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Determinants of farm-level adaptation strategies to flood: insights from a farm household-level survey in coastal districts of Odisha

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ABSTRACT

Farmers choose different strategies to cope with disasters. The scientific information on what adaption strategies do farmers across different socio-economic and regional strata choose to cope with disasters can help policymakers to make informed farm-level support interventions. Odisha is a flood-prone state in eastern India. The flood adaptation strategy choices of farmers in Odisha have not been much studied in the literature. Along with identifying the most commonly adopted *ex ante* and *ex post* adaptation strategies of farmers, we also identified the common factors influencing the choice of these adaptation strategies. We used the Likert scale and the ordered probit model to analyse the primary data collected from the field survey conducted at the three selected coastal districts. It finds that migration, reduction in food consumption, and pest and disease management are the most common *ex post* strategies, whereas stocking of foodgrains and usage of flood-resistant seeds are the most common *ex ante* strategies adopted by the farmers. It also identifies that education, family size and the size of landholding are the main determinants of *ex post* adaptation strategies, whereas age, the size of landholding and family income are the major determinants of *ex ante* coping strategies.

Key words: Coastal Odisha, Determinants, *Ex ante* strategies, *Ex post* strategies, Flood, Farm households

HIGHLIGHTS

- The paper discusses the determinants of both ex-ante and ex-post adaptation strategies among the sample farmers in the three coastal districts of Odisha.
- The Likert scale technique shows that migration, reduction in food consumption, and pest and disease management are the most common ex post strategies, whereas stocking of food grains and usage of flood-resistant seeds are the most common ex ante strategies adopted by the farmers.
- Ordered probit result shows that socio-economic characteristics, namely, respondent's age, size of landholding and natural log of farm income were the common determinants of ex ante coping strategies among the farming households. On the other hand, family size, education and the size of landholding were found to be the common determinants of ex post strategies of migration and reduction of food consumption.
- Regional variation at the district level was also found to be a major determinant of adaptive strategies among the farming households.
- Such empirical study highlights the necessity for government investment in scientific modelling for early warning, awareness, and possible adaptive mechanisms that help farmers deal with natural disasters.

1. INTRODUCTION

Floods pose a significant threat to the sustainability of riverine settlements and their livelihoods all over the world. They have killed around 157,000 individuals and affected over 2.3 billion people around the world in the last two decades, i.e. from 1995 to 2015 (Mondal *et al.*, 2020). Asia is under severe threat of floods. The highest number of deaths and devastation due to floods have occurred in Asia in comparison with other parts of the world (NATCOM, 2004). The United Nations Economic and Social Commission for Asia and the Pacific (ESCAP, 1998) also reported that floods continue to be a severe disaster faced by Asian countries. India is found to be the most flood-affected country in South Asia after Bangladesh. The risk associated with the events of flood disrupts the livelihoods of the majority of people in the developing countries. As a majority of the population in developing countries depend on climate-sensitive sectors like agriculture for their living, the occurrence of such events adversely affects their lives and livelihoods. Agriculture is a prime source of livelihood for the majority of the population in India. Indian agriculture, which is called the Gamble of Monsoon, is predominantly dependent on rainfall (Prasad Rao, 2010; Patnaik & Narayanan, 2015). Flood events disproportionately harm the agrarian population of India. They create crop losses, livestock losses and crop failures and alter their crop cycles. They give them income shocks, reduce their consumption levels and create vicious cycles of poverty. They can also trap them in a burden of debt. This burden and impact fall on different sections of the agrarian population disproportionately depending upon their adaptive capacity.

How do different socio-economic categories of farmers adapt to the misfortunes of flood, what are their main strategies of adaptation and what determines their choice of adaptation strategies are interesting research questions. Many researchers around the world have studied farmers' adaptive behaviour to climate change. These studies have focused on identifying the various adaption options undertaken by farmers (Bryan *et al.*, 2013; Panda *et al.*, 2013; Piya *et al.*, 2013; Wood *et al.*, 2014; Patnaik & Narayanan, 2015), their choice of adaptation options over no adaptation (Deressa *et al.*, 2009; Gbetibouo, 2009; Wang *et al.*, 2010; Hisali *et al.*, 2011; Gebrehiwot & van der Veen, 2013) and factors that influence their adaption decisions (Maddison, 2007; Solomon *et al.*, 2007; Bryan *et al.*, 2009; Deressa, 2010; Deressa *et al.*, 2011; Sarker *et al.*, 2013; Ashraf *et al.*, 2014; Bahinipati, 2015; Mondal *et al.*, 2020; Jha & Gupta, 2021).

From the above literature, it is observed that a range of adaptive strategies are chosen by farming households across the world to cope with the adverse impact of extreme climatic conditions. Some of them are *ex ante* adaptation strategies (also called pro-active adaptation measures – adaptation measures undertaken before the occurrence of the event) and others are *ex post* adaptation strategies (called reactive adaptation mechanism – adaptation measures undertaken after the occurrence of the event). Changes in the crop patterns, changes in agro-economic practices, cultivation of climate-resilient crops/seeds, pest and disease management (PDM) and changes in the livelihood strategies like income diversification and opting off-income are found to be the most common strategies among the farming households. Social and economic factors such as race and ethnicity, health, education, infrastructure, income and size of landholding are found to be the crucial determinants of the choice of these adaptive strategies among farmers across the world.

The state of Odisha is one of the eastern coastal states of India experiencing a frequent occurrence of natural disasters such as floods/cyclones due to its unique geo-climatic conditions. Considering that agriculture is the main source of income for a majority of the state population, the occurrences of such events cause a devastating effect on the lives and livelihoods of the state population. The continuous exposure to such events has a detrimental effect on the adaptive capacity and well-being of the people in the state (Bahinipati, 2015). The attempt to study the farmer's adaptation strategies to floods in the state of Odisha is scarce in the available literature. Roy *et al.* (2002), Bahinipati (2014, 2015), Panda (2017), Patnaik *et al.* (2016) and Arora & Birwal (2017) have studied the differences in coping strategies to different types of shocks, such as cyclones, floods and droughts. The available literature has missed to check the determinants of the choice of various *ex ante* and *ex post* adaptation strategies among farming households of Odisha.

Using a Likert scale, this research investigates the key ex-ante and ex-post flood adaptation techniques used by farming households in three coastal districts of Odisha, and an ordered probit model is used to identify the major determinants of the choice of these adaptation strategies among the sample households. The data for the same are collected from the three districts selected through a field survey with a structured questionnaire. The analysis identifies that migration, reduction of food consumption (RFC) and PDM are the most common *ex post* strategies, whereas stocking of foodgrains and usage of flood-resistant seeds (FRSs) are the most common *ex ante* strategies adopted by farmers. It also identifies that education, family size and the size of landholding are the main determinants of *ex post* adaptation strategies, whereas age, the size of landholding and family income are the major determinants of *ex ante* coping strategies. It offers policy implications in prioritising the disaster support interventions for the farming households in the state. The *ex ante* and *ex post* adaptation strategies followed by sample households in the study regions are explained in Supplementary Material, 2. Apart from the above-mentioned strategies, *crop diversification/switching to different crops*, *mixed cropping*, *keeping the susceptible part of land barren to avoid loss* and *saving money* are some of the other common *ex ante* strategies found in the study regions. On the other hand, RFC, migration and PDM are the most common *ex post* strategies followed by sample households in the study regions. The rest of this paper is structured as follows: Methodology, Descriptive statistics, Results and discussions and Concluding remarks with policy suggestions.

2. METHODOLOGY

2.1. Study area

Odisha is one of the eastern coastal states of India. It has a coastline of 480 km and is surrounded by a number of perennial rivers (e.g. Mahanadi, Brahmani, Baitarani, Rushikulya, Birupa, Budhabalanga and Subarnarekha) and their tributaries. It makes the state prone to cyclones and floods. According to the study of Bhatta (1997) and Chittibabu *et al.* (2004), both cyclones and floods occurred for 126 years in Odisha during the 1804–2010 period, and particularly, the outbreak of flood was reported for nine consecutive years during 2001–2010. A study by Bahinipati & Patnaik (2015) opined that the intensity of these events is likely to increase over the years in the state. The Government of Odisha (Government of Odisha, 2011) reported that economic losses due to natural disasters (cyclone, flood and drought) were around INR 1,050 million during the 1970s, which increased to INR 6,817.5 million, INR 70,806.35 million and INR 105,040 million, during 1980, 1990 and 2000, respectively. Furthermore, between 1953 and 2011, an average of 0.33 million hectares of agricultural land were reported to be damaged by floods, resulting in a financial loss of INR 316.2 million per year and a total economic loss of INR 2,906.42 million (Bahinipati, 2015). The occurrence of unseasonal cyclonic rainfall in 2010 caused a major crop loss across 24 districts in Odisha, and the value of this loss was around 60,000 million (Government of Odisha, 2011). In 2013, the severe cyclonic storm 'Phailin' caused agricultural losses worth INR 23,000 million in 18 districts, with overall damage costs estimated to be around INR 143,734.7 million (Government of Odisha, 2013). The recent cyclonic storm 'Fani' left 64 dead, affecting about 16.5 million people in over 18,388 villages in 14 of the 30 districts in the state. The overall loss and damage cost was estimated as INR 29,315 crore (INR 293,150 million) due to this event (Government of Odisha, 2019). Similarly, the occurrence of flood during August 2020 affected over 1.4 million people in 20 districts of the state and left 17 dead. Coastal districts were reported to be severely affected by this flood, among the other affected districts in the state (Government of Odisha, 2020). A composite Flood Vulnerability Index (FVI) was developed to understand the intensity of vulnerability in the six coastal districts of Odisha (i.e. Kendrapara, Cuttack, Bhadrak, Jagatsinghpir, Puri and Balasore). The result of the FVI shows that Kendrapara district is the most vulnerable, whereas Bhadrak and Cuttack districts, respectively, are found to be moderate and the least vulnerable districts among the other coastal districts of Odisha. To achieve the objective of the present study, we conducted a household-level survey based on the FVI results in the three coastal districts of Odisha as mentioned above.

2.2. Data source

The study is undertaken using quantitative methodology. A Likert scale is used to identify the most preferred coping strategies among the farmers, and an ordered probit regression model is used to identify its socio-economic determinants. The primary data for the study are collected through a quantitative field survey of 459 sample farming households in the selected three coastal districts of Odisha. The study region is selected through a multi-stage purposive sampling method. Based on the Flood Hazards Atlas Report (2019), three blocks of each district, along with three villages in each block, are purposively chosen from the selected districts (Kendrapara, Bhadrak and Cuttack), and therefore, a household-level survey is conducted in a total of nine villages of the selected three districts. Because the study's main objective is to learn more about farm-level adaptive strategies, the villages under consideration are also selected with care, bearing in mind that agriculture is the primary source of income for the majority of households. During the survey periods, the selected villages of the highest and moderately affected blocks of all the three districts were badly affected by floods and heavy rainfall which occurred in the month of 26 August 2020–4 September 2020. The highest and moderately affected villages (Supplementary Material, 1) regularly experience floods and cyclones every year. Hence, the current study solely focuses on the highest and moderately affected blocks for further investigation.

A stratified random sampling method was used to select farm households in the selected villages to cover households representing different categories of land ownership. In doing so, a two-step sampling procedure was followed. First, all the households at the village level were stratified into three categories, namely, marginal (<1 ha), small (1–2 ha), medium and large (>2 ha). Second, using a simple random sampling method, 17 farm households were chosen from each category, resulting in a block of 51 farm families and a district of 153 sample households being selected for the study. As a result, information has been collected from 459 sample farming households from the three study districts. However, this particular study concentrated only on 306 sample farmers from highly and moderately affected blocks of the study districts. A structured questionnaire was developed to conduct the household survey, which contains household-level information, farm-level adaptive strategies to cope with floods and institution-level initiatives.

2.3. Socio-economic profile of the sample households

Table 1 shows that the average age of farmers belonging to Kendrapara district is higher than that of the farmers belonging to the Bhadrak and Cuttack districts, which also holds true for the average farming experience. Since we have conducted field work immediately after the harvesting period, we have found that the percentage of men-headed household is more than that of the female-headed households in all the three sample districts. We have also found among the social categories that sample respondents belonging to Other Backward Class (OBC) are higher than those among other categories. In the study regions, among the respondents, Below Poverty Line (BPL) cardholders are more than that of the other two groups (APL and others). Most of the households in the study regions have thatched and semi-pucca houses. Respondents belonging to Cuttack district have better access to basic amenities such as electricity and toilet facilities than those in Kendrapara and Bhadrak districts.

2.4. Empirical model

The target variable for the study, i.e. farmers' opinions about their adaptive strategies, is ordinal. Farmers in the study regions were asked to respond to four different choices of their adaptation level of a particular coping strategy (i.e. 1 = 'not preferred', 2 = less preferred, 3 = moderately preferred and 4 = highly preferred). To analyse such

Table 1 | Details on farm household head.

Characteristics of farm household head	Bhadrak	Kendrapara	Cuttack
Average age	49.77	53.6	49.6
Max. age	88	85	78
Min. age	30	30	29
Average farming experience	28.21	29.63	26.2
Max. farming experience	67	60	62
Min. farming experience	2	3	5
Sex (%)			
Male	97.36	98.02	97.0
Female	2.63	1.97	3.0
Caste (%)			
General caste (GC)	16.67	38.24	11.76
Other backward caste (OBC)	59.8	39.22	66.67
Schedule caste (SC)	22.55	19.61	20.59
Schedule tribe (ST)	0.98	2.94	0.98
Welfare scheme (%)			
BPL	65.69	63.73	56.86
APL	31.37	33.33	37.25
Others	2.94	2.94	5.88
Type of house (%)			
Pucca	16.67	14.71	20.59
Semi-pucca	40.2	49.02	41.18
Thatched	43.14	36.27	38.24
Electricity	74.51	81.37	83.33
Toilet	27.45	29.41	30.39

Source: Field Survey.

ordinal data, the literature employs ordered logit and probit models.[1] To assess the factors explaining their preferences for using a particular strategy, we estimated an ordered probit model. It was generated by a continuous unobserved latent variable on crossing a threshold. In this case, the threshold represents farm households' preference for the level of adaptive strategies. However, the selection of two models is chiefly a matter of convenience, as also which model is most commonly used in the relevant area of research (Long, 1997). This study employed the ordered probit model, as it has a wider applicability to assess the ordinal nature of a target variable. As described in Wooldridge (2002), the ordered probit model is based on latent regression and denoted

[1] These two models are essentially the same, the only difference being their distributions. The logit model follows the cumulative standard logistic distribution function, while the standard normal distribution is followed in the probit model. However, both models provide similar results (Long, 1997; Greene, 2012).

as follows:

$$y_h^* = x_h\beta + e, \quad \frac{e}{x} \sim \text{normal } (0, 1)$$

where y_h^* represents the latent and continuous measures of adaptation strategy by a farm household h, x_h is a vector of explanatory variables, β is the vector of parameters to be estimated and e describes a random error term, which follows a normal distribution.

Here, y_h^* is unobservable, but we do have an observed choice, and y_h^* is determined from the model as follows:

$$y_h = 1 \quad \text{if } y_h^* \leq \propto_1 \quad \text{(Not preferred strategy)}$$

$$y_h = 2 \quad \text{if } \propto_1 < y_h^* \leq \propto_2 \quad \text{(Less – preferred strategy)}$$

$$y_h = 3 \quad \text{if } \propto_2 < y_h^* \leq \propto_3 \quad \text{(Moderatly preferred strategy)}$$

$$y_h = 4 \quad \text{if } \propto_3 < y_h^* \leq \propto_4 \quad \text{(Highly preferred strategy)}$$

The parameter $\propto$ represents thresholds or cut-off points, which can be estimated along with the parameter β. Given the standard normal assumption for e, we can derive the conditional distribution of y given x:

$$\text{Prob}\left(y_h = \frac{1}{x}\right) = \text{Prob}\left(y_h^* \leq \frac{\propto_1}{x}\right) = \text{Prob}\left(x\beta + e \leq \frac{\propto_1}{x}\right) = \Phi(\propto_1 - x\beta)$$

$$\text{Prob}\left(y_h = \frac{2}{x}\right) = \text{Prob}\left(\propto_1 < y_h^* \leq \frac{\propto_2}{x}\right) = \Phi(\propto_2 - x\beta) - \Phi(\propto_2 - x\beta)$$

$$\text{Prob}\left(y_h = \frac{3}{x}\right) = \text{Prob}\left(\propto_2 < y_h^* \leq \frac{\propto_3}{x}\right) = \Phi(\propto_3 - x\beta) - \Phi(\propto_2 - x\beta)$$

$$\text{Prob}\left(y_h = \frac{4}{x}\right) = \text{Prob}\left(\propto_3 < y_h^* \leq \frac{\propto_4}{x}\right) = \Phi(\propto_4 - x\beta) - \Phi(\propto_3 - x\beta)$$

$$\text{Prob}\left(y_h = \frac{n}{x}\right) = \text{Prob}\left(\propto_{n-1} < \frac{y_h^*}{x}\right) = 1 - \Phi(\propto_{n-1} - x\beta)$$

where Φ (˙) is the cumulative standard normal distribution. The sign of the estimated parameter β can be directly interpreted because of the increasing nature of the ordered classes. The ordered probit model can be estimated using maximum likelihood (ML).

The log-likelihood function is the function that is numerically maximised subject to $\propto_1 < \propto_2 < \propto_3 < \cdots < \propto_{n-1}$. The ML estimates that β and $\propto$ are consistent and asymptotically efficient and, accordingly, it is assumed that the error term also follows a normal distribution.

The parameter estimate in the ordered probit model only explained the direction of the effect of explanatory variables on the dependent variable but did not represent the actual magnitude of change or probabilities in the coefficients. This is because the coefficients of the ordered probit model differ by a scale factor. To overcome this problem, we have estimated the marginal effect of the ordered probit model. The marginal effects or marginal probabilities are functions of the probability itself and measure the expected change in probability of a particular choice being made with respect to a unit change in an independent variable from the mean (Green, 2012).

$$\frac{\partial\, Pr\, y_h \; = j\; (j = 1, 2, \; \ldots, n)}{\partial x_h} = \{\Phi\; (\propto_{j-1} - x_h\beta - \Phi(\propto_j - x_h\beta)\}\beta$$

where Φ is the normal density function, j is the threshold parameter and x_h is the explanatory variable.

The cross-sectional econometric analysis is associated with the problem of multicollinearity and heteroscedasticity. Multicollinearity is checked using the variance inflation factor (VIF) and contingency coefficients (CC). The mean of the VIF value for all the independent variables is 1.22 which is <10 suggesting no problem of multicollinearity. Similarly, values of the CC have shown no multicollinearity problem among dummy variables. In addition, the issue of heteroskedasticity of the model was addressed using the robust standard error procedure. According to Woodridge (2013), the robust standard error could effectively solve heteroskedasticity since it gives a relatively accurate *P*-value to ensure the significance of the model.

3. DESCRIPTIVE STATISTICS

This section presents the descriptive statistics of the explanatory variables used in the econometric analysis (Supplementary Material, 3). Farm-level adaptive response depends upon the *family size* as it determines the feasibility of adapting any particular strategy. The average household size of the surveyed household is 6.42 members. The minimum household size is two members and the maximum is 30 members in the study regions. The expected impact of family size is positive/negative depending upon the nature of the adaptive strategy. The dependent members of the family (including females, children and old age people) can have a positive or negative impact on their adaptive capacity.

The farmer's or *household head's* parameters can influence their perception, willingness to adapt and adaptive choices. The average age of farmers in the study area is 51 years. The youngest farmer is 29 years old and the oldest farmer is 88 years old. The average age of the sample farmers can have a positive or negative impact on their adaptation decision. Most of the sample farmers in the study region are male farmers. The percentage of male farmers is about 97% and the percentage of female farmers is about 3% only.

Several studies have established a positive relationship between *education* and the likelihood to adopt strategies (Maddison, 2007; Deressa *et al*., 2009; Jha & Gupta, 2021). The average year of schooling of the sample farmers is 7.36 years. The maximum year of education is 15 years and the minimum is 0 year of schooling. Education variables are taken as a categorical variable, and these are illiterate, elementary education, secondary & higher secondary (SHS) education and college education.

The size of landholding is also considered as a wealth indicator and can have both positive and negative consequences of adaptation decisions and choices. The average land size held by the farm household is 3.77 acres. It ranges from a minimum of 1 acre to a maximum of 30 acres of land. Similarly, secondary occupation *livestock ownership* also hypothesises to increase the adaptation to climate change. A household's income is identified to play an essential role in enhancing climate change adaptation. The average livestock owned by the surveyed households is 6.56 units (which include cow, buffalo, chicken, duck, bullock, etc.). In the present study, we have taken livestock possession as a dummy variable, i.e. if dummy = 1, livestock owned and if dummy = 0, no livestock is owned by the sample households.

The household occupational structure, i.e. both *farm* and *non-farm income* sources, also has a significant implication on their adaptation decisions and choices. The secondary occupation is supposed to positively impact the adaptive capacity due to the income from different sources. The influence of farm and non-farm income sources again depends upon the nature of the adaptive strategies undertaken by households. It is observed from the field that an average monthly farm income, i.e. income from agriculture alone, is INR 1,238.95 with a minimum income of zero and a maximum of INR 9,050. On the other hand, the average monthly non-farm income is INR 4,363.04 with a minimum income of zero and a maximum of INR 52,000. The off-farm income includes income from sub-occupation, namely wage labour, self-employment, business and salary income.

4. RESULTS AND DISCUSSION

4.1. FRSs as an *ex ante* strategy

Estimates (in Table 2) derived from the model are found to replicate a positive influence of independent variables (e.g. education, age, land size and farm income) on the households' behaviour towards the utilisation of FRSs at different levels. The model has proven to be sound in terms of statistical diagnostics (Prob. $> \chi^2$, pseudo-R^2 of 0.114 and log pseudo-likelihood of −239.238).

When compared with D-3, figures in Table 1 present D-2 as more adaptive towards using FRSs as an *ex ante* strategy in terms of its likelihood, whereas D-1 is less likely to adapt such strategies. The same findings are validated in terms of the marginal effect of different farmer choice categories. The estimates of the marginal effect show that the fourth category of sample farmers of D-2 is (21.8%) more likely to use FRSs as an *ex ante* strategy, whereas it is less likely to be used by first, second and third choice categories of sample farmers (with 6.3%, 4.9% and 10% likelihood, respectively). Contrary to that, the fourth category of sample farmers of D-1 is (13.8%) less

Table 2 | Ordered probit model results with marginal effects for flood-resistant crop.

		Marginal effect (δ_y/δ_x)			
Variables	**Parameter**	**Not Pref.**	**Lower Pref.**	**Moderate Pref.**	**High Pref.**
District 1	−0.430**	0.047*	0.032**	0.060**	−0.138**
District 2	0.794***	−0.063***	−0.049***	−0.106***	0.218***
Family size	−0.047	0.004	0.003	0.007	−0.014
Illiterate	−0.942**	0.168	0.076**	0.102***	−0.346**
Elementary education	0.855**	−0.100*	−0.062**	−0.113***	0.276**
Secondary & higher secondary education	0.612**	−0.061	−0.043	−0.084**	0.189**
Respondent age	0.013*	−0.002*	−0.001*	−0.002*	0.004*
Land size	0.059*	−0.005*	−0.004	−0.008	0.018*
Livestock possession	−0.014	0.001	0.001	0.002	−0.004
Ln farm Y	0.060**	−0.005**	−0.004**	−0.009**	0.018**
Ln off-farm Y	0.032	−0.003	−0.002	−0.005	0.010
Number of observations	306				
Wald χ^2 (11)	51.60				
Prob. $> \chi^2$	0.000				
Pseudo-R^2	0.114				
Log-pseudo-likelihood	−239.238				

Marginal effects (δ_y/δ_x) calculated at the mean for continuous variables and a discrete change from 0 to 1 for dummy variables. District 3 is the reference category for the district variable, and college education is the reference category for the education variable which is categorical. District 1 represented as D-1, District 2 as D-2 and District 3 as D-3.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

likely to use such strategy, whereas for first, second and third categories of farmers, the likelihood to use FRSs as *ex ante* strategies increases by 4.7%, 3.2% and 6%, respectively.

4.1.1. Education

Education is a categorical variable in our study and is an important factor in influencing farmer adaptation decisions. Education allows farmers to access appropriate information and encourages the adaptation of improved crop varieties, FRSs, high-yielding varieties of seeds and other improved technology in farming practices. Education level was considered necessary to approach information on improved technologies (Norris & Batie, 1987). Education was found to increase the probability of taking adaptive measures such as FRSs, soil conservation and changing planting dates (Deressa *et al*., 2009; Heyi & Mberengwa, 2012; Temesgen *et al*., 2014) and to influence adaptation positively (Deressa *et al*., 2011). The findings of our study are also corroborated with the above studies. The empirical analysis of our study shows that farmers' adaptation of FRSs as an *ex ante* strategy is positively and significantly influenced by both elementary and SHS levels of education. With reference to college education, an additional schooling year for farmers of the fourth category with elementary education will make them (27.6%) more likely to adapt FRSs, while the farmers of first, second and third categories will be made (10%, 6.2% and 11.3%, respectively) less likely to adopt. Similarly, in comparison with college education, every additional year of schooling of sample farmers in SHS education will lead to an increase in the likelihood of adopting FRSs as an *ex ante* strategy by 18.9% for the fourth category of choice and will reduce it by 8.4% for the third categories of choice, respectively. However, the likelihood of adopting FRSs for illiterate farmers as an *ex ante* strategy is reduced by 34.6% for the fourth category of choice and will increase by 16.8%, 7.6% and 10% for the first, second and third choice categories, respectively, as compared to the base category.

4.1.2. Age

The consideration of age in our study is a way to reflect the importance of experience. Here, it is assumed that older farmers have considerable experience in farming practices. They have extensive observation-based knowledge of the reality of climate change and probably understand the necessity of adaptation to farmers' livelihoods (Amare & Simane, 2017). This accounts for a greater likelihood of their undertaking adaptive measures (Hassan & Nhemachena, 2008; Deressa *et al*., 2009). The result of our analysis is supported by the findings of preceding studies, which show a positive and significant relationship between respondent age and the use of FRSs as an *ex ante* strategy. The marginal effect result revealed that a 1-year increase in the farmer's age increases the probability of adopting FRSs as an *ex ante* coping strategy by 0.4% for the fourth category and decreases for the other categories of the sample farmer in the study regions.

4.1.3. Land size

Our analysis revealed a positive and significant relationship between land size and dependent variables. According to the marginal effect result, an increase of 1 acre of land will significantly increase the probability of adopting FRSs as an *ex post* strategy by 1.8% for the fourth category of choice. Based on their experience of crop damage due to the occurrence of floods every year, the sample farmers began to adopt improved technology with high-yielding varieties (HYVs) seeds, a flood-resistant crop for cultivation, to reduce the possible loss from floods. Our result is in consistent with the findings of Trinh *et al*. (2018) which reported that households with large farmlands are more likely to change crop varieties, switch to new cultivar types and follow-up weather forecasts to cope with climate change.

4.1.4. Farm Y

Income represents the level of affluence of farm households. It contributes to whether farmers are willing to conduct adaptive measures. A high-income allows farmers to adopt measures that are expensive and probably more effective in response to climate change. Income is normally found to contribute positively to the adoption of agricultural technologies, i.e. climate-resilient crops (Franzel, 1999; Knowler & Bradshaw, 2007; Jin *et al.*, 2016). This finding is understandable because rich farmers would have a higher capacity to buy and plant new crop varieties (Desessa *et al.*, 2009). The ordered probit model result shows a positive and significant relationship between farm income (log farm Y) and the dependent variable in our study. While analysing the marginal effects, it can be seen that a 1% increase in farm income leads to a 1.8% increase in the probability of using FRSs as an *ex ante* strategy for the fourth category of the sample farmers, while the likelihood of using FRSs as an *ex ante* strategy decreases for the other three categories of choice; although the off-farm income is found to be insignificant with a positive sign, which also signifies that income, in general, has a positive impact on the use of FRSs as an *ex ante* strategy.

4.2. Stocking foodgrains: an *ex ante* strategy

The transitory demand for additional food stock has proven itself as an effective *ex ante* strategy for D-2 in the likelihood of adoption terms, whereas D-1 is found to be reluctant towards such adaptability. The fourth category farmers of D-2 and the first, second and third category farmers of D-1 are more likely to keep foodgrain buffer stock as an *ex ante* strategy (with 25.4%, 8.1%, 5% and 35.2% likelihood, respectively). Aforementioned findings shown in Table 3 also indicate the robustness of the model with Prob. $>\chi^2$, Wald pseudo-R^2 of 0.1806 and log pseudo-likelihood of −196.671. The table simultaneously established factors like age, land size, livestock

Table 3 | Ordered probit model results with marginal effects for stocking foodgrain.

		Marginal effect (δ_y/δ_x)			
Variables	**Parameter**	**Not Pref.**	**Lower Pref.**	**Moderate Pref.**	**High Pref.**
District 1	−1.418***	0.081***	0.050**	0.352***	−0.483***
District 2	0.748***	−0.029*	−0.022*	−0.203***	0.254***
Family size	−0.008	0.000	0.000	0.002	−0.002
Illiterate	0.155	−0.005	−0.004	−0.043	0.052
Elementary education	0.130	−0.004	−0.003	−0.035	0.042
Secondary & higher secondary education	0.023	−0.001	−0.001	−0.006	0.007
Respondent age	0.017**	−0.0004*	−0.0003*	−0.005**	0.005**
Land size	0.080**	−0.002*	−0.002*	−0.022**	0.025**
Livestock possess	0.630***	−0.029*	−0.021	−0.175***	0.225***
Ln farm Y	0.052**	−0.001	−0.001	−0.014**	0.017**
Ln off-farm Y	−0.013	0.0003	0.000	0.003	−0.004
Number of observations	306				
Wald χ^2 (11)	67.40				
Prob. $>\chi^2$	0.000				
Pseudo R^2	0.1806				
Log pseudo-likelihood	−196.671				

Marginal effects (δ_y/δ_x) calculated at the mean for continuous variables and a discrete change from 0 to 1 for dummy variables. District 3 is the reference category for the district variable, and college education is the reference category for the education variable which is categorical. District 1 represented as D-1, District 2 as D-2 and District 3 as D-3.

*$p<0.10$; **$p<0.05$; ***$p<0.01$.

possession and farm income as significantly influencing farmer's pro-adaptive attitude towards stocking foodgrains as an *ex ante* strategy.

4.2.1. Age

Incremental age is highly associated (positively) with savings and (negatively) with consumption, in monetary terms. In real terms (as foodgrains case here), in the presence of imminent disaster, the likelihood of using stocking of food grains as an *ex ante* strategy reserves greater adaptability among farmers with the growing age. Following the findings by Deressa *et al*. (2009) and Gebreyesus (2016), our study also establishes that for the fourth category sample, with an additional age, the likelihood of stocking grains as a strategy increases by 0.5%. The other three samples are found to have less likelihood towards such adaptation. Older farmers, based on their previous experience,stock foodgrains such as rice, atta, oil and other basic food items well in advance to prepare for floods. Storing paddy and pulses not only helps them satisfy their food needs, but it also helps to save them for future cultivation cycles. Stocking foodgrains also helps them to generate monetary income during an emergency period in the sense that they can sell their food grains and earn money out of that.

4.2.2. Land size

Although mild, the land size and the farm income are found to positively influence farmers' attitude towards the adoption of a foodgrain stocking strategy as an *ex ante* strategy. The results indicate that an increase of 1 acre landholding can potentially induce the likelihood of adoption by 2.5% for the fourth category choice of the sample households. Foodgrain storage is a common practice among small, medium and large landholders in the study areas.

4.2.3. Livestock and farm income

According to our result, incremental possession of livestock bears a huge potential to induce stocking of food grains by 22.5% for the fourth choice category here. On the other hand, as farm income rises by 1%, the likelihood of 'stocking of food grain' as an *ex ante* strategy rises by 1.7% for 4th choice category, whereas it decreases for the other three categories of choice of the sample farmer in the study regions. These findings replicate the fact that an increase in income in terms of farm income and as absolute possession of land and livestock always makes stocking of foodgrains more affordable and profitable. These are corollaries of the findings established in Franzel (1999), Knowler & Bradshaw (2007) and Jin *et al*. (2016), who defined agri-adaption as a direct positive function of financial well-being and income.

4.3. Migration: an *ex post* strategy

As the figures mentioned in Table 4 indicate, migration is more likely to be a post-disaster strategy in terms of adaptability in both districts. For both D-2 and D-1, farmers belonging to the fourth preference category are 19.6% and 13.7% more likely to adopt migration as a post-disaster strategy, whereas farmers belonging to the first preference category of the sample in both districts are less likely to adopt such strategy with almost equal magnitude (of marginal effect). Such interesting results are backed by the soundness of the model, which is characterised by Wald χ^2 (11) = 54.98, Prob. $> \chi^2$ and log pseudo-likelihood of -211.219.

4.3.1. Family size

The explanation extends from the early literature of population growth, which claims that the factors behind having a larger family size were induced by the potential employment and thereby employment generation by members of the family. Similarly, as found in the area of study, families with more young adults tempted to earn more by engaging in activities outside the resident state (Odisha here) by migrating to more industrialised

Table 4 | Model result for migration (post-disaster strategy).

		Marginal effect (δ_y/δ_x)			
Variables	**Parameter**	**Not Pref.**	**Lower Pref.**	**Moderate Pref.**	**High Pref.**
District 1	0.358*	−0.139*	0.0012	0.0010	0.137*
District 2	0.512***	−0.199***	0.0015	0.0013	0.196***
Family size	0.093***	−0.036***	0.0004	0.0003	0.035***
Illiterate	0.793	0.307	0.0007	0.0003	−0.308
Elementary education	0.166**	−0.064**	0.0007	0.0006	0.0623**
Secondary & higher secondary education	0.283***	−0.109***	0.0012	0.0010	0.106***
Respondent age	−0.018**	0.007**	−0.0001	−0.0001	−0.007**
Land size	−0.053*	0.020*	−0.0002	−0.00012	−0.020*
Livestock possession	−0.319	0.125	−0.0008	−0.0008	−0.124
Ln farm Y	−0.021	0.008	0.0001	−0.0001	−0.008
Ln off-farm Y	0.092**	−0.035**	0.0004	0.0003	0.034**
Number of observations	306				
Wald χ^2 (11)	54.98				
Prob. $> \chi^2$	0.000				
Pseudo-R^2	0.1152				
Log pseudo-likelihood	−211.219				

Marginal effects (δ_y/δ_x) calculated at the mean for continuous variables and a discrete change from 0 to 1 for dummy variables. District 3 is the reference category for the district variable, and college education is the reference category for the education variable which is categorical. District 1 represented as D-1, District 2 as D-2 and District 3 as D-3.
$*p < 0.10$; $**p < 0.05$; $***p < 0.01$.

states and cities like Chennai, Bangalore and Surat. Thus, from Table 4, we also found that increased family size induces migration as a post-disaster migration strategy, with a favourable likelihood of 3.5% in the fourth category of sample farmers, while it is equally less likely adopted strategy in the first category of the sample. The result of our analysis has been corroborated with the findings of Yirga (2007), Tizale (2007) and Amare & Simane (2017), which reported that households with large families are forced to divert a part of the labour force to off-farm activities to generate more income and reduce consumption demands. Keister & Nee (2001) have found that larger families are more likely to allocate labour to off-farm activities. Zhao's (1999) study concluded that a reduction in family land or an increase in household labour increases the villagers' propensity to migrate.

4.3.2. Education

Education is expected to enhance migration, in general, because educated people are better equipped to access and evaluate job information from distant localities. Most of the previous research also agrees that education is positively related to off-farm employment (Guang & Zheng, 2005; Heyi & Mberengwa, 2012; Temesgen *et al.*, 2014; Amare & Simane, 2017). The result of our study is corroborated with the above studies. The empirical result shows that, as compared to college education, an additional year of schooling among the sample farmers in elementary education will increase their likelihood of adopting 'migration' as an *ex post* strategy by 6.23% for the fourth category of choice and will significantly reduce it by 6.4% for the first category of choice. Similarly, the marginal effect result of SHS education shows that every additional year of schooling among the sample farmers will increase their likelihood of adopting migration as an *ex post* strategy by 10.6% for the fourth category of choice, and it will reduce by 10.9% for the first category of choice, as compared to the reference category.

4.3.3. Age

An inverse relationship between age and the likelihood of migration has been observed in our analysis. The estimate of marginal effect shows that an additional increase in the age of the household head will significantly reduce the likelihood of migration by 0.7% for the fourth category of choice in the study regions. Consistent with our findings, Guang & Zheng (2005), Zaiceva (2014) and Gebreyesus (2016) reported that the likelihood of migration decreases with age. Peasants from a younger age cohort have a better chance of securing off-farm employment through migration than those from an older age cohort.

4.3.4. Land size

It is observed from the field that migration is an *ex post* coping strategy mostly preferred by farmers belonging to marginal and small sizes. The result shows that an increase of 1 acre of land reduces the probability to adapt 'migration' as an *ex post* strategy. Similar observations were also made by Bazezew *et al.* (2013) and Gebreyesus (2016) in their studies. Even though large landholders encounter the damage caused by the floods during the Kharif season, the cultivation of vegetables and other cash crops like groundnuts and pulses provides an opportunity to earn a good amount of income in the Rabi season. During the Rabi season, farmers in the most severely impacted blocks (except Chandabali block of D-1) of the study districts preferred to grow vegetables, groundnuts and flowers. According to them, the inundation of river water during the flood season enhances the fertility of the soil and, therefore, the productivity of the Rabi crop increases. The result of the marginal effect shows that an increase in 1 acre of land will significantly decrease the probability of migration by 2.0% for the fourth category of choice, and it will increase for the first category of choice of the sample households in the study regions.

4.3.5. Off-farm Y

Agriculture, in general, is a gamble on climate change, and farmers, in the coastal regions are severely affected by such events. Therefore, the ability to create off-farm income to alleviate poverty and reduce reliance on subsistence agriculture significantly enhances the probability of migration in the study region. The findings of our analysis are also consistent with the study of Matsumoto *et al.* (2006). Farmers choose off-farm income for financial and social reasons. Due to a lack of alternative job opportunities in the study region, migration is the only source of off-farm income for marginal and small farmers. The marginal effect result shows that a 1% increase in off-farm income will lead to an increase in the likelihood of adopting migration as an *ex post* strategy by 3.4% for the fourth category of choice, and it will decrease for the first category of choice of the dependent variable. Off-farm income presents an incentive that diverts farmers' attention from agricultural activities, which has resulted in a greater likelihood of adoption of migration as a post-disaster strategy.

4.4. RFC as an *ex post* strategy

This practice is mostly found among marginal and small farms. They reduce their consumption expenditure on milk, butter, fruits and non-veg items like meat and eggs in their daily routine of meals (Table 5).

The empirical result of the above table, as compared to D-3, presents that the probability of adapting RFCs as an *ex post* strategy is higher in D-2. As agriculture is the primary source of income for farming households, crop damage leads to a decrease in household income, which, in turn, has an adverse impact on their consumption patterns (Trinh *et al.*, 2018). It is observed from the field that flood victims cope with the negative effects of the floods by skipping meals and breakfast. Flood water intrusion inside the house and kitchen hampers food

Table 5 | Model result for RFC (post-disaster strategy).

		Marginal effect (δ_y/δ_x)			
Variables	**Parameter**	**Not Pref.**	**Lower Pref.**	**Moderate Pref.**	**High Pref.**
District 1	0.208	−0.070	−0.012	0.053	0.030
District 2	0.327**	−0.108**	−0.021	0.081**	0.048*
Family size	0.040**	−0.014**	−0.002*	0.011**	0.005**
Illiterate	−0.698	0.192	0.078	−0.130	−0.141
Elementary education	−0.715***	0.223***	0.048**	−0.167***	−0.111**
Secondary & higher secondary education	−0.424*	0.143*	0.022	−0.107*	−0.059*
Respondent age	−0.010	0.003	0.001	−0.002	−0.001
Land size	−0.173***	0.059***	0.009**	−0.045***	−0.023***
Livestock possess	−0.317*	0.101*	0.024	−0.076*	−0.050
Ln farm Y	0.046**	−0.016**	−0.002*	0.012**	0.006**
Ln off-farm Y	−0.021	0.007	0.001	0.005	0.003
Number of observations	306				
Wald χ^2 (11)	58.91				
Prob. $> \chi^2$	0.0000				
Pseudo-R^2	0.0801				
Log pseudo-likelihood	–366.688				

Marginal effects (δ_y/δ_x) calculated at the mean for continuous variables and a discrete change from 0 to 1 for dummy variables. District 3 is the reference category for the district variable, and college education is the reference category for the education variable which is categorical. District 1 represented as D-1, District 2 as D-2 and District 3 as D-3.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

preparation for farming households. This might be one of the reasons for them to skip meals and breakfast during those times. The marginal effect results show that the third and fourth categories of sample farmers of D-2 are (8.1% and 4.8%) more likely to adapt RFCs immediately after the flood event, whereas first and second choice categories of sample farmers are less likely to adapt RFCs by 10% and 2.1%, respectively. It is observed that the probability of adapting 'reduction of food consumption' as an *ex post* strategy is higher for D-2 than for D-3 and D-1.

4.4.1. Family size

The above table shows that there is a significant positive relationship between RFCs and family size. The marginal effect result shows that an increase in one member of the family will increase the likelihood of adapting RFCs as an *ex post* strategy by 1.1 and 0.5% for third and fourth choice categories of sample farmers, respectively, and will decrease for the other two categories. The result of our study is consistent with Umoh's (1997) study, which opined that *per capita* consumption of non-food items increases, while *per capita* food consumption decreases with family size.

4.4.2. Education

From our analysis, an inverse relationship was observed between the RFCs and the educational attainment of respondents. In comparison with college education, the marginal effect result of elementary education shows that an increase in 1 year of schooling among the sample farmers will reduce the likelihood of adopting RFCs as an *ex post* strategy by 16.7% and 11.1% for both the third and fourth categories, respectively, and it will significantly increase by 22.3% and 4.8% for first and second categories of choice of the sample farmers. Similarly, the estimate of the marginal effect of SHS education shows that every additional year of schooling among the sample farmers will lead to a decrease in their likelihood of practicing RFCs as an *ex post* strategy by 10.7% and 5.9% for the third and fourth categories of choice, and it will increase by 14.3% for the first category of choice, respectively. The result of our study is in line with Umoh's (1997) submission that there is a significant difference in the consumption pattern between literate and illiterate individuals. The finding follows the expectation that educated people should earn more income and, thus, comparatively record higher food expenditure and consumption than uneducated people.

4.4.3. Land size

The ordered probit result reveals an inverse relation between the probability of adopting RFCs as an *ex post* strategy and the land size holding, i.e. an additional increase in landholding size will lead to an increase in the probability of food consumption. The marginal effect result shows that an increase in landholding by 1 acre will increase the probability of adapting RFCs as an *ex post* strategy by 5.9% and 0.9% for the first and second categories, respectively, and will decrease for third and fourth categories of choice. Although the farming households encounter crop damage during the flood period, i.e. Kharif season, they grow vegetables and other cash crops like groundnuts and pulses during the Rabi season. The fertility of soil during the Rabi season enhances the productivity of crops, which, in turn, increases their farm income.

4.4.4. Livestock possession

An inverse relationship can be observed between the number of livestock possessed by the farming households and their adaptation to RFCs as an *ex post* strategy. According to the marginal effect result, one unit increase in livestock owned by the sample household will reduce the probability of adopting RFCs as an *ex post* strategy by 7.6% for the third choice category of sample households when compared with families with no livestock. To cope with the impact of flood, victims in the study regions were found to sell their livestock, i.e. chickens, ducks and goats, to generate income, which, in turn, helps them to improve their consumption pattern.

4.4.5. Farm income

Farm income is positively related to the probability of adapting RFCs as an *ex post* strategy to cope with the adverse impact of the flood. The marginal effect result reveals that a 1% increase in farm income will lead to an increase in the likelihood of reducing food consumption by 1.2% and 0.6% for the third and fourth categories of choice, respectively.

4.5. PDM as an e*x post* strategy

In the rainy season or the wet period, the possibility of fungal and bacterial diseases increases (Padgham, 2009). On the other hand, the level of salinity in the soil has increased due to saltwater intrusion in to the agricultural field. As a result, there is a high possibility of the occurrence of insects and pests like stem borer, gall midge and leaf folder; and diseases like sheath rot and bacterial leaf blight; and weeds like wild rice, *Echinocloa* spp., *Cyperus* spp. and *Schemoplectus* spp. (Singh & Sasmal, 2004). Farmers are, therefore, following various PDM techniques to counteract it. Farmers in the study areas control pests and diseases using FRS varieties such as Durga, Sabita, Lunishree, Sarala, Swarna and others, fertilisers, pesticides such as monocrotophos, neem cake in agricultural fields, crop rotation, green manure and compost, and mechanical cultivation.

Table 6 *shows that* sample farmers of D-1 and D-2 are more likely to adapt PDMs as an *ex post* strategy as compared to D-3 farmers. The marginal effect result for D-1 shows that the likelihood to use PDMs as an *ex post*

Table 6 | Model result for the PDM (post-disaster strategy).

		Marginal effect (δ_y/δ_x)			
Variables	**Parameter**	**Not Pref.**	**Lower Pref.**	**Moderate Pref.**	**High Pref.**
District 1	1.422***	−0.184***	−0.067***	−0.070***	0.321***
District 2	0.959***	−0.104**	−0.045**	−0.050**	0.199***
Family size	−0.043	0.003	0.002	0.002	−0.007
Illiterate	0.805	−0.115	−0.043	−0.045	0.202
Elementary education	0.971**	−0.100	−0.044*	−0.049*	0.193*
Secondary & higher secondary education	0.996**	−0.088*	−0.041*	−0.048*	0.178*
Respondent Age	0.030***	−0.002***	−0.001**	−0.002**	0.005***
Land size	0.030	−0.002	−0.002	−0.001	0.005
Livestock possess	0.476*	−0.050	−0.023	−0.026	0.099
Ln farm Y	0.064**	−0.005**	−0.003*	−0.003*	0.011**
Ln off-farm Y	0.095**	−0.007**	−0.004*	−0.005*	0.016**
Number of observations	306				
Wald χ^2 (11)	47.24				
Prob. $> \chi^2$	0.000				
Pseudo-R^2	0.1693				
Log pseudo-likelihood	−146.637				

Marginal effects (δ_y/δ_x) calculated at the mean for continuous variables and a discrete change from 0 to 1 for dummy variables. District 3 is the reference category for the district variable, and college education is the reference category for the education variable which is categorical. District 1 represented as D-1, District 2 as D-2 and District 3 as D-3.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

strategy increases by 32.1% for the fourth choice category, whereas it is less likely to use by first, second and third choice categories of sample farmers (with 18.4, 6.7 and 7%, respectively). Farmers in the Chandabali block of D-1 reported that seawater mixed with river water makes the agricultural land unproductive during the rainy season, forcing them to use PDM techniques to prepare the fields for the Rabi season cultivation. Similarly, for the D-2, PDM practices followed after the disaster increased by 19.9% for the fourth category of sample farmers, and it is likely to decrease by 10.4, 4.5 and 5% for the first, second and third categories of sample farmers, respectively.

4.5.1. Education

The ordered probit model shows that the education level of farmers is positively and significantly related to the dependent variable. The findings of our study are corroborated by Bahinipati (2015) and Amusa & Simonyan (2017), which explain that educated farmers have more access to information regarding the occurrence of floods/cyclone events and their consequences, and therefore, it helps them to adapt more effectively to adverse impacts compared with illiterate farmers. In comparison with college education, the marginal effect result of elementary education shows that an additional year of schooling among the sample farmers will increase their likelihood of practicing PDMs as an *ex post* strategy by 19.3% for the fourth category of choice and will significantly reduce it by 4.4% and 4.9% for the second and third categories of farmers, respectively. Similarly, the marginal effect result of SHS education shows that every additional year of schooling among the sample farmers will lead to an increase in their likelihood of practicing PDMs by 17.8% for the fourth category of choice and reduce by 8.8%, 4.1% and 4.8% for the first, second and third categories of choice of the sample farmers, respectively.

4.5.2. Age

The age of the head of household can be used to capture farming experience. A positive and significant relation is observed between age and the dependent variable. The estimate of marginal effect shows a 1-year increase in farmer age results in a 0.5% increase in the likelihood of adapting PDMs as an *ex post* coping strategy for the fourth choice category sample farmer in the study regions, whereas it decreases for the rest three categories of choice among the sample households in the study regions. This finding has been corroborated by the study of Kebede *et al*., (1990), Maddison (2007), Amusa & Simonyan (2017), which found that the age of farmers has a positive impact on their adaptive behaviour.

4.5.3. Farm income and non-farm income

A positive and significant relationship is observed between the income level of farmers (farm and non-farm sources) and the adaptation of PDM as an *ex post* strategy to cope with flood impact. Farmers' income levels represent their economic well-being and enable them to raise their expenditure on inputs and diverse adaptive measures to cope with climate change. To cope with pest and disease attacks, farmers employ different pest management measures like biological, cultural, mechanical and genetically modified varieties of seeds. The marginal effect of the natural log of farm income shows that a 1% increase in income will increase the likelihood of adopting PDMs as an *ex post* strategy by 1.1% for the fourth category of choice of the sample households. Similarly, a 1% increase in off-farm income results in a 1.6% increase in the probability of adapting to PDMs as an *ex post* strategy for the sample farmer's fourth category of choice.

5. CONCLUSION AND POLICY IMPLICATION

The present study attempted to identify the major flood adaptation strategies among the farming households of Odisha and the determinants of the choice of adaptation strategies based on a cross-sectional sample survey data collected from November 2020 to January 2021 in the three villages each from the three coastal districts of Odisha (namely Kendrapara, Bhadrak and Cuttack). From the Likert scale analysis, it was identified that migration, RFC and PDM were the most preferred *ex post* coping strategies by farming households (>50%). On the other hand, the common *ex ante* strategies reported by most of the farming households were stocking foodgrains and using FRSs.

An ordered probit regression model was employed to explore the determinants of adaptive strategies among the farming households in the study regions. From our analysis, it was observed that the socio-economic characteristics, namely, respondent's age, size of landholding and farm income were the common determinants of *ex ante* coping strategies among the farming households. On the other hand, family size, education and the size of landholding were found to be the common determinants of *ex post* strategies of migration and reduction of food consumption. Income from both farm and off-farm sources, education and the age of the respondents were the major determinants for using PDM practice as an *ex post* strategy among the farming households. Apart from this, the regional variation at the district level was also found to be a major determinant of adaptive strategies among the farming households.

From the field, it was observed that the likelihood of undertaking adaptation strategies was higher during the *ex post* period than during the *ex ante* period among flood-affected farm households. This might be due to the lack of prior information about the occurrence of floods or the perception of both moderately- and less-affected farmers that these extreme events were not a major threat to their livelihoods. This emphasises the need for government investment in scientific modelling for the early prediction of natural disasters so that farmers can undertake better adaptation decisions. From our study, it can be recommended that the government take the initiative to strengthen the agricultural extension activities to generate awareness among the farmers about the impact of floods, and the possible adaptation mechanisms that could be undertaken to mitigate expected crop loss.

AUTHOR CONTRIBUTIONS

N.P. contributed to the analysis and design and drafted the concept. Both N.P. and S.M. advised on the paper and assisted in paper conceptualisation. N.P. contributed to the comprehensive writing of the article. Both N.P. and S.M. read and approved the final manuscript.

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COMPETING INTEREST

The authors declare that they have no competing interests.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

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