Original Research Article

Analyzing Farmer Resilience to Floods - A Post-Disaster Study in the Flood Plains in Kerala, India

ABSTRACT

Extreme weather and climate events lead to substantial economic impacts, loss of lives and livelihoods, and adverse effects on human well-being and the environment. In a scenario where intensity and incidence of climate change induced extreme weather events are common, disasters will continue to be a regular phenomenon, compelling us to learn to live with it. The resilience of rural communities to weather adversities need to be explored, to cope with, adapt to disasters. In the background of the unprecedented deluge that engulfed in Kerala, the southernmost tip of India, in 2018 the study was undertaken to analyse the resilience level of the affected farmers. Although people of the state have experienced minor floods in past years, the flood of 2018 left the people of the state wholly devastated, with the turbulent water taking away most of their assets and livelihood options. The study used the factor analysis and logit model to analyse farmer resilience. The study was conducted by selecting 120 sample farmers from along the flood plains of Chalakudy river, one of the worst affected flood plains. Through factor analysis, seven factors representing eight components of resilience were identified. The analysis identified risk orientation as the highly influencing factor in building resilience. Logistic regression analysis revealed education and subsidiary occupation as having a positive influence, while family size and crop diversification index negatively influence resilience.

Keywords: *2018 Kerala floods, Disaster effects, Risk orientation, Farmer resilience*

1. INTRODUCTION

Natural disasters are rare but highly dangerous, resulting in significant loss of life, livelihoods and assets. The disaster-induced economic damage has been increasing in the past few decades and is likely to continue growing because of urban development, population growth and ecosystem alteration (IPCC, 2012). Climate-related disasters represent the most significant number of natural disasters and influence more individuals than any other type of natural hazard. Extreme weather and climate events often have extreme financial effects, for example, loss of lives and livelihoods, food, water and energy scarcity and adverse effects on human well-being and the environment (USAID, 2009).

According to the WHO (2019) statistics, natural disasters in their various forms (earthquakes, floods, landslides, droughts, hurricanes, wildfires, heat and cold waves) steal 90,000 lives while affecting 160 million people every year globally. The period between 1998 and 2017 witnessed natural disasters taking away 1.3 million lives leaving behind 4.4 billion people injured, homeless, displaced or in need of emergency assistance (Wallemacq, 2018). Despite human lives and livelihoods being kept at risk by natural disasters, flooding affected more lives and livelihoods than any other type of disaster. Between 1994 and 2013, floods alone affected nearly 2.5 billion people, constituting 55 percent of the total disaster-affected population (CRED, 2015).

India is second only to China in terms of the cumulative number of people affected by natural disasters between 1994 and 2013. India accounts for about 819 million people affected by natural disasters and has lost about 98,660 lives during this period (CRED, 2015). Despite different regions of the country facing various forms of natural hazards every year, floods contribute the majority of losses and are more frequent than any other disaster. India is the second largest flood-affected nation after China (Wallemacq, 2018). Since the country is one of the most climate-vulnerable (especially related to flood) countries globally, the farmers are incredibly predisposed to agricultural damage (Huq et al.,2015).

Kerala state, located along the western coast of India, became highly prone to various natural disasters like floods and land/mudslides. Floods have become the most common phenomenon for the last four years. Among Indian states, Kerala stands fourth in the state-wise vulnerability to flooding, measured in average annual flood damage as a percentage of the State GSDP (Gross State Domestic Product). The State is also in the fourth position regarding the average annual area affected by floods as a percentage of the State's geographical area (Parida, 2017).

Kerala encountered the most dreadful floods since 1924, between June and August 2018. The State received torrential rainfall, which was 42 percent above the typical normal, and in the period between the 1st to 19th of August, the State received 164 percent higher rainfall (IMD, 2018). The extreme downpour and the subsequent deluge affected all aspects of human lives, including socioeconomic conditions, transportation, infrastructure, agriculture and livelihood. Despite having experienced the impact of floods in varying degrees for years, the taint of fear left by the deluge in farmers' minds made many rethink their decision to continue farming.

Resilience to floods is a valuable concept to study the capacity of rural households to cope with, adapt to and benefit from disasters. The term resilience was conceptually introduced by Holling (1973), according to whom resilience is a measure of the ability of ecological systems to absorb changes in state variables, driving variables, parameters and persistence. The capacity of farmers to face, cope with, and change as a result of traumatic experiences varies throughout life. The ability to adapt to traumatic situations is called resilience (Revich & Shatte, 2002). Few (2003) defined resilience as the ability of humans to minimize the impacts of a disaster through some form of adaptation. According to Vugrin *et al.* (2011), "Given the occurrence of a particular disruptive event (or set of events), the resilience of a system to that event (or events) is the ability to reduce efficiently both the magnitude and duration of the deviation from targeted system performance levels". Moreover, the process of recovery of the system is more efficient when the time of recovery and amount of potentially used resources are less.

Resilience needs to be assessed from economic, social, human, natural and physical capital perspectives. Of these, the essential factor in most cases is economic capital. A flood is a calamity that lasts for a long time and may easily harm cash crops, negatively impacting overall economic loss (Rahman, 2014). The recovery process is hastened when economic capital is sufficient (Mayunga, 2007). Norris and Stevens (2007) endorsed it when they stated that economic factors are necessary to support individual resilience. According to Freudenburg (1992), individuals or households with only one income source have lower resilience levels than those with more income sources.

Widiarto (2013) attempted to assess agricultural loss caused by the 2007 flood and its household impact in Indonesia by studying the resilience of farmers in the village towards flood in human capital and economic capital. The study concluded that resilience is closely related to the socioeconomic condition of the farmer and the intensity of flood loss. Nguyen and James (2013) measured household resilience in the Vietnamese Mekong river delta and found that household income and flood based farming practices were critical in tiding over flood situations.

This paper analyses the farmer's resilience to floods in the post-disaster scenario along the flood plains of the Chalakudy river in the southern State of India, Kerala after the major floods of 2018. The study also attempted to identify the perceived factors that help build resilience and understand socioeconomic variables' influence on resilience.

METHODOLOGY

1.1 Study area

Chalakkudy river basin was selected as study area since its one of the major river basin in the central part of Kerala, India. The river basin was purposefully selected as these areas were badly affected by the floods of 2018. The study was conducted by selecting ten panchayats, across three blocks, viz. *Chalakudy* and *Mala* blocks in Thrissur district and *Parakkadavu* block in Ernakulam district of Kerala. The quantum of loss and livelihood destruction caused by flooding of Chalakkudy river was very such severe in these two districts.

Data and methods

2.2.1 Data

The present study is based on primary data. Primary data was collected from the respondents using pretested structured interview schedule through the personal interview method.

2.2.1.1 Construction of questionnaire

A questionnaire was prepared to keep in view the objective of identifying factors contributing to resilience using factor analysis. Appropriate statements were carefully prepared to elicit answers in a dichotomous response of agreement/disagreement. Framed statements were measured on a modified Likert scale developed by Nguyen and James (2013) to measure household resilience to floods in the Vietnamese Mekong River Delta.

2.2.2 Methods

2.2.2.1 Likert scale

Devised initially by Rensis Likert in 1932, the Likert scale, a set of statements (positive or negative) offered to the respondents corresponding to an actual or hypothetical situation under study, was developed to measure attitude in a scientifically accepted and validated manner. In the present study, the respondents were asked to show their agreement or disagreement with the given statements on a five-point metric scale with measurements ranging from one to five corresponding to strongly disagree to strongly agree, respectively.

2.2.2.2 Factor analysis

Factor analysis was employed to identify the underlying components of resilience. Factor analysis is essentially a method of meaningful reduction of data (Dillon and Goldstein, 1984). The purpose is to reduce many variables to a smaller set of underlying variables by creating factors (Kim and Mueller, 1978). There are several ways to conduct factor analysis (principal components, unweighted least squares, generalized least squares, maximum likelihood, principal axis factoring, alpha factoring, image factoring) and choice of methods (correlation matrix or covariance matrix) (Ather and Balasundaram, 2009). However, the principal component analysis method was employed in this study.

2.2.2.3 Cronbach's alpha coefficient

Cronbach's alpha was employed to test whether the multiple-question Likert scale survey is reliable. Lee Cronbach developed Cronbach's alpha or Coefficient alpha (α) in 1951. It measures reliability or internal consistency. Cronbach's alpha coefficient will tell if the test designed accurately measures the variable of interest.

Cronbach's alpha coefficient is calculated as,

$$\propto = \frac{\boldsymbol{k}}{\boldsymbol{k-1}}\left(\boldsymbol{1} - \frac{\sum_{i-1}^{k} \sigma_i^{2}}{\sigma_t^{2}}\right)$$

Where, k = the number of items in a scale

σ_i^2 = the variance of i^{th} item

σ_t^2 = the variance of the scale (total) scores

Cronbach's alpha reliability coefficient normally ranges between 0 and 1. The closer Cronbach's alpha coefficient is to one, the greater the internal consistency of the items in the scale. George and Mallery (2003) provided the following rules of thumb: ">0.9 - Excellent, >0.8 - Good, >0.7 - Acceptable, >0.6 - Questionable, >0.5 - Poor and <0.5 - Unacceptable".

2.3 Socio-economic profiling and characterization

The primary data was collected from the list of farmers who had applied for the natural calamity compensation in each of the agricultural offices in the selected panchayaths. The number of respondents from each panchayath was decided proportionate to the total number of farmers applied for the claims, so as to make the total sample size of 120.The primary data was collected through direct personal interviews of the sample respondents during field surveys using a pre-tested structured interview schedule and tabulated data to facilitate easy comprehension and analysis of the socioeconomic characteristics of the respondents. The estimates were used to study the influence of these socioeconomic characteristics on resilience by fitting a logistic regression.

2.4 Model specification of resilience function of the farmers

The resilience index worked out for the individual farmers was fitted as a function of the farmer's age, education, experience in farming, family size, land area, crop diversification index, education of the respondent, education of the family members and subsidiary occupation.

The specified resilience function is as follows:

$$\mathrm{Ln}\left(\frac{P_i}{1 - P_i}\right) = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + b_4x_4 + b_5x_5 + b_6x_6 + b_7x_7 + b_8x_8$$

Where,

P_i = Probability of having high or low resilience

1 = Respondent is having high resilience

0 = Respondent is having low resilience

x_1 = Age (years)

x_2 = Education of the respondent (= 0, if below SSLC, = 1, if SSLC or above)

x_3 = Subsidiary occupation (= 0, if no, = 1, if yes)

x_4 = Experience in farming (years)

x_4 = Education of family members (= 0, if below SSLC, = 1, if SSLC or above)

x_5 = Family size (nos.)

x_6 = Land area (acres)

x_7 = Crop diversification index

b_0 = Intercept

b_1, b_2, b_3,…b_8 = Regression coefficients

2.5 Herfindahl index

The extent of crop diversification for individual farms in the study area was examined using the Herfindahl index. The index for an individual farm was calculated using the formula,

$$\text{Herfindahl index} = \sum_{i=1}^{N} P_i^2$$

Where, N = Total number of crops

P_i = Average share of i^{th} crop in total cropped area

Herfindahl index is the concentration index; thus, a lower value is always preferred. Perfect diversification is indicated by an index equal to zero, whereas a farm with an index equal to one clearly manifests mono-cropping/specialization.

RESULTS AND DISCUSSION

3.1 Factors perceived as contributing to building farmer resilience

The factors playing a crucial role in building resilience were selected by subjecting 32 statements (Table 3) to factor analysis after testing for adequacy of distribution of values and reliability of the scales used.

The results from factor analysis, as presented in Table 2 reveal that 28 of 32 statements reliably contributed to the scale and formed the basis for measuring household resilience to floods. The responses to the statements were best described by seven factors representing seven components of resilience. These seven factors represented 68 percent of the variance. The first factor, including four statements (1, 2, 3, 4) relating to savings that enable to continue cropping despite the damage and loss, represents 15 percent of the variance. The second factor, representing 11 percent of the variance, consisted of four statements (29, 30, 31, 32) relating to the level of confidence of farmers that their houses and other assets will not be affected (submerged/collapsed/washed away) by future floods on par with the floods of 2018. The third factor consisting of four statements (25, 26, 27, 28) relating to the level of indebtedness which is enough to withdraw farmers from taking up successive season cropping, represented 910 percent of the variance.

The fourth factor, representing 9 percent of the variance, consisted of four statements (21, 22, 23, 24) relating to government assistance in relief funds and its significance in helping the farmers to recoup. The fifth factor, including five statements (10, 11, 12, 14, 15) relating to the orientation of farmers towards the risks and uncertainties in farming, represented 9 percent of the variance. The sixth factor, representing 8 percent of the variance, consisted of four statements (6, 7, 8, 9) relating to the confidence level of farmers that their crops will not be affected by future floods as severe as the floods of 2018. The seventh factor consisting of five statements (16, 17, 19) relating to insurance as a supporting pillar to overcome crop loss, provides necessary liquidity to continue cropping in the next season despite the huge loss incurred, represented 8 percent of the variance.

Reliability analysis showed that Cronbach's alpha coefficients are in the range between 05 - 0.95, clearly indicating high internal consistency of items in the scale (factor one is 0.92; factor two is 0.94; factor three is 0.89; factor four is 0.82; factor five is 0.76; factor six is 0.81 and factor seven is 0.61)

The resilience categories, as presented in Table 4 were decided based on the mean and standard deviation of the resilience indices for the respondents. The composite resilience index for all the respondents was estimated at 0.48. Meanwhile, the composite resilience index for the respondents of Chalakkudy, Mala and Parakkakadavu were 0.51, 0.45 and 0.48 respectively. The standard deviation of the resilience indices of farmers was estimated as 0.07. However, the resilience indices of the farmers along the flood plains varied between 0.32 and 0.67.

3.2 Socio-economic factors influencing resilience level of farmers

The binary logistic regression model was fitted to find out the socio-economic factors influencing the resilience of an individual farmer, and the estimates are presented in Table 5. The model was satisfactory, with a significant Chi-square value and the likelihood ratio test at 111. The signs of all the independent variables conformed with the hypothesis (Table 1). Four out of eight factors viz. education, subsidiary occupation, family size and crop diversification index, were found to significantly influence the probability of a farmer becoming resilient (Table 5).

It was observed that for the fitted binary logistic resilience function, the Cox and Snell R2 value was 0.36 and Nagelkerke R2 value was 0.49. The respondent's education was found to influence resilience at a one percent level of significance positively. It was found that respondents with a higher level of education are around four times more likely to occupy the above-average resilience group than the respondents with a lower level of education, keeping all the other variables fixed. It may be attributed to the fact that education will help the farmers to think positively and find novel ways to overcome the aftermath of a disaster; thus, education positively contributes to building resilience. The subsidiary occupation was found to influence resilience positively at a five percent level of significance. The supporting source of finance will help in post-disaster recovery, including cleaning up the debris, repairing and replacing damaged assets, taking up next season's crop *and similar activities*. The analysis found that respondents with a subsidiary occupation are around 25 times more likely to occupy the above-average resilience group than those without any subsidiary occupation keeping all the other variables fixed.

Family size negatively influenced resilience at a five percent level of significance. The study revealed that respondents with fewer dependents are around 0.4 times more likely to occupy the above-average resilience group than those with more dependents in the family, keeping all the other variables fixed. It may be attributed to the fact that as the family size increases, the ability of the farmer to recoup with limited means decreases, as the priority should be given to primary things like food and shelter. The crop diversification index was also found to influence resilience at a five percent level of significance negatively. It was found that respondents with a high crop diversification index are more likely to occupy the above-average resilience group than those with low crop diversification index keeping all the other variables fixed. This was attributed to the fact that as the crop diversification index increases, diversity in farming decreases and thus potential risk of losing the crop to disaster increases, making the farmers less resilient.

Table 1: Independent variables selected in the logistic model

Sl. No.	Particulars	Expected sign
1	Age	+
2	Subsidiary occupation	+
3	Education of the respondent	+

4	Experience in farming	+
5	Education of family members	+
6	Family size	-
7	Land area	+
8	Crop diversification index	_

Table 2: Sample factor analysis table

	Factors						
	Savings	**Other losses**	**Level of indebtedness**	**Relief fund**	**Risk Orientation**	**Damage level**	**Insurance**
	S2=0.943	O30=0.940	L26=0.885	Rf23=0.904	Ro14=0.739	D7=0.814	I17=0.932
	S1=0.936	O29=0.938	L25=0.882	Rf24=0.888	Ro15=0.693	D8=0.811	I19=0.913
	S4=0.917	O31=0.898	L27=0.748	Rf21=0.763	Ro12=0.669	D9=0.703	I16=0.674
	S3=0.875	O32=0.844	L28=0.706	Rf22=0.571	Ro10=0.665	D6=0.629	
					Ro11=0.595		
Eigen value	4.691	3.555	3.088	2.877	2.727	2.497	2.456
Percentage variance	14.658	11.109	9.650	8.990	8.522	7.803	7.676
Cumulative percentage	14.658	25.767	35.417	44.407	52.929	60.732	68.408

Table 3: Statements regarding resilience

Items	Statements	Strongly Disagree	Disagree	Undecided	Agree	Strongly Agree
1	I am confident that I will not borrow money to continue farming after floods					
2	I am afraid that I cannot take up next crop without external source of money					
3	I am confident that crop loss will not limit my ability to take up next season crop					
4	I will be forced to borrow money to continue farming if my crops are completely destroyed					
5	I have the potential to continue cropping even if the harvest is poor					
6	I am sure that my crops will not be completely destroyed by the highest floods as in 2018					
7	I am afraid I will lose all that I invest if floods as high as 2018 occurs					
8	I am confident that my field will not be inundated by the highest floods as in 2018					
9	If floods as high as 2018 occurs, my crops will be completely destroyed					
10	I am aware that agriculture will not give regular and steady income					
11	I am confident that I can earn enough money even if one or two seasons are lost					
12	I have diversified crop production activities to reduce risk					
13	I can well absorb economic loss due to any unexpected occurrences					
14	I am prepared to accept the weather uncertainties in agriculture					
15	I can least absorb economic loss due to unpredicted weather and climate					
16	Crop insurance is all about procedural formalities and zero assistance for the needy					
17	Crop insurance provided me financial security during the time of crisis					
18	Delayed payment affected my ability to take up next season crop					
19	Insurance claim amount proved to be a great relief after the flood loss					
20	Inadequate compensation added to our woes					
21	I was able to recoup after the flood event because of the assistance from the Government					
22	No/poor assistance from government added to my worries					

23	Prompt payment of relief fund helped me manage my debts and take up next crop					
24	Untimely and inadequate disbursal of relief fund proved to be of no use					
25	I was not able to take up next crop for my debts and repayments were very high					
26	My debts were not large enough to stop me from taking up next crop					
27	Debts were my major concern which pulled me back from continuing cropping					
28	My debts never influenced my decision regarding next season cropping					
29	I am confident that my house will not get submerged by the highest floods as in 2018					
30	I am confident that none of my material possession will be damaged by the highest floods as in 2018					
31	My house will be submerged by floods as high as 2018 flood					
32	I am worried that my material possessions will be damaged or even be swept away by the highest floods as in 2018					

Table 4: Resilience level of the farmers

Resilience index	Resilience level	Chalakudy	Mala	Parakkadavu	Flood plain
<0.41	Low	4 (9.09)	7 (17.50)	5 (13.89)	15 (12.50)
0.41-0.55	Moderate	33 (75.00)	27 (67.50)	23 (63.89)	81 (67.50)
>0.55	High	7 (15.91)	6 (15.00)	8 (22.22)	24 (20.00)
	Total	**44 (100.00)**	**40 (100.00)**	**36 (100.00)**	**120 (100.00)**

Note: Figures in parentheses indicate per cent to column total

Table 5: Estimates of the logistic model for resilience

Sl. No.	Variable	B	Standard Error	Wald Statistic	Sig.	Exp (B)	Probability
1	Constant	3.29	2.16	2.33	0.13	26.93	0.96
2	Age	0.007	0.04	0.03	0.86	1.01	0.50
3	Education of the respondent	1.37*	0.55	6.25	0.01	3.93	0.80
4	Subsidiary occupation	3.22**	1.20	7.19	0.007	25.09	0.96
5	Experience in farming	0.020	0.04	0.32	0.58	1.02	0.50
6	Education of family members	0.53	0.53	0.99	0.32	1.70	0.62

7	Family size	-0.76**	0.22	11.77	0.001	0.47	0.32
8	Land area	0.035	0.05	0.41	0.52	1.04	0.51
9	Crop diversification index	-6.80**	1.683	16.321	0.000	0.001	0.0009

*Note: ** denotes significant at 1 % level of probability and * denotes significant at 5 % level of probability*

2. CONCLUSION

The unexpected spell of rainfall in August 2018 inflicted heavy damage on the life and assets of thousands of people in Kerala. A large number of rural agricultural households borne the brunt of the unprecedented deluge. The farmers need to be reoriented to overcome risks and uncertainties in farming through diversifying crop production activities and investing in other related enterprises. Such measures would ensure continuous flow of income at times of complete crop failures, the most critical perceived factor that builds the resilience. This would also capacitate the farmers to bounce back into farming after a face-off with a disaster.

Crop insurance would act as a pillar to lean upon during crop loss providing the necessary liquidity to continue cropping in the next season despite the huge loss incurred. The Government relief fund in the form of compensation for loss suffered would aid the farmers to recoup faster. The level of confidence of households that their assets will not be affected (submerged/collapsed/washed away) by future floods as large as the floods of 2018, too, play a vital role in building resilience. Education being a significant factor in building resilience, trainings on disaster risk reduction, skill upgradation in agri related enterprises, and encouraging farmers to diversify their farms and to take up subsidiary occupations to tide over unexpected and unprecedented situations like that of the 2018 floods should find a place in the agriculture policy of the state.

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