Original Article *Journal of Sustainability and Environmental Management (JOSEM), Vol. 1, No. 3 (2022), 321 – 331*
p-ISSN 2822-1729, e-ISSN 2822-1737 Available online at https://www.nepjol.info/index.php/josem

Rainfall and Temperature Perception among Farmers in India: A Study of Bundelkhand Region

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Abstract: Climate change has impacted the crop yield and affected the livelihoods of the farmers. Using a systematic random sampling technique, 200 samples were collected from two districts, viz., Jhansi and Jalaun of Bundelkhand region, India from September to November 2017, while rainfall and temperature data were collected from 1969 to 2017 from the Indian Meteorological Department of India to find the link between farmers' perception on rainfall & temperature, and district's rainfall and temperature pattern in long-term. Different statistical tools such as the Man Kendall test was employed to examine the rainfall and temperature trends, while the Breusch-Pagan test was used to check heteroscedasticity in the model. Further, the binary logistic regression model was also used to examine the determinants of farmers' perceptions using socioeconomic variables. The results confirm based on the majority of the farmers' perception that temperature has increased, while rainfall has declined. These results are in a similar line with the district's rainfall and temperature trends. The regression results suggest that gender, education, and access to toilets are less likely to influence the farmers' perception of climate change, while age, income, and access to electricity are significantly likely to influence the farmers' perception of climate change. Hence, policy should be implemented to enhance rural farming communities' awareness of climate change by providing training and creating awareness

Keywords: *Agriculture, Binary logistic model, Climate adaptation, Climate change, Mann kendall, Rainfed, Vulnerability*

Conflicts of interest: None
Supporting agencies: None

Received 02.06.2022; Revised 03.08.2022; Accepted 22.08.2022

Cite This Article: Jatav, S.S. (2022). Rainfall and Temperature Perception among Farmers in India: A Study of Bundelkhand Region. *Journal of Sustainability and Environmental Management*, 1(3), 321-331.

1. Introduction

The special report of the Intergovernmental Panel on Climate Change (IPCC, 2018) stated that anthropogenic activities had caused approximately 1^0C of global warming from pre-industrial levels, with a likely range of 0.8^0C to 1.2^0C. Since the pre-industrial period, the land surface air temperature has risen nearly twice (IPCC, 2020). Global warming has resulted in an increased frequency, intensity, and duration of heat-related events. The frequency and severity of droughts in the rainfed area have increased dramatically, while the rate of heavy precipitation events has increased manifolds in the tropical regions. The catastrophic impact of climate change is that it has led to a shift of climate zones in many agro-regions, including expansion of arid climate zones and contraction of polar climate zones. As a result, many plants and animal species have experienced changes in their ranges, abundances, and shifts in their seasonal activities. Climate change creates additional stress on land, exacerbating existing risks to livelihoods, biodiversity, human and ecological health, infrastructure and food systems.

Agriculture will be more affected regionally by climate change than any other sector as it is directly linked with natural resources. Yet much of the climate change debate is about the reduction of the factors causing climate change such as industrial CO_2 emissions (IPCC, 2014). With current carbon-reduction agreements unlikely to stabilize concentrations of greenhouse gasses in the atmosphere over the next few decades, it is projected that agricultural productivity may continue to decline in some regions, while rainfed regions would get affected greatly (Mendelsohn et al., 1994).

Farmers in developing countries have always faced multiple risks. For example, in India, major concerns for farmers are weather variability, lack of access to modern technology, and correct & updated timely weather information (Jatav, 2021; Jatav et al., 2021 a & b). Campbell et al (2016) observed that the knowledge of the link between weather variability and crop yield has marginally increased. However, understanding only one risk is an inadequate picture of all types of risk for farmers. In this connection, Komarek et al (2020) found that there are five types of farmers' risks in agriculture namely, production risk, market risk, institutional risk, personal risk, and financial risk. Production risks stem from uncertain weather conditions, pests, and diseases. Market risks largely focus on short-term fluctuation in prices, costs, and market access, whereas, Institutional risks are related to unpredictable changes in the policies and regulations that affect agriculture (Harwood et al., 1999). Sources of institutional risk such as unpredictable changes in the actions of informal trading partners, rural producer organizations, or changes in social norms affect agriculture. Personal risk is specific to an individual and relates to problems with human health or personal relationships that affect the farm or farm household such as injuries from farm machinery, the death or illness of family members from diseases, negative human health effects from pesticide use, and disease transformation between livestock and human (Tukana and Gummow, 2017). Financial risk refers to the risk associated with how a farm is financed. It is defined as the additional variability of a farm's operating cash flow due to the fixed financial obligations inherent in the use of credit (de Mey et al., 2016).

Undoubtedly, aforesaid, risks have increased the vulnerability of agriculture in particular and the livelihoods of farmers in general (Singh, 2019). The IPCC report (2007) highlighted that because of these risks, farmers remained in poverty and low production traps. Vulnerability is the outcome of an inherent complex socioeconomic and demographic structure. Therefore, though farmers have surplus production, due to ineffective market mechanisms (supply-chain management), they hardly get remunerative prices for their products. This leads to lower farm income, while their farm-production costs are much higher (poverty trap). The fifth assessment report (AR5) of IPCC (2014) highlighted the components and interchange relationship between exposure, sensitivity, and systems capacity in the context of climate variability and change. Unpredictable, regional weather conditions have exposed farmers to climate change, while lack of access to basic amenities and complex social systems have increased the degree of sensitivity (Singh, 2020a). In other words, geophysical conditions of a locality and sensitivity to climate change stresses are the primary causes of risks. The socio-cultural setting plays a crucial role in multiplying the effect of climate stressors and shaping vulnerability. Singh (2020b) suggests that differences in vulnerability and exposure arise from many non-climatic factors such as households belonging to the backward social group, higher dependency on the head of household, and lack of employment opportunities in the non-farm sector. There is a consensus among social scientists about some of the major factors, such as lack of access to resources including information, knowledge, and technology, limited access to political power and representation; social capital, including social networks and connections; beliefs and customs; age; health; and type and density of infrastructure and networks are identified as factors that influence social vulnerability (Singh and Nayak, 2020; Jatav et al., 2021a).

Agriculture was often the first sector to face the adverse consequences of climate change. Hence, farmers' willingness to adopt new measures or improve their ability to adapt is crucial to mitigating the negative impacts of climate change (Singh, 2020a). There is consensus among the farmers across the agro-climatic regions that farmers most suffered from three negative impacts of climate change: (i) change in the flowering period due to phonological change (Singh and Nayak, 2014; Singh and Nayak, 2018a & b; Somboonsuk et al., 2018;), (ii) deterioration of soil fertility due to drought and floods (Udmale et al., 2014 & 2015; Singh and Alka, 2019), and (iii) unpredictable rainfall and strong winds in the harvesting season that caused yield reduction (Tripathi and Mishra, 2017; Spear et al., 2019; Singh, 2020a; Singh et al., 2019).

The above discussion signaled that climate change and heterogeneous climates have impacted crop yield and livelihoods of farmers, and the socioeconomic settings of society are key determining factors for the degree of vulnerability. Hence, this study aims to understand farmers' perception of climate change in the rainfed areas i.e., the Bundelkhand region. Further, the important research questions are: What are the socioeconomic and biophysical barriers that restrict farmers to cope with climate change? Do farmers synergize the weather forecast information and indigenous knowledge to optimize their risk aversion capacity?

2. Materials and methods

2.1. Study area and data source

The study was undertaken in the Bundelkhand region of Uttar Pradesh, India. Uttar Pradesh is the most populous state of India and plays a vital role in India's food and nutritional security by contributing to about 18% of the country's total food grain production in 2016-17 (GoI, 2018). Geographically, Uttar Pradesh is divided into four economic regions, viz., Western, Central, Eastern, and Bundelkhand. This study was undertaken in two districts of the Bundelkhand region, viz. Jalaun and Jhansi, owing to the preponderance of droughts in the region (Fig. 1). Compared to any other region, Bundelkhand is historically more vulnerable to climate change. The region had experienced drought once every 16 years during the 18th and 19th centuries, whereas, the frequency of the same increased thrice from 1968 to 1992, and now it become a recurrent annual phenomenon (GoI, 2017). The average annual rainfall of the region continued to be below average during 2004-2017.

Further, primary and secondary data were collected to examine the link between rainfall and temperature trends and farmers' perception. Secondary data on rainfall and temperature were collected from the Indian

Meteorological Department of India. The data at the village level necessitated capturing regional changes in climate. District-level level data as a proxy for the study villages on rainfall and temperature were collected from 1901-2017. Villages in the Jhansi and Jalaun districts portray fairly similar characteristics, typical of the dry region (GoI, 2017). Therefore, the adequacy of using data from the districts as a proxy for villages in the area is justified. From September to November 2017, primary data was collected from farmers.

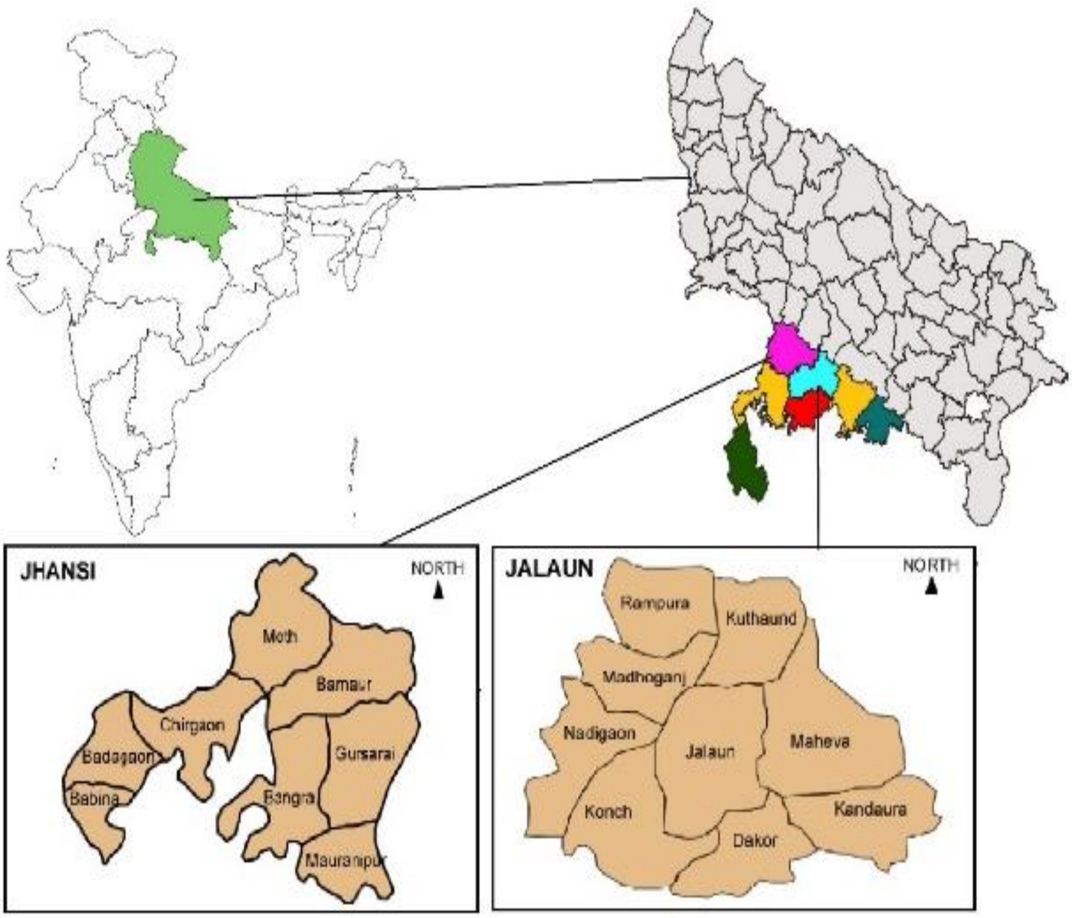

Figure 1: Map of the study area

2.2. Sample size and sampling technique

A detailed and comprehensive field survey was conducted to elicit information on farmers' perceptions regarding climate change, agricultural extension services, and the selection of adaptation strategies used by farm households to cope with climate change. A multi-stage sampling technique opted for the sample selection. In the first stage, from a total of 13 districts in the Bundelkhand region, 2 districts (one developed district i.e., Jhansi, and one developing district i.e., Jalaun) were selected based on different hydrological, climatic, soil, and agricultural parameters. There are five sub-divisions (i.e., *Tehsils*) in each selected district, and in the second stage, all five *Tehsils* from each district were chosen for the survey. In the third stage, one Development Block was chosen purposively from each *Tehsil*. In the fourth stage, one village (micro administrative unit) from each Development Block was chosen randomly. Finally, 20 households from each village were selected randomly. Thus, a total of 2 Districts, 10 *Tehsils*, 10 Development Blocks, 10 Villages, and 200 farm households were selected for the study. This study has adopted three criteria in the selection of farm households. First, villages were selected in a way that was closer to the district headquarters. Secondly, the sample households had easier access to inputs, institutional facilities, and management. Lastly, the study includes all land size groups, such as marginal (<1.0-hectare, ha), small (1-2 ha), semi-medium (2-4 ha), and medium (4-10 ha), and large (>10 ha) categories of farms. The preliminary information on the farm-households was collected from the office of the Head of the village (i.e., *Pradhan*).

A well-designed survey schedule was used to record farmers' perceptions, understanding of climate change, experiences with climate variability, and extreme events over the past decade. Likewise, their choice of adaptation and a possible reason for observed changes, if any. During the survey, information was specifically asked farmers about their experience with changing temperature and rainfall patterns over the past five years.

2.3. Estimation method

In case of meteorological data, the most recent observational approach to filling missing data has been adopted (Chepkoech et al., 2018), while missing data have been filled in by frequency analysis in primary quantitative data. Meteorological data containing daily records were used to calculate the average annual values. The first analysis was performed using the line graph, box, and disperse plots, for example, normality and outlier check.

Descriptive statistics were calculated with frequencies and percentages. Analysis of Variance (ANOVA) model was applied to draw inference on farmers' perception, which is determined by factors such as social, economic and demographic.

The study also examined the homogeneity of the variance exceeding 0.05. According to Pallant (2016), if the homogeneity of the variance is greater than 0.05, it indicates that the homogeneity of the variance assumption is not violated.

To understand the determinants of farmers' perception, a binary logistic regression model was used because its underlying assumptions are less restrictive than those of other models and it is free from problems with the use of ordinary least square model (Gujarati, 2014). The coping strategy (farmers' perception) is the dichotomous dependent variable (Y) of this model having a binary value of one (1) if farmers perceived that temperature has been increased during the past five years, and zero (0) if otherwise (Singh, 2020a; Jatav et al., 2021). The model also assumes that the use of adaptation strategies (farmers' perception) is a log-linear function of the exogenous variables X_1, X_2 of the term.

$$L_i = Ln\frac{P_i}{1-P_i} = Z_i = B_0 + B_1X_1 + B_2X_2 + \cdots B_nX_n + \text{Ui} \quad (1)$$

That is Ln is the log of the odds ratio, which is not only linear in X_i but also linear in the parameters. Where, Li= logit model, Pi is the probability of farmers perception on temperature increased.

$$P = \frac{1}{1+e^{-2}} = \frac{e^z}{1+e^z} \quad (2)$$

Where,

$$Z = B_0 + B_1X_1 + B_2X_2 + B_nX_n + \text{Ui} \quad (3)$$

Therefore, the probability of not perceiving of changing temperature is:

$$1 - P = \frac{1}{1+e^2}\frac{P}{1-P} = \frac{1+e^z}{1+e^z} \quad (4)$$

Now, P/(1-P) is simply the odds ratio in favour of farmers' perception i.e., the ratio of the probability of farmers perception that temperature has been increased to otherwise.

Thus, if P= 0.9, it means that odds are 0 to 1 in favour of farmers' perception. Therefore, if P goes from 0 to 1 (that is, as z varies from -X_i to+X_i), the logit, Li goes from –X to +X. although the probability lies between 0 and 1, the logit is not so bounded. Questions were categorically asked to the farmers on their perceptions such as 'do you perceived that temperature has been increased during the past five years'. Finally, the study hypothesized that there are different factors affecting farmers' perception on increasing temperature over the past five years to deal with changing climate.

Multicollinearity and heteroscedasticity assumptions were checked prior to the calculation of the regression. A simple correlation matrix was computed to determine the multicollinearity of the variables in the model (Table 1). Gujarati (1995) establishes a thumb rule, which states that, when the correlation coefficient is 0.8 or higher, multicollinearity is a serious problem. The study also tested to find out whether heteroscedasticity was present in the model using Breusch-Pagan test. The results show that null hypothesis is constant variance should be rejected ($X^2(8) = 35.7$; $p < 0.001$). In effect, the White covariance matrix which provides consistent estimates of standard errors, was computed so as far the *t* and *F* test to be asymptotically valid.

Finally, for meteorological data, linear regression, Mann Kendall test and linear plots were employed to investigate climate trends. As Jaiswal et al (2015) suggested that Mann Kendall test, which assumes that meteorological data is randomly ordered and independent, aided in the testing the hypothesis that there is no trend in climate, using rainfall and temperature as proxies. Non-parametric linear regression and linear plots also aided in examining patterns and relationships in climate data (rainfall and temperature), while Pearson product-moment correlation aided in examining the relationship between climate data and farmers' perception to climate change.

Table 1: Results of correlation matrix

	Perception	Age	Gender	Income	Literacy Rate	Home	Electricity	Drinking water	Toilet
Perception	1								
Age	0.0049	1							
Gender	-0.0019	-0.2352	1						
Income	0.0043	0.2342	-0.3245	1					

Literacy rate	0.0432	-0.2387	0.0543	0.0642	1				
Home	0.0456	0.3465	0.5674	-0.4324	0.0875	1			
Electricity	0.0238	0.2367	0.0043	0.5643	0.0547	0.0234	1		
Drinking water	-0.1254	-0.7653	0.0436	0.1543	0.0654	0.0765	0.0235	1	
Toilet	-0.1432	-0.4532	0.0765	0.1654	-0.1654	0.0875	-0.0654	0.1543	1

Source: Field Survey Data, 2017

3. Results

3.1. Socio-economic characteristics of the surveyed households

The socio-economic features of sample households reflect the backwardness of the region compared to that of the national level. The literacy rate is relatively lower i.e., 50.24%, and 49.76% in Jalaun and Jhansi, respectively, compared to the national average (Table 2). The workforce participation rate was found 50%. Further, the mean annual income of the household is also low and widely varied. The mean land size of farm households in these two districts (0.26 ha and 0.35 ha, respectively) is also low as compared to the national level (1.18 ha).

Nearly 15% of the population belongs to scheduled castes and scheduled tribes (backward social groups in India) categories.

Furthermore, 35% of Jalaun and 20% of households in Jhansi don't have an electricity connection. Nearly 50% & 40% of the sample population don't have sanitation and drinking facilities within the premises home. Nearly 30% of the population is living in extreme poverty. In totality, the results show that the majority of the sample household is deprived of basic amenities.

Table 2: Socio-economic characteristics of surveyed farm households

Characteristics	Jalaun	Jhansi	India
Female (%)	44.74	44.18	48.00
Illiterate population (%)	50.24	49.76	74.01
Work Force Participation Rate (%)	49.94	50.06	44.10
Mean Income ($)	334.00	374.00	2198.00
Mean land size (Acre)	0.26	0.35	1.18
Mean age of the household (Years)	31.36	30.04	29.00
Scheduled caste population (%)	13.82	7.81	16.60
Scheduled tribe population (%)	2.80	5.10	8.60
Hindu Religion (%)	84.21	84.37	79.80
Marital Status (%)	52.39	53.32	45.60
Households having electricity connection (%)	65.00	80.00	89.70
Households having sanitation facility (%)	57.00	51.00	51.77
Households using safe drinking water facility (%)	61.00	60.00	99.14
Households living below poverty line (%)	29.00	26.00	23.60

One US$= 69.49 Indian Rupees (INR)

3.2. Variability in rainfall, and minimum & maximum temperatures

The distribution pattern of rainfall for India is very uneven and varies considerably from year to year and region to region. In the Bundelkhand region (Jhansi and Jalaun districts), there is high variability in rainfall (Figure 2). Rainfall variability has been defined as the deviation of rainfall from the mean or the ratio of the standard deviation to the mean or the variability of the coefficient of variation (Rathod and Aruchami, 2010). The mean annual rainfall in Jhansi and Jalaun is about 350 millimeters. The calculated variability in rainfall from 1969-2017 for the Jhansi and Jalaun revealed that it has declined in both the districts (Figure 2).

As far as variability in temperatures (minimum & maximum) is concerned, the variability has declined from 1969-2017 (Figures 3 & 4). However, both minimum & maximum temperatures trends show a sharp and steady increase. In Jhansi and Jalaun, agriculture is solely a source of income that is adversely affected by the variability in these climatic factors. Hence, unpredictable rainfall and continuous increase in temperatures have great concern for livelihood security.

To detect linear trends in rainfall and temperatures, the Mann-Kendall test was deployed. The Mann-Kendall test, which tested the hypothesis that 'there is no trend in rainfall and temperature' are presented in Table 3. However, results confirm that there are significant trends in minimum and maximum temperatures at $p = 0.006$ and $p = 0.001$, respectively. The test results for annual rainfall don't follow a linear trend ($p = 0.243$).

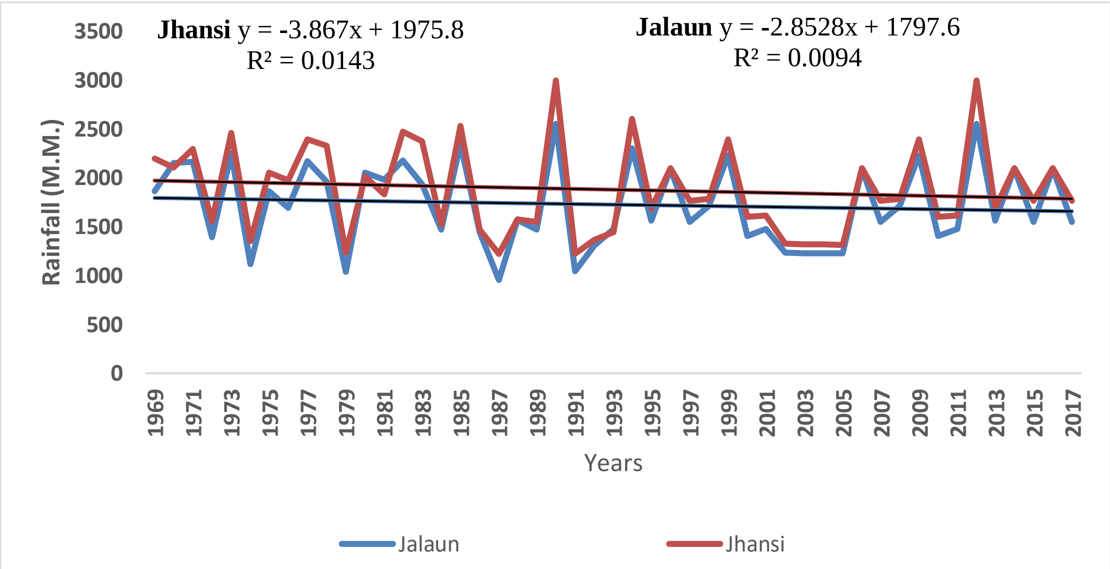

Figure 2: Variability in annual rainfall

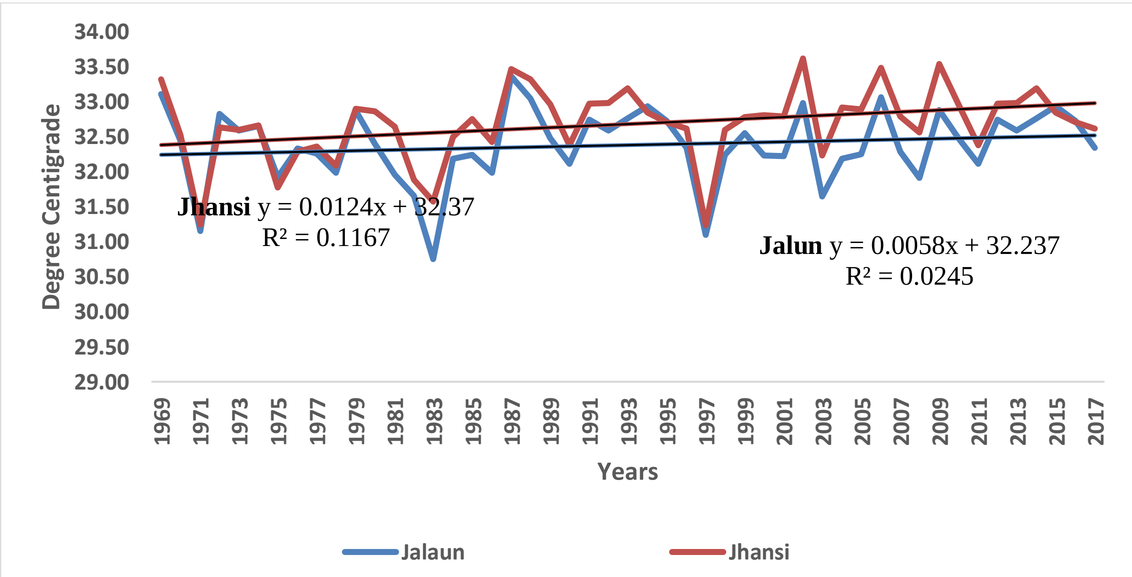

Figure 3: Variability in maximum temperature

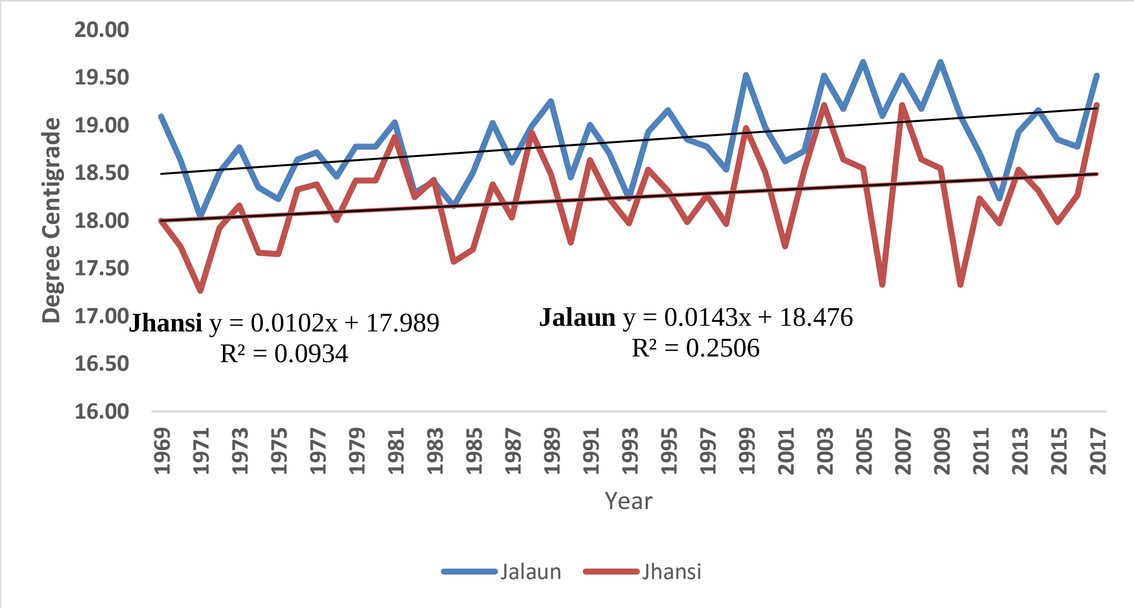

Figure 4: Variability in minimum temperature

Table 3: Mann-Kendall and regression analysis for temperature and rainfall

Variables	Mann-Kendall Test			Regression Analysis		
	MK Statistics (s)	*p*-value	Test interpretation	Regression equation	R^2	*p*-value
Annual Rainfall	0.119	0.181	No Trend	Y = -632.08X+4.50	0.048	0.243
Maximum Temperature	0.277	0.041	Trend Detected	Y = -893.77X+7.48	0.234	0.006*
Minimum Temperature	0.454	0.034	Trend Detected	Y = -521.09X+8.52	0.355	0.001*

* p is significant at 0.05

3.3. Farmers' perception of climate change

The calculated results of farmers' perception of climate change reveal that both rainfall and temperatures trend has been changed over the past 20 years. More than 80% of farmers strongly perceived that there have been changes in both annual and seasonal rainfall pattern (Figure 5). About 90% of farmers strongly noticed an increase in the incidence of heat waves. More than 80% of farmers perceived that the monsoon rainfall pattern has been changed both early withdrawal and the late withdrawal of monsoon rainfall. Our results are in the line with Indian Meteorological Department (IMD) temperature record for the Jhansi and Jalaun, which suggests a significant increase in annual temperature levels by about 0.01/0C over year from 1969-2017.

The results also suggest that the surveyed villages were witnessing elevated precipitation and rising temperature. Nevertheless, the findings have shown that there is no substantial link between the expectations of climate change among farmers and meteorological evidence, as seen in Table 4, as a marginally favorable rainfall link (r = 0.091, p= 0.020) and a weak negative correlation with temperature (r = -0042, p = 0.060). There is also a negative relationship between average rainfall and average temperature (r = -0.045, p = 0.029), which indicates that as temperature increases, there is a reduction in rainfall and vice versa. Because the farmers reported less rainfall in the season, their experiences confirm the relationship between rainfall and temperature. Season at high temperatures, with less sunlight and a resulting low temperature during the wet season.

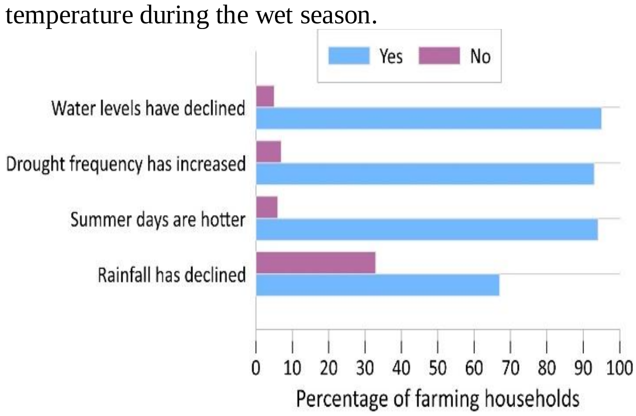

Figure 5: Farmers' perception of climate change

Table 4: Correlation between climate data and farmers' perceptions

Variables	Farmers' perception	Average Rainfall	Average Temperature
Farmers' Perception	1		
Average Rainfall	0.091 (0.020)	1	-0.064 (0.022)
Average Temperature	-0.042 (0.060)	-0.045 (0.029)	1

Note: Values in parenthesis are the probability statistics

3.4. Climate change impact on agriculture

Several studies point out that farmers' perception of climate change's impact on agricultural productivity and livelihoods depends on their recent experiences (Bryan et al., 2009). Deressa et al (2009 & 2011) find that farmers' memory of past climatic variability may be distorted in systematic ways, reflecting wishful thinking by distortions consistent with decision goals as well as being shaped by personality characteristics and pre-existing beliefs.

The present study findings reveal that climate change adversely impacts agricultural productivity in particular and livelihood security in general (Figure 6). About 88% of farmers perceived that climate change has declined the quality of common property resources, i.e., water and soil. Farmers' perceptions of a reduction in crop yields, higher salinity due to uneven rainfall distribution, and an increase in pests & diseases range from 59 to 70%, while more than 50% of farmers perceived that net income has declined over the past five years due to adverse impacts of climate change. As far as livelihood security is concerned, adverse impacts of climate change have reduced agriculture employment & consumption expenditure. Farmers are well aware of the adverse impact and trying to cope with it by reducing their social and economic expenditure, and selling their jewellery.

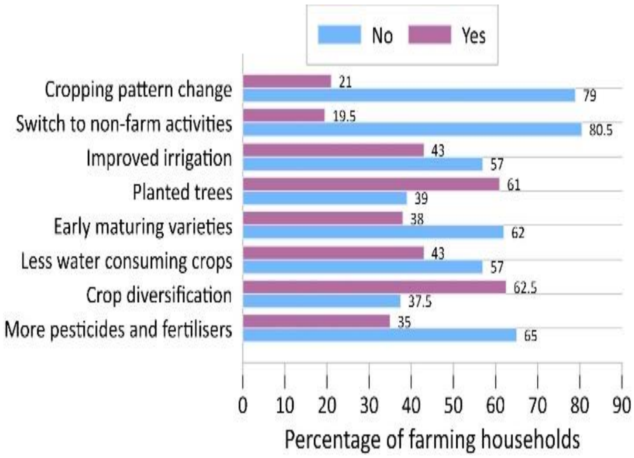

Figure 6: Adaptation strategies adopted by surveyed farm households

3.5. Determinants of farmers' perception of climate change

The binary logistic regression is applied to understand the impact of socioeconomic characteristics of farmers on their perception of climate change. The model statistics such as Pseudo R^2 explained 31% of the goodness of fit. Also, LR chi^2 value signifies that the model is statistically significant at a 1 % level (Table 5).

The results confirm that gender, education, and toilets are less likely to influence farmers' perception of climate change, while age, income, literacy rate, and access to electricity are significantly influencing farmers' perception of climate change. In totality, well-educated, experienced, and rich farmers are well-aware of climate change and they have mobilized their resources to overcome the adverse effects of climate change.

Table 5: Predictors of climate change perception

Variable	Coefficient	Odd Ratio
Age (continuous)	0.0087*	1.25
Gender (Male= 1, otherwise= 0)	-0.0621*	0.29
Income (continuous)	0.2019*	3.26
Literacy Rate (above from secondary= 1, otherwise= 0)	0.8123*	4.26
Home (having all seasonal house= 1, otherwise= 0)	0.8687***	2.45
Electricity (having electricity connection= 1, otherwise= 0)	0.9171*	1.25
Drinking Water (access of safe drinking water= 1, otherwise= 0)	-0.7273**	1.59
Toilet (access of toiled within premises= 1, otherwise= 0)	-0.4092**	2.42
Constant	1.6835	0.24
LR Chi^2	25.98	
Prob > chi^2	0.0081	

Pseudo R^2	0.3113
Log likelihood	−72.993
No. Observation	200

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

4. Discussion

The study captures farmers' perception of climate change using micro-level data which was collected through an extensive field survey. This study finds that there is a general consensus between researchers, policymakers, and farmers that climate change is adversely affecting the agriculture and livelihoods of the farmers. Macro-level studies observe that change in climate results in disturbances of biological actions and ecosystems through shorter seasons of rainfall, droughts, and low crop productivity in rainfed areas (Udmale et al., 2014; Tripathi and Mishra, 2017). Micro level studies (Singh, 2020 a & b; Deressa et al., 2009 & 11; Bryan et al., 2009; Parmeshwar et al., 2014; Nambi et al., 2015; Dhanya and Ramachandran, 2016; Raghavendra and Suresh, 2018) have revealed that small farmers (our case too) are highly vulnerable, their farm productivity has declined substantially which leads to hunger, malnutrition, and diseases and reduces household income as a result of impacts of climate and weather extremes. In other words, it implies that smallholder farmers are largely vulnerable to the extremes of climate and weather events due to the fact that their livelihoods are purely dependent on rainfed agriculture on small farmlands using family labor and little modern inputs. As far as awareness and perception of surveyed farmers about climate change are concerned, there was clear evidence from field survey data that farmers are well aware of climate change. The study carried out in the Bundelkhand region establishes that farmers' perception is perfectly matched with rainfall and temperature data collected from the meteorological department. It justifies that surveyed farmers are in the right direction and they are mobilizing their fixed and variable assets using traditional knowledge, sharing local expertise with fellow farmers, and taking expert advice from government officers to deal with climate change.

5. Conclusion

The results from this study claimed that most farmers are well aware of climate change. The majority of surveyed farmers perceived that temperature is increasing, while rainfall is declining. In order to validate farmers' perception of climate change, the Man Kendall test was used and the results are in favor of farmers' perception. Though farmers are well aware of climate change and trying their best to deal with it. However, due to socioeconomic and demographic constraints, farmers are not in a position to fully utilize their indigenous skills and local resources. With this evidence, the study suggests the following recommendations. First, though farmers are using traditional and local knowledge which is in a similar line with the finding of the meteorological data to deal with climate change, regional climate condition is changing dramatically. Therefore, it is important to enhance awareness of rural farming communities on climate change by providing ICT-based training to adjust their farm and livelihood strategies. Second, there is a need to increase the number of agricultural extension service officers in surveyed districts/villages to help educate farmers on water conservation techniques. Third, there is also need to integrate farmers in all phases of developing the traditional knowledge base, as well as in capitalization and validation of technical, socio-economic and organizational solutions that are available in research. Lastly, it is well acknowledged that the identified factors are crucial for climate policy and decision-making in information dissemination, more attention needs to be paid to the experience of farmers to work closely with scientist in production of weather forecasting knowledge.

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