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Understanding and Risk Perceptions of Climate Change among Small-scale Farmers in the Pishin Lora Basin, Balochistan: The Role of Education, Indigenous Knowledge and Social Networks

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ABSTRACT
Climate change and water scarcity are the most critical phenomena of disasters across the world to increase the vulnerability of populous dependent on water related occupations. This paper analyzes farmers' understanding and risk perceptions of water scarcity, climate variability, and climate change impacts in the Pishin Lora Basin, Balochistan. By applying the disproportionate stratified sampling method, 264 smallholder farmers were interviewed through a structured questionnaire in two selected districts Pishin & Mastung of Pishin Lora Basin-river. Quantitative data was analyzed by computing correlation coefficients and regression models. The results show that a high majority of farmers claim that they have observed changes in the climate over the last 30 years, yet most of the farmers are less concerned about it. A high majority of farmers link climate change and water scarcity to the displeasure of Allah due to the sins of humans. Farmers with such perceptions are less likely ready to take adaptive measures to deal with the impacts of climate change. The results reveal significant association of education with community understanding of climate change, adaptation, and skills. The study recommends a relevant and well-coordinated communication strategy that could inform the farming community specifically the marginalized smallholder farmers about advanced climate science.

Keywords: *Climate Change; Risk Perception; Indigenous Knowledge; Adaptations; Small-Scale Farmers; Pishin Lora Basin*

1. Introduction

Climate change is one of the most significant phenomena of disasters established across the world. It is one of the significant environmental challenges faced by the world due to its impacts on different biophysical systems causing disturbance for the major food and water sources through temperature surges, droughts, and varying patterns of rainfall (Yamba et al., 2019; Bendell, 2018; Berg & Lidskog, 2018; USGCRP, 2017). UNFCCC in its article 1.1 states the adverse effects of climate change as "*Adverse effect of climate change means changes in the physical environment or biota resulting from climate change which have significant deleterious effects on the composition, resilience or productivity of natural and managed ecosystems or on the operation of socio-economic systems or on human health and welfare*" (UNO, 1992). It has the most severe detrimental impacts on poverty and inequality (Ulrichs & Slater, 2016) which will intensify the already adverse situation of people living in less

developed regions (Speranza, 2010). The combination of shocks related to climate change, political instability, and global financial crises are understood to be major threats to any advancements made for poverty reduction (Hallegatte et al., 2016; Bastagli, 2014).

A high majority of small-scale farmers in PLB are facing threats that emerged from climatic conditions. They have their own understanding of climate change, water scarcity, extreme weather events, resilience, and adaptive measures in practice. Within the catchment area of the Pishin-Lora Basin, there may be high variations among local farmers. So, for any intervention in the study area, it is very much significant to accumulate information in terms of how farming communities respond to changing conditions of environment and climate and what is their resilience level. However, there are either no known studies regarding small-scale farmers' resilience to climate change impacts in the catchment area of Pishin-Lora Basin, Balochistan.

This paper analyzes farmers' understanding and risk perceptions of climate change, water scarcity and their impacts in the PLB. It also explores the determinants and the way these determinants affect perceptions and adaptive behavior of smallholder farmers. The research questions were;

1. What are farmers' understanding, risk perception, and indigenous knowledge related to water scarcity and climate change resilience?
2. What are the potential factors and how do they influence farmers' perception and adaptive behavior?

2. Climate Change Impacts and Local Knowledge of Smallholder Farmers

Researches show that there is a strong nexus between climate change impacts and farmers' resilience. Resilience is considered a significant concept to characterize and measure the capabilities of people to forecast, absorb, recover, or accommodate the impacts of hazards or disastrous events in an efficient and timely manner (Patel et al., 2017; Deeming et al., 2014; Berkes & Ross, 2013; Almedom, 2013; Walker & Westley, 2011). The livelihood of farming communities has become highly vulnerable due to the current changes in climate and the occurrence of EWEs that require adaptation to actual and forecasted climate changes (Assan et al., 2018). Only those communities can survive with their water-related occupations that are resilient to climate change impacts and adapt accordingly (LEAD-Pakistan, 2017). A number of factors serve to the effectively resilient farming community such as farmers' knowledge bank, technology, capital, social support system, the physical environment, and access to support services (Assan et al., 2018; Zizinga et al., 2017). Resilience and adaptation not only depend on research and modern technology, but it is equally significant to improve the capability of marginalized community to cope with climate shocks via indigenous knowledge and changes in behavior aimed at livelihood improvement (Yamba et al., 2019; Ayeb-Karlsson et al., 2016)

Climate change and water scarcity pose critical risks to small-scale farmers and impends to weaken global steps for food security, poverty reduction, and sustainable development (Lipper et al., 2014; Vermeulen et al. 2012). Though small-scale farming communities have substantial knowledge and experience to deal with climate variability and use the local skills and knowledge to deal with its impacts, however, the long-term, sustained, and unprecedented changes in climate go beyond their traditional strategies to cope with climatic events (Pettengell, 2010). It is, therefore, critical to strengthen the adaptation capacity and resilience of small-holder farmers to reverse rising hunger and mitigate extreme poverty (UNO, 2021).

2. Materials and Methods

Study Area and Sampling

The universe of this research study was the catchment area of the Pishin-Lora Basin located in the uplands of Balochistan. Geographically, Balochistan province is the largest province of Pakistan but the poorest and least populated one. A very high majority of the population depends on agriculture and livestock for their livelihood. Pishin-Lora Basin is known as one of the major basin rivers and severely drought affected since 1997 (Ashraf et al., 2016; Halcrow, 2007). It is spread over five districts including Pishin, Quetta (the capital and most populous district of the province), Mastung, and some parts of Killa Abdullah and Kalat. Primary data was collected in two districts (Pishin and Mastung) as they are completely watered by Pishin-Lora Basin and agriculture is commonly adopted by a large population as a source of income. Primarily, two districts (Pishin and Mastung) among the five catchment districts of the Pishin-Lora Basin were selected on the basis of previous records of climate change impacts and extreme weather events (EWEs). There are 4 Tehsils and 52 Union Councils (UCs) in Pishin and 3 Tehsils and 20 UCs in Mastung. 12 UCs from each District were purposively selected for the field survey by implying cluster sampling technique. Each selected UC has been considered as a separate cluster in the study. Later, for the field survey, 11 households of small-scale farmers from each UC were selected using the UNICEF pencil-spin selection method (Haque et al. 2022; Ogbu & Guha-Sapir, 2021). All selected UCs were from rural areas of both districts as the selected UCs have small-scale farming as a dominant source of income and extensive record of extreme weather events, water scarcity, and hydro-climatic hazards based on reconnaissance survey and secondary records (Ashraf et al., 2016).

According to Agriculture Census Report, 2011, the number of small-scale farmers in Pishin and Mastung is 23806 & 1989 respectively (GoP, 2012). Small-scale farmers have characteristics of homogenous nature; therefore; a very large sample size is not required.

To determine the sample size for the field survey, the Arkin & Colton (1963) formula was used. Based on a total number of small-scale farmers (N=25795), the total sample size (n=264) was selected for both districts. Due to huge variation in the total number of small-scale farmers between selected strata the districts, disproportionate/non-proportional stratified sampling technique was implied to ensure balanced allocation & fractional sampling. Therefore; an equal number of elements i.e. 132 households from each district were selected. The disproportionate allocation of sample size helped for a more balanced comparative analysis across the districts (Khan et al., 2020; Nayeem & Huma, 2017; Statistics Canada, 2017; Etikan et al., 2016; Daniel, 2011**)**

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Data Collection and Analysis

Since the nature of the study is explanatory and the problem has existed in the area for a long period of time, therefore; the study adapted a mix of quantitative and quantitative data sources by employing;

- Structured questionnaire (based on research objectives, components of resilience and study variables).
- Focus Group Discussions (FGD) guided by study themes.
- Key Informant Interviews (KII), guided by semi-structured questions.
- Field Observation (A supplementary tool to validate filed data)

Correlation coefficient analysis was carried out to check the relationship among various continuous and categorical data variables. Multiple and logistic regression analysis was carried out to gauge relationship levels among dependent and predictor variables of the study. Regression analysis also assisted to predict the odds/probability of occurring the value of interest the in dependent variable to assist in prediction trends. A major part of the data was analyzed through the resilience index which was developed to assess the resilience of the community through its five components.
Data analysis and graphical illustration of data were carried out using Statistical Package for Social Science (SPSS) version 21, and MS Excel respectively.

Eq. 1

Mathematical Expression for Calculating Regression Coefficients (Linear Regression)

$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_n X_n + E_i$

Where:
The response Y depends on **predictor** variables $X_1, X_2 \ldots\ldots, X_n$
Y = the response / dependent variable (a continuous variable)
$E_i = 0$, or equivalently
$X_1, X_2 \ldots\ldots, X_n$ = the predictor / independent variables
$\beta_0, \beta_1, \beta_2 \ldots\ldots, \beta_n$ = regression coefficients
βi is a regression coefficient of each X_i that can be continuous, discrete, or categorical variable to determine the factors (predictors, X_s) associated with Y (continuous response variable).
β_0 is intercept
β_1 is coefficient of X_1; β_2 is coefficient of X_2 and β_n is coefficient of X_n
β_1 indicate the change in the mean response EY per unit increase in X_1 when X_2 holds constant.
β_2 indicate the change in the mean response EY per unit increase in X_2 when X_1 holds constant.

Eq. 2

Mathematical Expression for Calculating Logistic Regression Model (Binary Logistic Regression)

$$\text{Logit (p)} = Ln\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k$$

In Binary logistic regression the response variable is a binary response variable (*Y* = 1, 0r 0). This model is a construction of the relationship between *p* (the probability of an event of interest, *P* (*Y* = 1)) and a linear combination of predictors / independent variables (*Xs*) with the logit link function.

3. Results

3.1 Information, Concern and Personal Agency

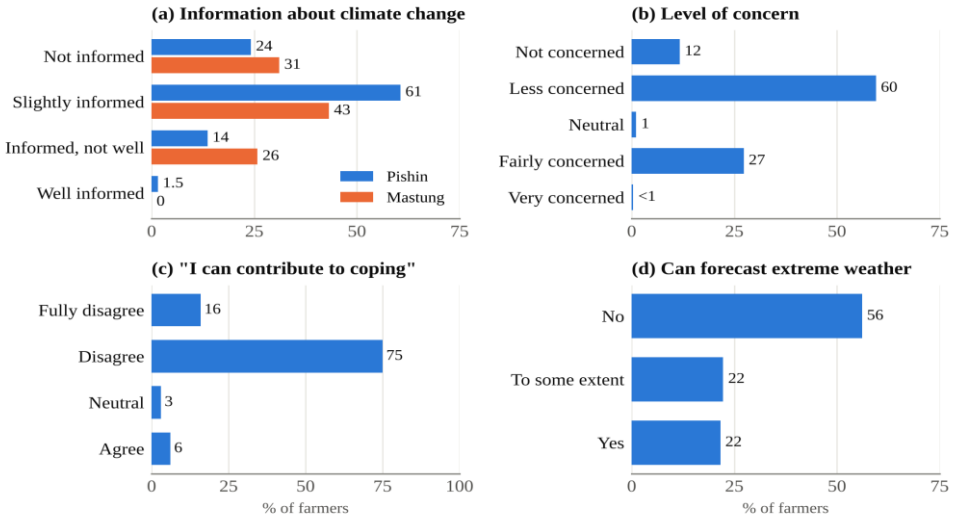
Farmers' knowledge of climate change was limited (Figure 1a). Overall, 28% reported being not informed at all (Mastung 31%, Pishin 24%) and 52% were only slightly informed (Pishin 61%, Mastung 43%), while 20% considered themselves informed but not well informed. Fewer than 1% described themselves as well informed.

Concern followed the same pattern (Figure 1b). Only about 27% of farmers were worried about climate change at the local level; 60% were less concerned and 12% were not concerned at all. Such farmers tend to attribute climate change to natural processes, human sins, fate or the displeasure of Allah, and are consequently less inclined to undertake preparatory or mitigation measures (Haque et al., 2022; Qasim et al., 2016; Ainuddin & Routray, 2012a).

Perceived personal agency was weak (Figure 1c). About 68% of farmers held that their own behavior is unimportant in responding to climate change, against 18% who considered it significant. Likewise, 91% disagreed that they could contribute to coping with its impacts and only 6% agreed. Strong attachment to conventional thinking, religious interpretations and limited grasp of scientific explanations appear to underlie these views. Confidence in forecasting was similarly low (Figure 1d): 56% of farmers (56% in Pishin, 58% in Mastung) felt unable to anticipate extreme weather events (EWEs), 22% could do so to some extent and 22% were confident. Those able to forecast drew on past experience, indigenous knowledge, media-based scientific information and the predictions of senior community members.

Figure 1

Information, Concern, Personal Contribution and Forecasting Ability of Farmers



Source: Field survey, 2022

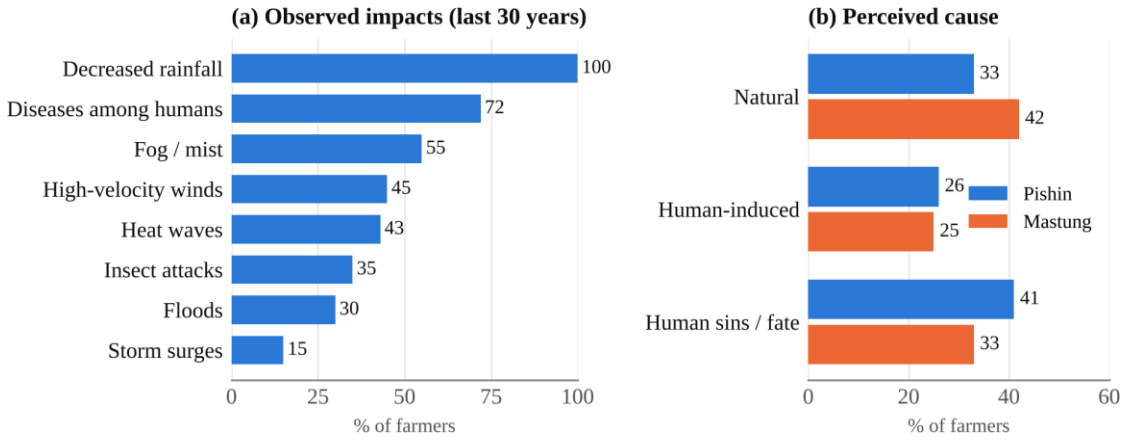
3.2 Observed Impacts and Perceived Causes

Over the previous 30 years, a decrease in rainfall was the impact reported by every farmer (100%), followed by diseases among humans (72%), fog/mist (55%), high-velocity winds (45%), heat waves (43%) and insect attacks (35%) (Figure 2a). Fog, wind and heat raise management costs and complicate water management on farms. Floods were not seen as recurrent in the basin (30%), and storm surges were rarely linked to climate change (15%). It should be noted that severe floods struck the study area in August 2022, after data collection was complete, causing heavy human, agricultural and infrastructural losses.

Perceptions of causes differed (Figure 2b). Combining the natural and divine explanations, roughly three-quarters of farmers in each district saw climate change as beyond human influence: 41% in Pishin and 33% in Mastung linked it to human sins and fate, while 33% and 42%, respectively, regarded it as a natural phenomenon. Only about a quarter of farmers in both districts (26% and 25%) held human activity responsible. This last group was the one most inclined to stress mitigation, prepare for future risks and consider adaptation, whereas the first two groups were less likely to do so.

Figure 2

Perceived Impacts and Causes of Climate Change at the Local Level



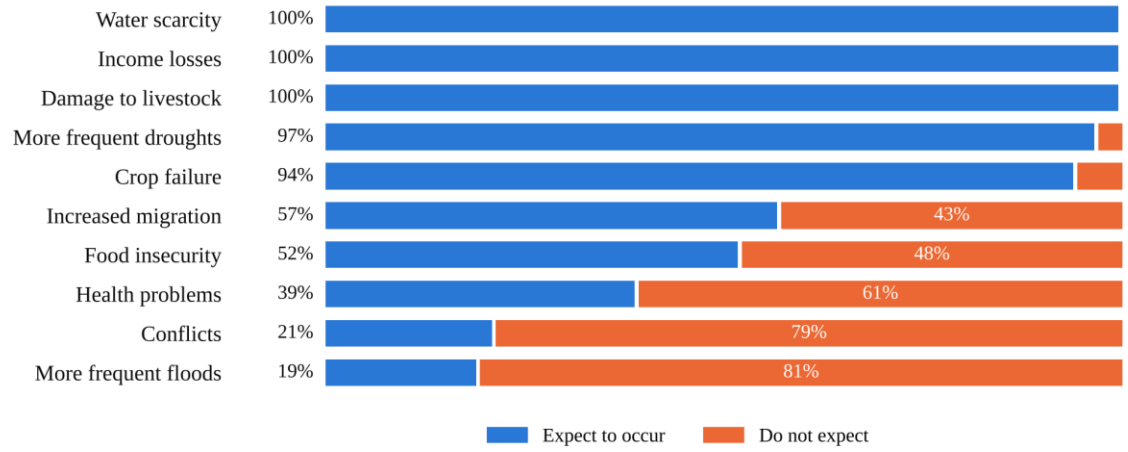
Source: Field survey, 2022

3.3 Perceived Future Risks

Despite these causal beliefs, 79% of farmers expected the effects of climate change to worsen locally, while 21% were uncertain. Expectations were dominated by drought-related losses (Figure 3). All farmers anticipated water scarcity, income losses and damage to livestock, and almost all expected more frequent droughts (97%) and crop failure (94%). Smaller majorities anticipated increased migration (57%) and food insecurity (52%), whereas 39% expected more health problems and 21% more conflicts. Farmers were least concerned about flooding, with 81% not expecting more floods. This view reflects three decades of recurrent drought, and the floods of August 2022 were therefore largely unanticipated.

Figure 3

Farmers' Perception of Future Climate Change Risks



Source: Field survey, 2022

3.4 Logistic Regression Models

Multiple and logistic regression analysis was carried out to gauge relationship levels among dependent and predictor variables of the study. Regression analysis also assisted to predict the odds/probability of occurring the value of interest in the dependent variable to assist in prediction trends. Tables 2, 3 & 4 represent statistics of the logistic regression models used for prediction.

Model 1: Willingness to adopt modern irrigation techniques.

Binary logistic regression (Table 2) was computed to examine the association and impact of formal education, farm size, agriculture experience, family size, family employment, family literacy, experience in advanced irrigation, and participation in support activities on *farmers' willingness to adopt modern irrigation techniques*.

Table 2

Logistic Regression Model 1 Predicting the Likelihood of Farmers' Willingness to Adopt Modern Irrigation Techniques

	Variables	*B*[a]	*SE*[b]	Wald	*Df*[c]	Sig.	*OR*[d]	95% *CI* for *OR*[e]
1.	Formal education	.90	.36	6.13	1	.013	2.45	[1.20-4.97]
2.	Farm size	-.11	.21	.27	1	.603	0.90	[0.59-1.36]
3.	Agriculture Experience	-.06	.04	2.45	1	.118	0.94	[0.88-1.01]
4.	Family size	.07	.09	.65	1	.421	1.07	[0.90-1.28]
5.	Family employment	-.10	.23	.17	1	.678	0.91	[0.58-1.43]
6.	Family literacy	.06	.13	.24	1	.026	1.07	[0.83-1.38]
7.	Experience of advance irrigation	1.83	.31	35.26	1	.000	6.24	[3.41-11.42]
8.	Support activities for CC resilience	-.18	.18	1.01	1	.314	0.83	[0.58-1.19]
	Constant	-1.17	1.29	.83	1	.362	0.31	

Note. [a]*B*=regression coefficient; [b]*SE*=standard error; [c] *Df:* degree of freedom; [d]*OR*=odds ratio; [e] 95% *CI* for *OR*= 95% Confidence Interval of Odds Ratio *(exp* β_i*)*

The model was statistically significant and has a good fitting in the data, x^2 (8, *N*=264) 76.56, *p* = .000, suggesting that it could distinguish between those willing to and not willing to adopt modern irrigation techniques in agriculture.

The model explained between 25.2% (Cox & Snell R square) and 38.1% (Nagelkerke R square) of the variance in the dependent variable and correctly classified 79.9% of cases.

As shown in table 2, the probability values of three predictor variables i.e. formal education, family literacy, and past experience with modern irrigation systems significantly contribute to the model, however, the rest of the predictor variables including farm size, agriculture experience, family size, family employment and the number of activities for climate change resilience did not significantly contribute to the model.

Formal Education: The probability value of formal education of farmers (.013, p<05) is predicting a significant relationship between the two variables. The reference category is *without education (coded as '0'*). The odds ratio *[OR=Exp(β)]* for farmers with formal education relative to without formal education is *OR*=2.45. This indicates that relative to farmers those without formal education, the odds of willingness to adopt modern irrigation are 2.5 times higher for the farmers with formal education.

Model 2: Ability to forecast extreme weather events.

Binary logistic regression (Table 3) was used to examine the association and impact of age; formal education; family training of CC; usefulness of indigenous knowledge & local experience; effectiveness of scientific knowledge; social networking; participation in capacity building sessions; and participation in awareness raising session on *farmers' ability to forecast Extreme Weather Events (EWEs).*

Table 3

Logistic Regression Model 2 Predicting the Likelihood of Farmers' Ability to Forecast Extreme Weather Events (EWEs)

	Variables	*B*[a]	*SE*[b]	Wald	*Df*[c]	Sig.	*OR*[d]	95% *CI* for *OR*[e]
1.	Age	.01	.02	.44	1	.507	1.01	[.96, 1.05]
2.	Formal education	1.49	.31	23.39	1	.000	4.43	[2.42, 8.10]
3.	Family training of CC	-.19	.37	.27	1	.603	0.83	[.40, 1.69]
4.	Usefulness of IK & LE	-.69	.30	5.32	1	.021	0.50	[.28, .90]
5.	Effectiveness of SK	.38	.28	1.76	1	.044	1.46	[.84, 2.55]
6.	Social networking (SN)	.24	.38	.38	1	.028	1.27	[.60, 2.70]
7.	Participation in CB	.17	.56	.10	1	.758	1.19	[.40, 3.57]
8.	Participation in awareness	-.15	.49	.10	1	.757	0.86	[.33, 2.26]
	Constant	-1.02	1.01	1.03	1	.310	0.36	

Note. [a]*B*=regression coefficient; [b]*SE*=standard error; [c] *Df:* degree of freedom*;* [d]*OR*=odds ratio*;* [e] 95*% CI* for *OR*= 95% Confidence Interval of Odds Ratio *(exp β$_i$)*

The model was statistically significant and has a good fitting in the data, x^2 (8, *N*=264)38.71, p = .000, suggesting that it could distinguish between those having the ability to forecast EWEs and those who do not have the ability.

The model summary explained variation in the dependent variables for this model ranging from 13.6% (Cox & Snell R square) and 18.3% (Nagelkerke R square) and correctly classified 70.8% of cases.

As shown in table 3, the probability values of four (04) predictor variables i.e. formal education, the usefulness of indigenous knowledge (IK) & local experience (LE); effectiveness of scientific knowledge (SK); and social networking (SN) significantly contribute to the model, however, the rest of the predictor variables including age; family training of CC; participation in capacity building (CB); and participation in awareness sessions did not significantly contribute to the model.

The Usefulness of indigenous knowledge (IK) & local experience (LE): The probability value of variable usefulness of indigenous knowledge and local experience (.021, p<05) is predicting a significant relationship between the two variables. The reference category is *IK & LE not useful (coded as '0'*). The regression coefficient *(B)* for this variable is -.69. The odds ratio *[OR=Exp(β)]* for farmers who believe that indigenous knowledge and local experience is useful is *OR*=0.50, taking the inverse, we get the odds ratio for farmers who think IK and LE is useful relative to those who do not believe it the usefulness is *OR*=1/0.50 = 2. This indicates that relative to farmers who disagree with the usefulness of IK & LE, the odds of farmers' ability to forecast EWEs is 2 times higher for those who agree with usefulness of IK & LE. This shows that farmers with more attachment to local knowledge and experiences are less likely to gain scientific knowledge and thus less able to forecast EWEs.

Model 3: Farmers' information about climate change.

Binary logistic regression (Table 4) was used to examine the association and impact of age; family literacy; agriculture experience; ability to forecast EWEs; usefulness of indigenous knowledge & local experience; and participation in awareness sessions on *farmers' information of climate change.*

Table 4

Logistic Regression Model 3 Predicting the Likelihood of Farmers' Information of Climate Change

	Variables	*B*[a]	*SE*[b]	Wald	*Df*[c]	Sig.	*OR*[d]	95% *CI* for *OR*[e]
1.	Age	-.05	.02	5.37	1	.021	.95	[.92 - 1.0]
2.	Family literacy	.21	.08	6.28	1	.012	1.23	[1.05 - 1.45]
3.	Agriculture Experience	.08	.03	8.50	1	.004	1.09	[1.03 - 1.15]
4.	Ability to forecast EWEs	.86	.27	9.96	1	.002	2.37	[1.39 - 4.04]
5.	Usefulness of IK & LE	-.64	.30	4.55	1	.033	.52	[.29 - .95]
6.	Participation in awareness session	.38	.31	1.50	1	.221	1.46	[.08 - 2.66]
	Constant	-.04	.99	.00	1	.970	.96	

Note. [a]*B*=regression coefficient; [b]*SE*=standard error; [c] *Df:* degree of freedom*;* [d]*OR*=odds ratio*;* [e] 95*% CI* for *OR*= 95% Confidence Interval of Odds Ratio *(exp β$_i$)*

The model was statistically significant and has a good fitting in the data, x^2 (6, N=264) 38.03, p = .000, suggesting that it could distinguish between those informed about climate change and those who are not informed.

The model summary explained variation in the dependent variables for this model ranging from 13.6% (Cox & Snell R square) and 18.2% (Nagelkerke R square) and correctly classified 66.3% of cases.

As shown in table 4, the probability values of age; family literacy; agriculture experience; ability to forecast EWEs; and usefulness of indigenous knowledge & experience significantly contribute to the model, however, participation in awareness sessions did not have a significant contribution to the model.

Age: The probability value of variable age (.021, p<05) is predicting a significant relationship between the two variables. The regression coefficient *(B)* is -.05 and the odds ratio *[OR=Exp(β)]* is *OR*=0.95. This predicts with each unit of age (year) increase, the likelihood of information level of farmers regarding climate change decreases by .95 times. Taking the inverse, the variable explains an increase of .95 times increases in information of CC with each unit of age decrease among farmers. This suggests that the more farmers belong to the younger generation, the more they are informed about climate change and related matters.

Family literacy: The probability value of variable family literacy (.012, p<05) is predicting a significant relationship between the two variables. The odds ratio *[OR=Exp(β)]* for the number of family members with basic literacy is *OR*=1.23. This suggests that with the increase of each additional family member with basic literacy in a farming family, the odds 1.23 times higher is predicted to be informed about climate change.

Ability to forecast EWEs: The probability value of the variable ability to forecast EWEs (.002, p<05) is predicting a significant relationship between the two variables. The odds ratio *[OR=Exp(β)]* for farmers' ability to forecast extreme weather events is *OR*=2.37. This explains that farmers, who have the ability to forecast EWEs, are 2.37 times more informed about climate change.

4. Discussion and Conclusion

The results reveal that there is a significant positive association between the education level of farmers and the level of concern about climate change; willingness to adopt modern irrigation methods; and ability to forecast extreme weather events. Similarly, the more farmers are concerned about climate change, the more they believe that they can contribute to mitigating climate change impacts. It is also observed that religious belief in climate change shows a strong negative relationship with farmers' level of concern about climate change. Family income is a major factor that influences household irrigation facilities and public transportation. Social networking, membership in civil society organizations, and gender balance in decision-making also show a significant positive association. Regression analysis of resilience variables shows that the three models are statistically significant and have a good fitting in the data. Model 1 predicts the likelihood of farmers' willingness to adopt modern irrigation techniques; model 2 predicts the likelihood of farmers' ability to forecast extreme weather events (EWEs); and model 3 predicts the likelihood of farmers' information on climate change.

Smallholder farmers have developed their understanding and perception of climate change through traditional knowledge, community informal gatherings, and religious belief about climate variability and water scarcity. Farming communities in remote rural areas of PLB have issues with access to scientific knowledge of climate change. Though farmers have developed an understanding of the impacts and future risks of climate change, they are less like to know

climate change itself and its scientific causes. Thus, they are less prepared for hazard mitigation and adaptation. Farmers mostly don't rely on scientific knowledge and skills of climate-smart agriculture because it is mostly perceived that scientific knowledge is ineffective in dealing with climate change impacts in accordance to their socioeconomic, geographical, and environmental conditions.

The policy-makers need to focus upon the already identified dimensions and indicators in this thesis that impend resilience of the farming community to climatic stressors by specifically focusing upon institutional, physical, economic, social, and human components. This research study highlighted the development of resilience of the small-scale farming community to the impacts of climate change by focusing on traditional knowledge, local experiences of farmers, and the grass-root challenges that develop the risk perceptions and choices for adaptations for farmers. It is imperative that grass-root level participation be ensured to guide decision making process. It is also need of time to address on urgent basis the risk perceptions, factors of vulnerability, social capital, and coping & adaptive capacity of smallholder farmers. The study identified that a lack of effective communication regarding climate change is a major barrier to improving farmers' perceptions. The study, therefore, emphasizes policy-makers to focus on the need for a relevant and well-coordinated communication strategy that could inform the farming community specifically the marginalized smallholder farmers about advanced climate science. This strategy for effective communication needs to be based upon accurate, local, and scientific data and easily understood by local farmers. The scientific knowledge needs to be informed by indigenous knowledge and local experience because it was identified that several measures are not in line with the socio-economic, geographical, and environmental condition of local communities in PLB due to which they find it ineffective to cope with climatic stressors. Further, such gaps in communication can be overcome by multiple means including proper facilitation of workshops, seminars, awareness sessions, etc. through the bottom-up approach of the farming community especially the smallholder farmers not only in PLB but all regions of Pakistan where devastating impacts of climate change have been observed. Wining farmers' trust in climate science is pivotal for enhanced resilience. Facilitation of face-to-face effective workshops is strongly needed in affected areas to engage small-scale farmers in climate-related matters that will break down the barriers of gape in place and time and allow mutual sharing of climate experience and knowledge.

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