of weather uncertainty due to their extensive farming experience. Farmers with larger land areas under cultivation may encounter more uncertain weather events, leading to increased cultivation costs due to unfavorable conditions. Conversely, farmers with lower levels of education tend to view weather uncertainty more negatively. Higher education and better training may mitigate the impact of weather uncertainty. Those who rely more on other family members' earnings often face more significant weather uncertainty. Farmers with smaller Landholdings are particularly vulnerable to extreme weather events. Regions with less irrigation suffer more from weather uncertainty, as irrigation can mitigate extreme weather effects. Weather uncertainty significantly affects crop yields. Seeking more weather information helps reduce uncertainty. Larger farms experience more pronounced effects from weather uncertainty. Similar studies also reveal that the factors affecting different categories of climate change perceptions depend upon a series of factors, including both socio-economic and

psychological considerations, viz. gender, age, education, soil fertility status, climate change information, and access to credit services (Kingra&Misra, 2021), being located in an area with external water supply, owning fields with salinization issues, cultivating drought or salt-sensitive crops, farm revenue, drought risk experience, and perceived control (Duinen et al., 2014; Dang et al., 2019).

### Predicting perceived weather uncertainty on selected socio-ecological variable

Table 2: Stepwise Regression Analysis: Weather uncertainty (y) vs. 23 Causal Variables (x1-x23)

Sl. No.	Variables	Reg. coef. B	SE B	Beta	t value
1	Landholding(x9)	0.394	0.066	0.394	5.931
2	Irrigated land (x11)	-0.423	0.068	-0.423	-6.264
3	Yield of crop (x14)	-0.186	0.074	-0.186	-2.502
4	Crop diversity index (x13)	-0.169	0.079	-0.169	-2.139
5	Dependency ratio (x6)	-0.320	0.073	-0.320	-4.363
6	Cost of cultivation (x15)	0.281	0.092	0.281	3.045

*R square: 70.90 percent; The standard error of the estimate: 0.556*

Table 2 presents the stepwise regression analysis for screening out the most dominant causal variable impacting weather uncertainty (y). It has been found that the following variables, Landholding(x9), irrigated land (x11), yield of crop (x14), crop diversity index (x13), dependency ratio (x6), cost of cultivation (x15) have been retained at the last step. These six variables (dominant) together have contributed 70.90 percent variance embedded in the dependent variable perceived weather uncertainty. Interestingly, these six variables have made a net contribution of 91.60percent of the total variance explained. These six variables have tremendous strategic importance. Weather uncertainty and landholding size are closely

associated. The more land under irrigated farming, the less impact weather has on generating uncertainty. Irrigated land provides higher security and less uncertainty due to controlled management and consistent income. Crop yield serves as a strong predictor and indicator of weather uncertainty. Yield fluctuations are directly linked to weather variations. Crop diversity is essential for estimating weather uncertainty intensity and mitigating its effects. Dependency ratio usage affects both costs and risk perception. When costs increase, risk implications are amplified, creating a ripple effect. Cultivation costs serve as a standard indicator for assessing uncertainty levels. Information seeking and sharing are crucial for addressing uncertainty and are logically connected to the dependency ratio. Several similar studies also support that the availability of specific and agro-ecologically relevant weather forecasts is essential to overcome perceptual problems and to support effective adaptation (Etana et al., 2020) along with the provision of climate change-related information through various outlets may be helpful to distribute timely and relevant information to farmers. Institutional measures and arrangements, such as improved agricultural extension services, can have an increased impact in facilitating information exchange and motivating farmers to take necessary action in due course time (Habtemariam et al., 2016). It is also essential to adequately reduce the problem of lack of money, resource constraints, and shortage of irrigation water to adapt the mitigation strategies related to weather-related uncertainties (Abid et al., 2015).

Table 3: Decomposition of total effect perceived weather uncertainty (y) into direct, indirect and residual effects on selected socio-ecological variables

Sl. No	Independent variables	TE	DE	IE	HIE
1	Age(x1)	0.253	0.078	0.175	0.143 (x15)
2	Education (x2)	-0.266	-0.023	-0.243	-0.125 (x18)

3	Family size (x3)	-0.053	-0.393	0.340	0.677 (x16)
4	Sex ratio (x4)	-0.061	0.124	-0.185	-0.618 (x18)
5	Cost of energy consumption (x5)	0.083	0.282	-0.199	0.641 (x16)
6	Dependency ratio (x6)	-0.426	-0.315	-0.111	-0.087 (x9)
7	Cultivated land (x7)	-0.206	-0.175	-0.031	1.137 (x16)
8	Homestead land (x8)	0.039	0.152	-0.113	0.658 (x16)
9	Landholding(x9)	<b>0.482</b>	0.336	0.146	-0.223 (x16)
10	Number of fragments (x10)	-0.156	-0.138	-0.018	1.003 (x16)
11	Irrigated land (x11)	-0.393	-0.392	-0.001	-0.085 (x16)
12	Cropping intensity (x12)	-0.059	0.021	-0.080	-0.669 (x18)
13	Crop diversity index (x13)	-0.389	-0.177	-0.212	-0.132 (x15)
14	Yield of crop (x14)	-0.292	-0.188	-0.104	-0.100 (x15)
15	Cost of cultivation (x15)	0.342	0.227	0.115	-0.115 (x16)
16	On-farm income (x16)	-0.134	1.215	<b>-1.349</b>	-1.198 (x18)
17	Off farm income (x17)	0.011	0.388	-0.377	-0.558 (x18)
18	Income per year (x18)	-0.120	<b>-1.231</b>	1.111	1.182 (x16)
19	Training received (x19)	-0.166	-0.026	-0.140	0.154 (x16)
20	Farming experience (x20)	0.133	0.047	0.086	0.511 (x16)
21	Information seeking behaviour (x21)	-0.406	0.001	-0.407	-0.222 (x9)
22	Health status (x22)	0.110	-0.058	0.168	0.092 (x18)
23	Stress (x23)	-0.070	-0.037	-0.033	0.117 (x16)

*TE= Total Effect; DE= Direct Effect; IE= Indirect Effect; HIE= Highest Indirect Effect;*

*Residual effect: 0.228*

Table 3 presents the path analysis wherein the total effect of the dependent variable has been decomposed into direct, indirect and residual effects of selected independent variables. Evidently, yearly income has exerted the highest direct effect on perceived weather uncertainty. The higher the weather uncertainty, the poorer has been the income. Again, On-farm income has come out with an intensive associative property to characterize the weather uncertainty by a clandestine maundering of the role and Contribution of other variables. The residual effect of 22.8 per cent is to conclude that even with a combination of 23 causal variables, around 23 percent of variants in consequent variables and around 23percent of variants in perceived weather uncertainty could not be explained. The variable irrigated land has routed the highest indirect effect of 11 other causal variables to characterize the perceived weather uncertainty.

### **CONCLUSION**

Uncertainty is an intrinsic characteristic of any system characterized by multiple contradictory factors that remain unpredictable or incomprehensible. In such situations, the system's complexity level is inversely proportional to its ability to withstand and recover from disruptions. Farmers, whose livelihoods depend on the success of their crops, are acutely aware of the potential destruction that irregular weather patterns can inflict. Variations in precipitation and temperature may cause severe impacts on crop production, leading to a subsequent decrease in food supply. The findings indicate that farmers have a wide range of views of uncertainty, which differ depending on the specific climate occurrences. age, education, and landholding size are important socio-demographic factors that majorly impact these beliefs. Elderly farmers and those with more extensive landholdings tend to experience increased uncertainty. Factors such as irrigation practices,

crop yield, and cultivation costs are solid determinants of weather uncertainty. The study also reveals the complex interaction between these variables, highlighting income per year as a significant direct contributor. Although causal factors have been thoroughly examined, a substantial percentage of the uncertainty variation remains unexplained, indicating the complex nature of weather-related challenges. This instability weakens farmers' endeavors and makes it highly challenging to rationalize any modifications to their current farming techniques. These observations emphasize the necessity of implementing specific interventions and policy actions to strengthen the ability of agriculture to withstand the uncertainties caused by climate change. The complex interaction of uncertainties in the Indian agricultural production system highlights the pressing requirement for proactive actions to reduce risks and enhance resilience. Neglecting to tackle these difficulties comprehensively could result in significant implications, impacting not only the agricultural sector but also the country's overall food security.

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