Effects of climate change on household economy and adaptive responses among agricultural households in eastern coast of India

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It is imperative to understand the effects of climate change on household members and the vulnerability level in and across agricultural households for India in general, and for eastern coastal part of the country in particular. This study covers primary data from 150 households from 2 blocks of Kendrapara district in Odisha. The household level unit of analysis is policy driven and follows the IPCC model on Vulnerability Analysis and Climate Change Adaptation Research. The model is expanded to include the *livelihood strategies* of the households, in order to empirically assess their vulnerability and adaptive responses. This study uses an econometric model on household vulnerability and adaptive capacity of rural households. The results imply that access to credit facilities and experiences of the households in farming are important factors to improve farmers' adaptation to climate change.

Keywords: Adaptive capacity, climate change, exposure, vulnerability.

Introduction

AGRICULTURE is a critical sector of the Indian economy. Though its contribution to the overall gross domestic product (GDP) has fallen from about 30% in 1990–91 to less than 15% in 2011–12, agriculture yet forms the backbone of development[1,2]. Being sources of livelihood and food security for a vast majority of low income, poor and vulnerable sections of the society, its performance assumes greater significance in view of the National Food Security Bill and the ongoing Mahatma Gandhi National Rural Employment Guarantee Act. Given that India is still home to the largest number of poor and malnourished people in the world, a higher priority to agriculture might achieve the goals of reducing poverty and malnutrition, as well as for inclusive growth. This sector is particularly sensitive to climate variability. Evidence shows that climate change is already affecting crop yields in many countries[3]. Followed by the evidence of IPCC-2007 (ref. 4), there is a growing consensus in the scientific literature that in the coming decades the world will witness higher temperature and variable precipitation levels. The effect of these climate changes might lead to low/poor agricultural productivity.

India is subject to a wide range of climatic conditions, from the Himalayan winters in the north, to the tropical climate of the southern peninsula, from the moist rainy climate in the northeast to the arid Great Indian Desert in the northwest; and from marine climates of the vast coastline (and islands), to the dry continental climate in the interior. The coastal zone is an important and critical region for India that is densely populated across 7500 km, with Arabian Sea on the west and Bay of Bengal on the east. The total area occupied by the coastal districts is around 379,610 km with an average population density of 455 persons per km (ref. 5). The coastal ecosystems sustain a large proportion of the population in India. However, the pressure on coastal areas has been increasing due to inter-state migration and economic dynamism of coastal urban agglomerations. Out of almost 35 urban agglomerations with million plus population identified in Census 2011 (ref. 5), around 18 are situated in the coastal states. Among these urban agglomerations, eight agglomerations lie on the coastline. The activities in many of these areas tend to exceed the capacity of the natural coastal-ecosystem. Hence, these regions become more exposed and vulnerable to natural and human induced hazards.

Vulnerability varies widely across regions, sectors, communities and households. International comparisons of vulnerability tend to focus on national indicators either between developed countries, or among countries with similar economic conditions. At national level, vulnerability assessments contribute in setting development priorities and monitoring progress. However, sectoral assessments provide more detailed strategic development plans. At a local or community level, vulnerable groups can be more easily identified and hence, coping strategies can be implemented. Although vulnerability assessments

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are often carried out at a particular scale, there are significant cross-scale interactions due to the interplay of economic, social and climate systems. Based on the above discussion, the focus of the present paper is firstly to assess vulnerability of households due to extreme climate events, and then to examine the adaptive measures to hedge against the shocks. The paper is organized as follows. The following sections presents a brief review of literature, outlines the conceptual framework and model specification, describes the data sources and variables construction, estimates the determinants of household loss due to the cyclone and offers a brief conclusion with relevant policy suggestions.

Review of literature

The literature on vulnerability has grown enormously over the past few years[6–14]. Vulnerability has also become a familiar term in climate change literature, which has produced its own conceptual discourse[15–17]. Before assessing vulnerability due to extreme climate events, it may be useful to first compare the definition of hazard, risk, vulnerability and resilience. A hazard is a potentially damaging physical event, phenomenon or human activity that might cause loss of life or injury, property damage, social and economic disruption and environmental degradation. Risk is defined as the probability and extent of damage due to a particular hazard. Resilience is the ability of a community to recover from shocks caused by natural, man-made or human-induced phenomena[18] and vulnerability is the state of susceptibility to damage from exposure to stresses associated with environmental and social changes and from the absence of capacity to adapt[19].

Agarwal[20] analysed the coping capacity of rural households to agricultural production cycles and calamities such as drought and famine. He discussed the effectiveness of coping mechanisms, the intra-household burden shared for coping, and appropriate state and non-state interventions that would strengthen survival mechanisms adopted by households. Dang[21] explored the possible contradictions and synergies between adaptation, mitigation strategies and implications for developing countries. His case study of Vietnam, demonstrates how to integrate both mitigation and adaptation strategies, that can provide additional benefit to social welfare. Dixit[22] reviews the nature of flood disaster in Himalaya-Ganga by focusing on Nepal, and argues that conventional approaches have not been able to provide the security envisaged. He suggests that vulnerability of people in risk-prone areas must be addressed by enhancing resilience capacity.

The socio-economic vulnerability assessment approach emphasizes the changes in the socio-economic status of individuals or groups[23]. Individuals in a community often vary in characteristics and these variations are responsible for varying vulnerability levels. In this case, vulnerability is considered an entry point to climate change crisis, that exists within a system before it encounters a hazard event. In general, the socio-economic approach focuses on identifying the adaptive capacity of individuals or communities based on their internal characteristics. The main limitation of the socio-economic approach is that it focuses only on variations within society. In reality, societies vary, not only due to socio-political factors but also environmental and other factors. Social groups with similar socio-economic characteristics, but different environmental attributes can have different levels of vulnerability and vice-versa. The biophysical approach assesses the level of damage that a given environmental stress causes, on both social and biological systems. For instance, the yield impacts of climate change can be analysed by modelling the relationships between crop yields and climatic variables[24]. Kelly and Adger[25] refer to biophysical approach as an end-point analysis responding to research questions such as, 'what is the extent of the climate change problem?' and 'do the costs of climate change exceed the costs of greenhouse gas mitigation?' In general, the biophysical approach focuses on sensitivity to climate change and misses much of the adaptive capacity of individuals or social groups, which is explained merely by their inherent characteristics. The integrated assessment approach combines both socio-economic and biophysical approaches to determine vulnerability.

Vulnerability mapping approach[26] another example, in which both socio-economic and biophysical factors are combined to indicate the level of vulnerability through mapping. Fussel[11] identified this approach as a risk-hazard approach and denoted the vulnerability relationship as a hazard-loss relationship in natural hazard research, a *dose-response* or *exposure-effect* relationship in epidemiology, and a *damage function* in macroeconomics. He argued that the definition by the Inter-Governmental Panel on Climate Change[27], that conceptualizes vulnerability to climate as a function of adaptive capacity, sensitivity, and exposure, accommodates an integrated approach to vulnerability analysis. According to Fussel, the risk-hazard framework corresponds most closely to sensitivity in the IPCC terminology. Adaptive capacity is largely consistent with the socio-economic approach. In the IPCC framework, exposure has an external dimension, whereas both sensitivity and adaptive capacity have internal dimension, which is implicitly assumed in the integrated vulnerability assessment framework[23]. Although the integrated assessment approach corrects the weaknesses of other approaches, it has its limitations, the main limitation being no standard method for combining biophysical and socio-economic indicators. Despite its weaknesses, however, this approach has a lot to offer in terms of policy decisions[28]. The econometric method is similar to the poverty and development literature. It uses household level socio-economic survey data to analyse the level of vulnerability of different social groups. The method is divided into three categories: (i) vulnerability due to expected poverty, (ii) vulnerability due to low expected utility, and (iii) vulnerability due to uninsured exposure to risk. All three share common characteristics in that they construct a measure of welfare loss attributed to shocks. Several conceptual approaches and methodologies have been employed to measure vulnerability to climate change[28,29]. Patnaik and Narayanan[30] constructed a picture of socio-economic context of vulnerability by focusing on indicators that measure both the state of development of the region, as well as its capacity to progress further. Their analysis was carried out at district level, and vulnerability of a particular district was measured by the frequency of occurrence of extreme events. They found that the districts in the states of Odisha and Andhra Pradesh are highly vulnerable than the other states in India.

Based on farm household and participatory rural appraisal data, collected from districts in various agro-ecological zones in Kenya, Bryan *et al.*[31] examined farmers' perceptions of climate change, ongoing adaptation measures, and factors influencing farmers' decisions to adapt. The results show that while many households have made small adjustments to their farming practices in response to climate change, few households can afford costly investments, for example agro-forestry or irrigation. They conclude that there is a need for greater investments in rural and agricultural development to support the ability of households to make strategic and long-term decisions that affect their future wellbeing.

Bahinipati and Patnaik[32] examined the influence of disaster-specific and generic adaptation measures, in reducing the damages resulting from climate extremes like cyclones and floods in India. They carried out a district-level analysis for the state of Odisha, India from 1999 to 2008 using fixed effects and negative binomial models. Controlling the influence of exposure and population they arrived at three major findings: (i) households and policy makers have learnt from previous disasters, i.e. there is a *learning effect*; (ii) the disaster risk management programme undertaken by the government has reduced the damages from climate extremes, and (iii) generic adaptation interventions are helpful.

Most of the present research deals with the effect of climate-related disasters either at a micro- or macro-levels. Some studies also deal with such negative externalities of climate-related disasters. However, studies to quantify the loss derived from sample characteristics and related to climate shocks are scanty, specifically for economically backward states in India. This paper contributes to the growing literature on this topic by addressing the three important issues: (i) *effects*, (ii) *vulnerability* and (iii) *adaptation* to climate changes, using household level data. In attempting the above three objectives, we have disaggregated the agricultural households based on the response related to the primary occupation of household members as an instrument. The effects are measured based on the response to the direct question related to the specific effect of each climate change factors, that effect at household level. Vulnerability was assessed in the form of hazard-loss approach captured through the question, related to the amount of income loss due to climate change. We address adaptation through the use of climate change adaptation index (CCAI) by categorizing the households into *none*, *low*, *average* and *high adaptation* capacity based on the number of actionable steps taken by the household to counter the climate change impacts. Based on the literature on vulnerability, coping and adaptation, this paper looks at bottom-up approach in determining the vulnerability of households for the sample households of Odisha.

Conceptual framework and the model specification

The degree of vulnerability or adaptation of a system is a function of character, magnitude and variations to which the system is exposed, the sensitivity and its adaptive capacity[27]. This reflects an integrated approach to vulnerability and forms the basis for the conceptual framework of this study. This prioritizes the bio-physical and socio-economic characteristics of households in assessing vulnerability. Figure 1 presents the conceptual framework, which is a modification of Adger and Kelly[33]. It provides a clear perception of vulnerabilities in terms of ecological, economic and social systems. To understand the vulnerability of climate change at household level we propose a theoretical model and arrived at the determinants of household loss due to climate shock, using appropriate econometric methods. Figure 1 indicates that when an agricultural household is exposed to extreme climate events, it becomes sensitive to such crises as decreased farm yield, low income, low health status, etc. The level of degeneration in sensitivity is determined by factors such as environment and socio-economic characteristics of the households. It is the sum total of the two factors (biophysical and socio-economic) that determines the aggregate household vulnerability.

Let us assume that, for a given population of $i = 1,\dots,n$ households, a household's total loss due to climate-related disasters ($H \geq 0$) is a function of the household's income ($I \geq 0$), conditional on the livelihood activities of the household. For expositional purpose, let us assume that household's total loss due to climate related disasters can be classified as either agricultural loss (h) or non-agricultural loss (uh). Further, the probability (p) of loss due to climate related disaster assumed to be an increasing function of the household's income and hence $p = p(I)$, where $0 \leq p \leq 1$, and $\partial p(I)/\partial (I) \geq 0$. It is also assumed that the production function $H = H(I)$ are linear for both h and uh and that $H_h(I) \geq H_{uh}(I)$ for all I (where

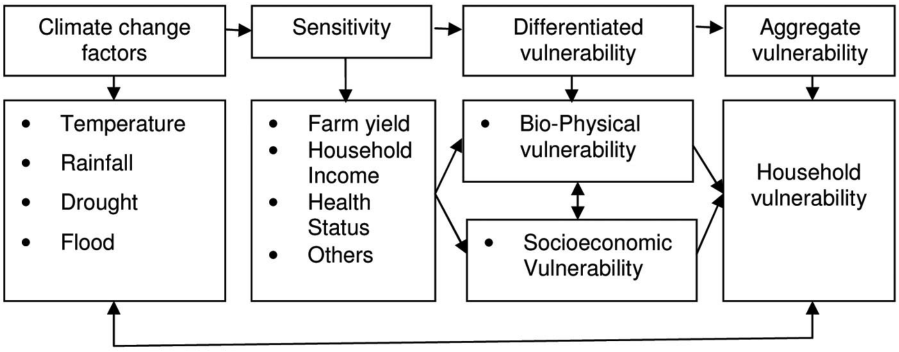

Figure 1. The conceptual framework.

$H_h(I)$ and $H_{uh}(I)$ denote the levels loss due to climate related disasters, that; $\partial H_h(I)/\partial I \geq \partial H_{uh}/\partial I$, and $\partial^2 H_h(I)/\partial I^2 \geq \partial^2 H_{uh}/\partial I^2 = 0$ for all I. Therefore, the expected loss due to climate related disasters of a household with a given level of income I can be written as

$$E(H/I) = p(I)H_h(I) + [1 - p(I)]H_{uh}(I). \quad (1)$$

Differentiating eq. (1) with respect to I gives an expression for the change in the expected loss due to climate related disasters of the household with respect to a change in income

$$\frac{\partial E(H/I)}{\partial I} = \frac{\partial H_h(I)}{\partial I} p(I) + \frac{\partial H_{uh}(I)}{\partial I}[1 - p(I)] + \frac{\partial p(I)}{\partial I}[H_h(I) - H_{uh}(I)]. \quad (2)$$

The second derivative of eq. (1) with respect to I is

$$\frac{\partial^2 E(H/I)}{\partial I^2} = \frac{\partial^2 H_h(I)}{\partial I^2} p(I) + \frac{\partial^2 H_{uh}(I)}{\partial I^2}[1 - p(I)] + 2\frac{\partial p(I)}{\partial I}\left(\frac{\partial H_h(I)}{\partial I} - \frac{\partial H_{uh}(I)}{\partial I}\right) + \frac{\partial^2 p(I)}{\partial I^2}[H_h(I) - H_{uh}(I)]. \quad (3)$$

Because the functions $H_h(I)$ and $H_{uh}(I)$ are assumed to be linear, the first two terms on the right hand side of eq. (3) are equal to zero. Equations (2) and (3) define the slope and curvature of the function describing the expected loss of a household with income level I, defined in eq. (3). To obtain the average loss due to climate related disaster of population, let us take a weighted average of the expected loss function for income level I over the n individual that comprises the population of the household. For any income distribution, the functional form can be written as

$$E(H) = E_i[E(H/I_i)], \quad (4)$$

where $E(H/I_i)$ is defined in eq. (1). Hence, for continuous income distribution, the mean for a population is

$$E(H) = \int_0^\infty f_I E(H/I)\mathrm{d}I, \quad (5)$$

where f_I is the frequency density function of I, 0 and ∞ are the lower and upper bounds of the income distribution respectively. The model for this study (vulnerability) is captured through an integrated approach to vulnerability using econometric method of *vulnerability as exposure to uninsured risk*. The model is a variant of vulnerability to shocks[34] as shown in the equation below

$$E(H)_{hb} = \alpha + \sum_i \lambda_i L(i)_h + \sum_i \beta_i L(i)_{hb} + \delta X_{hb} + \varepsilon_{hb}, \quad (6)$$

where $E(H)_{hb}$ is the log of total loss per household (household h residing in block b), $L(i)_h$ and $L(i)_{hb}$ represent the covariate shocks of the blocks and the idiosyncratic shocks as expressed by the households respectively. The covariate shocks are expressed in terms of sensitivity to climate change scenarios in the form of observed change in rainfall and temperature patterns, while the idiosyncratic shocks capture the exposure of households to shocks in different agric sub-sectors like cropping, livestock production, etc. X_{hb} captures the fixed household characteristics as depicted in the socioeconomic information of the respondents. It should be noted that if there are no shocks to the household as depicted in eq. (6), the income loss equation will be of the form

$$E(H)_{hb} = \alpha + \delta X_{hb} + \varepsilon_{hb}. \quad (7)$$

The impact of the shocks (covariant and idiosyncratic) will be the difference between eqs (6) and (7). If the shocks were to be fully insured against, then λ and β would equal zero. The econometric specification of equation (6) takes the following functional form

$$\ln \text{loss}_i = \alpha_0 + \underbrace{\beta_1 \text{Temp}_i + \beta_2 \text{Rain}_i}_{\text{covariate shocks}} + \underbrace{\beta_3 \text{Cropping}_i + \beta_4 \text{Livestock}_i}_{\text{idiosyncratic shocks}} + \underbrace{\begin{pmatrix} \beta_5 \text{Size}_i + \beta_6 \text{Edu}_i + \beta_7 \text{Age}_i + \beta_8 \text{Gender}_i \\ + \beta_9 \text{Nonfarm}_i + \beta_{10} \text{Agext}_i + \beta_{11} \text{Dist}_i \end{pmatrix}}_{\text{fixed household characteristics}} + u_i, \tag{8}$$

where ln loss is log of total loss reported by ith household, temp is perception of change in temperature over last twenty years, rain is perception of change in rainfall over last twenty years, cropping is households engaged in cropping activities, livestock is household with livestock, size is household size, edu is education of head of the household, age is age of head of the household, gender is gender of head of the household, nonfarm is households participating in nonfarm activities, agext is households involved in agriculture extensions, and dist is distance from the nearest town. Further, the model estimated to capture the adaptation level of households response to climate change challenges is as follows

$$AR_{hb} = \sum_b \delta_b (P_b) + \sum_i \beta_i L(i)_{hb} + \gamma X_{hb} + \varepsilon_{hb}. \tag{9}$$

In the equation above, AR_{hb} represents the adaptive response level of the household which is ordered in the sense that those who took the maximum three steps allowed in the instrument in combating the climate change challenge have 'high adaptive response', those who took two steps were classified as 'medium adaptive response', those who only took one step are categorized as 'low adaptive response' and those with score zero as 'no adaptive response' households. Further in eq. (9), P_b represents the idiosyncratic shocks vector of changes in rainfall and temperature while $L(i)_{hb}$ and X_{hb} are as described in eq. (6).

Data sources and variables construction

According to Blaikie[35], vulnerability is 'the characteristics of a person or group in terms of their capacity to anticipate, cope with, resist and recover from the impact of natural or man-made hazards'. This definition suggests that it cannot be described without reference to a specific hazard or shock. Hence, the question that must always be asked is, vulnerability to what? People living along coastal areas or rivers may be vulnerable to seasonal storms and flooding and hence, may face difficulties in achieving a satisfactory and sustainable quality of life. To empirically investigate the research question, we have chosen six villages of Rajnagar and Mahakalpada block from Kendrapara district of Odisha state in India (Figure 2). These two coastal blocks are mostly affected by cyclone, unexpected rainfall and variations in temperature. For a representative sample of villages we further divide the block into three categories based on geographical location, i.e. upper, middle and the lower basin. This classification is further used to select sample villages from each Grampanchayat, from the respective basins as shown in Figure 3. Since census of all the households were not feasible, a sample survey was undertaken. Twenty five households from each village were selected. The sample includes 150 households, which is a representative of around 10% of the total population of the sample villages and 23% of the poorer household based on the below poverty line classification[5].

The process of data collection involved discussions with various stakeholders (villagers, representative of non-government organizations and representatives of government institutions) during 2011–12. From literature review and exploratory discussions with the stakeholders, a comprehensive list of indicators and proxies was prepared for primary data collection. The questionnaire was finalized after a pilot survey. It was observed during the exploratory visits and pilot survey that the head of the household (responsible for major income generating activity) takes most of the decisions and hence, data was collected from the head of the household. Each of the households was selected from random sampling drawn from the population of the village. The household primary data collection is based on the following criteria: (i) village was divided in three zones based on the caste structure, (ii) households are selected based on distance from coastline, and (iii) the 10th household in each group was selected for a better representation of the village. In addition to the primary data collection, we have also used some indicators from secondary data sources. These secondary sources of data collection are from state government records and databases. Data classified as vulnerability, sensitivity, exposure, adaptive capacity, hazard loss, covariate, idiosyncratic and household characteristics are presented in Table 1.

The empirical analysis

The results of the climate change shock, as it affects the household (Table 2), show that most members of the household (around 80% of the population) were affected. Each of the variables serving as indicator has been classified into respective conceptual class to enhance policy

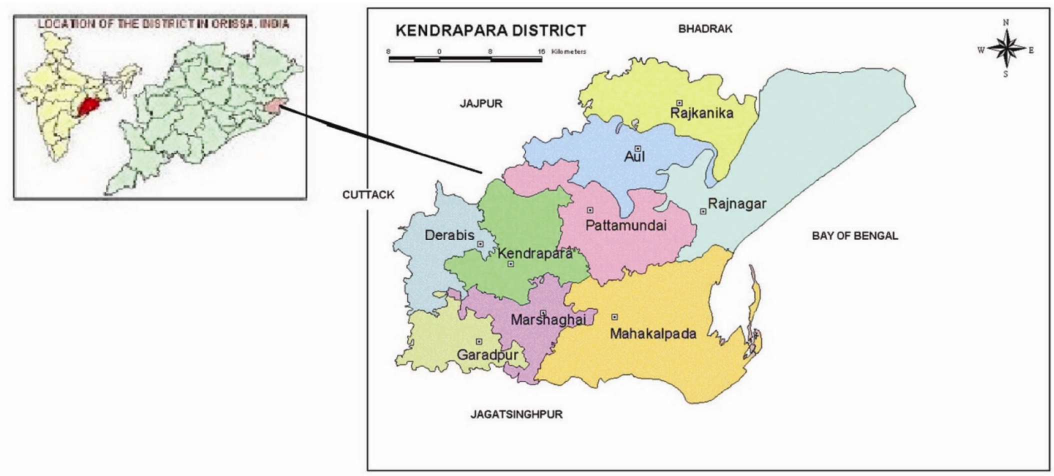

Figure 2. Map of Kendrapara district in Odisha, India. (Source: Official district website of Kendrapara district (http://kendrapara.nic.in); Map not to scale.)

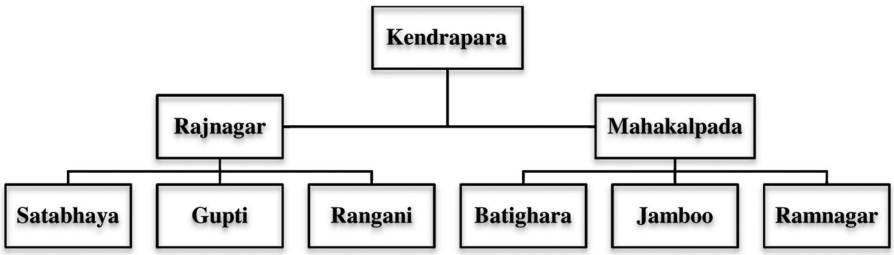

Figure 3. Selection of villages.

direction. The table gives a matrix of the climate change types and the household members that each of these factors affected. We note that the most potent climate change type that affects the household is delayed rainfall, followed by less rain, etc. From Table 2, it is evident that the major stimuli of climate change affecting agricultural households in study area are heavily skewed towards rainfall, as most of the identified changes are mainly cyclonic or flood-related. On an average the household adversely suffers from variation of rainfall, either in terms of the household member affected or economic shocks. Also, the fact that virtually all members of the households were often affected is an indicator that climate change poses a great threat to poorer households.

The descriptive statistics of the sample presented in Table 3, reports the household characteristics with quantitative variables, whereas Table 4 reports the descriptive statistics with qualitative variables. From Table 3 we observe that the mean age of the head of the household is around 50 years, with the oldest being 80 years old and the youngest being 28 years, in case of Mahakalpada block. Similarly, for the Rajnagar block, the oldest head of the household is 75 years and the youngest 24 years. The mean age of the head of the household of Rajnagar block is 50 years, similar to that of the Mahakalpada block. The mean age of head of the household remains similar for the whole sample. When we consider the household size, the mean household size is around 7 members for the whole sample that is identical for both study areas. However, the biggest family surveyed is located in Rajnagar block with 26 members. The amount of credit taken after a climatic event, is up to the tune of maximum of Indian Rupees (INR) 122,000 for Mahakalpada block and a minimum of INR 9,000. Almost all sample households took credit after an extreme climate event. The mean credit amount for the full sample stands at INR 33,033. The reported loss by households, varies minimally across the blocks. The mean loss reported is calculated at INR 16,593, with minimum loss of INR 8000 and maximum of INR 45,000. Valuation of asset, before the event, was reported at an average of INR 21,600 compared to INR 70,000 at the maximum and of INR 6000 at the minimum, for the full sample. Table 4 which reports descriptive statistics of the household related to qualitative information shows that, 62 households have a female head, for the Mahakalpada block compared to 61 households Rajnagar block. 108 household heads are educated for the entire sample, whereas the head of 57 households is educated for the Mahakalpada block and 51 in Rajnagar block. Participation in self-help

Table 1. Definition of variables

Conceptual basis	Classification into different shocks	Definition
Vulnerability	Hazard loss	Log of total loss
Sensitivity	Covariate	Perception of change in temperature over last 20 years Perception of change in rainfall over last 20 years
Exposure	Idiosyncratic	Households engaged with cropping Households with livestock
Adaptive capacity	Household characteristics	Household size Education of head of household Age of head of household Gender of head of household Engagement in non-farm activities Natural log of credit amount Value of assets Engagement in agricultural extension Distance to the nearest town Participation in SHG Access to credit facilities Distance to market Climate change adaptation index

Table 2. Perception of households on the effects of climate-related extreme events

Effects	Climate change factors related to rainfall					Others
	Delayed rainfall	Early rainfall	Erratic rainfall	Too much rain	Less rainfall	
Household members affected	92.5	70.8	69.4	95.6	82.5	81.6
Decline in crop yield	88.3	82.4	81.7	93.1	78.6	73.9
Decline in livestock productivity	92.3	87.6	38.4	98.3	79.6	47.3
Death of livestock	68.4	69.8	43.4	84.3	39.4	69.6
Food insecurity	71.4	70.9	69.6	81.4	73.9	68.3
Food price increase	81.4	82.3	79.4	73.3	69.4	69.7
Average	82.4	77.3	63.7	87.8	70.6	68.4

Source: Authors' calculation from primary data.

group (SHG) is found higher for Mahakalpada block and the total participation in SHG for the whole sample stands at 66 households. The question related to the households' perception of change in temperature and rainfall was one of the major variables of interest. From the table we observe that only 8 households are of the view that there is no change in temperature in Mahakalpada block, compared to 28 households in Rajnagar block. Similarly, in case of rainfall, 58 households in Mahakalpada block are of the view that there is no change in rainfall, compared to 67 households in Rajnagar block. Around 125 households are found to be engaged with cropping, and 107 households with livestock, whereas, only 29 households are engaged with non-farm activities and 116 households are engaged in agriculture extensions. Credit facilities are easily available for 116 households for the whole sample.

Equation (8) is estimated using the Ordinary Least Square (OLS) and eq. (9) is estimated using Ordered Logit Regression (OLR) model, to arrive at the determinants of adaptation level response. The results of OLS regression that capture determinates of vulnerability of agricultural households due to extreme climate events, are presented in Table 5. We have tested for the multicolinearity and heteroskedasticity in the sample. The result of the variance inflation factor (VIF) and Breusch-Pagan test for heteroskedasticity indicates that the data is free from both the errors. Hence, OLS is an appropriate model to estimate eq. (8). The R^2 of the model is arrived at 0.43, with the adjusted R^2 at 0.41. The F-test is found to be statistically significant at 5%. The results show that the model fits the data well and is generally significant with the independent variables having effects on the vulnerability level of the households as captured by the total income loss due to climate change. The variables are classified into various shocks due to extreme climatic events. For a better understanding, we have classified the regression results in three major sets of explanatory groups as adaptive capacity, exposure and sensitivity. Variables that significantly determine the vulnerability of

Table 3. Descriptive statistics of household characteristics in study area (quantitative variables)

	Mahakalpada sample			Rajnagar block sample			Full sample		
Variables	Mean	Maximum	Minimum	Mean	Maximum	Minimum	Mean	Maximum	Minimum
Age of head of the household	50.72 (13.45)	80.00	28.00	50.68 (12.30)	75.00	24.00	50.70 (12.85)	80.00	24.00
Education of head of the household	7 (6.09)	14	0.00	8 (8.56)	16	0.00	7 (6.97)	16	0.00
Household size	7.40 (3.95)	20.00	0.00	7.73 (4.27)	26.00	3.00	7.57 (4.10)	26.00	0.00
Total credit	31,520.00 (2055.97)	122,000.00	9000.00	34,546.67 (1961.42)	64,000.00	10,000.00	33,033.33 (2008.19)	122,000.00	9000.00
Total loss	17,466.67 (1578.00)	45,000.00	8000.00	15,720.00 (1283.09)	45,000.00	8000.00	16,593.33 (1354.90)	45,000.00	8000.00
Total asset	22,973.33 (1608.95)	70,000.00	6000.00	20,226.67 (1390.53)	70,000.00	6000.00	21,600.00 (1504.36)	70,000.00	6000.00
Distance from nearest town	33.55 (1.13)	35.00	32.00	33.40 (1.14)	35.00	32.00	33.47 (1.13)	35.00	32.00
Distance from nearest market	9.25 (1.49)	12.00	7.00	9.36 (1.49)	12.00	7.00	9.31 (1.49)	12.00	7.00

Source: Authors' calculation from primary data. Standard deviations are presented in brackets.

Table 4. Descriptive statistics of household characteristics in study area (qualitative variables)

	Mahakalpada sample	Rajnagar sample	Full sample
Gender of head of household	62.00 (0.38)	61.00 (0.39)	123.00 (0.39)
Participation in SHG	36.00 (0.50)	30.00 (0.49)	66.00 (0.50)
Perception of change in temperature	8.00 (0.31)	28.00 (0.49)	36.00 (0.43)
Perception of change in rainfall	58.00 (0.42)	67.00 (0.31)	125.00 (0.37)
Households engaged with cropping	58.00 (0.42)	67.00 (0.31)	125.00 (0.37)
Households with livestock	48.00 (0.48)	59.00 (0.41)	107.00 (0.45)
Household engaged with non-farm activities	16.00 (0.41)	13.00 (0.38)	29.00 (0.40)
Households' access to credit facilities	62.00 (0.38)	54.00 (0.45)	116.00 (0.42)
Households engaged with agriculture extensions	55.00 (0.45)	61.00 (0.39)	116.00 (0.42)

Source: Authors' calculation from primary data. Standard deviations are presented in brackets and the table describes counts of each of the variables.

agricultural households to extreme climate events in the adaptive capacity group are household size, education, age and gender of the head of the household, engagement in non-farm activities, and engagement in agricultural extension. Where, except household size, engagement in non-farm activities, and engagement in agricultural extension are positively related to the loss of the household while others are negatively related. Hence, the bigger household size, engagement in agriculture extension and non-farm activities, the larger is the income loss of households due to extreme climate event. While large households might spend more to meet their needs, those who are not into non-farming will be short of financial strength as their agricultural income would have suffered greatly due to the extreme climate event. In agreement with prior expectation, higher education level at household tends to less vulnerability to climate change shocks. Older farmers are less vulnerable which may be due to their experience in farming, and likewise female farmers. This result brought out the efficiency and ingenuity of female farmers, but it should be noted that land ownership is biased against female in the sample and hence, may limit the farm-size as a result of which female farmers are probably able to manage effectively their small-land holdings. In the exposure classification, both variables are statistically significant and positively related to household income loss. Results indicate that households that are into livestock production and cropping are highly vulnerable to extreme climate events. In the sensitivity classification, households that noticed significant changes in temperature in the past 20 years are less vulnerable to the extreme events.

As discussed earlier, we have constructed the CCAI for households to classify them into different classes of adaptation levels. This was based on the number of actionable steps against climate change factors as provided in the instrument for the survey. The maximum number of actionable steps allowed to state in the instrument is three, so those households which did not take any action get a score of zero and were classified to be of 'no adaptive

Table 5. Determinants of vulnerability due to extreme climate event

Independent variables	Coefficient	Standard error	*t*-statistics
Adaptive capacity			
Household size	2.014	1.013	1.990**
Education of head of household	–1.014	0.415	–2.443***
Age of head of household	–0.604	0.239	–2.523***
Gender of head of household	–0.853	0.234	–3.646***
Engagement in non-farm activities	0.528	0.140	3.769***
Engagement in agricultural extension	0.280	0.147	1.908*
Distance to nearest town	0.020	0.043	0.467
Exposure			
Households engaged with cropping	0.663	0.213	3.113***
Households with livestock	0.256	0.129	1.982**
Sensitivity			
Perception of Temperature change over 20 years	–1.008	0.525	–1.921*
Perception of Rainfall change over the last 20 years	–0.050	0.159	–0.315
Constant	8.660	1.462	5.924***
Number of observations	150	F (11, 139)	2.18**
Variance Inflation factor (VIF)	1.07	R^2	0.43
Breusch-Pagan test for heteroskedasticity	0.67	Adj R^2	0.41
Dependent variable: Vulnerability – natural log of total loss			

Source: Authors' calculation from primary data. ***, ** and * refer to statistically significant at 1%, 5% and 10% level.

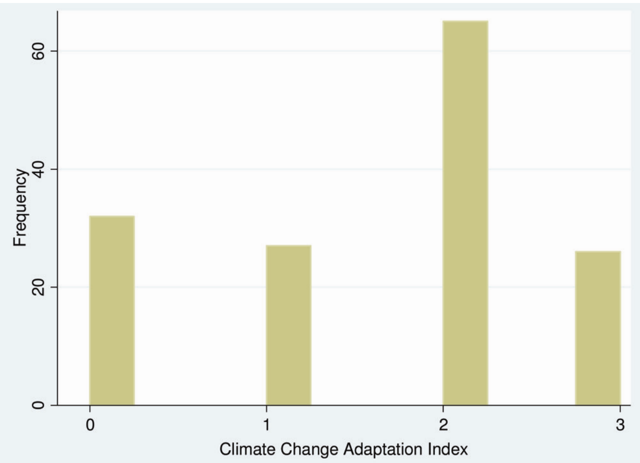

Figure 4. Frequency distribution of climate change adaptation index.

capacity', if one action was taken they get a score of 1, two actions get a score of 2 and a maximum of three actions get a score of 3. Score of 1 means low adaptive capacity, 2 is medium adaptive capacity, while 3 means high adaptive capacity. The frequency distribution of the CCAI is presented in Figure 4. Having constructed this index, OLR was estimated to determine the factors that affect the adaptation capacity of the agricultural households (Table 6). The factors that significantly influence the capacity of the households to adapt to climate change factors as reflected in the result are: significant change in temperature, significant change in rainfall, involvement in agricultural extensions, age and gender of the head of the household, availability of credit facilities, and the credit amount. The OLR for households not exposed to significant temperature and rainfall changes over the last 20 years being in a higher CCAI, is less than for those who were by values of –1.69 and –2.96 respectively. However, the log-odd of being in a higher CCAI category increases by 0.418 for households that are not into cropping. The more credit the household received, the higher the log-odd of moving up the CCAI statistically at 10% level. For the households that did not participate in agricultural extension; the log-odd of being in a higher CCAI is reduced by –0.761. Likewise, a year increase in age of the head of the household reduces the log-odd of being in a higher CCAI by –0.019. We also observed a lesser log-odd of moving to a higher CCAI for the female head of the household by a value of –0.491 which is in agreement with the result in Table 5, where female farmers are the least affected by climate change factors. Also, not having access to credit increases the log-odd of moving to a higher CCAI by 0.891, but very surprisingly every INR increase in credit amount given to households increases the log-odd to higher level of CCAI by 0.051. The results in Table 6, imply that availability of credit to households will improve their adaptive skills; however, there is caution on the amount to be given as too much credit might hinder the adaptive capacity, and this can be traced to diversion of funds for other uses rather than agri-business. Once again, the experience of farmers by age and the female farmers are important factors that can be tapped to improve farmers' adaptation to extreme climate events.

Table 6. Determinants of adaptation to extreme climate events

Independent variables	Coefficient	Standard error
Adaptive capacity		
Household size	0.018	0.559
Education of head of household	0.027	0.028
Age of head of household	–0.019**	0.009
Gender of head of household	–0.491***	0.081
Engagement in non-farm activities	–0.058	0.259
Engagement in agricultural extension	–0.761**	0.369
Distance to nearest town	–0.027	0.192
Natural log of credit amount	0.051***	0.021
Total value of assets (in natural log)	–0.005	0.008
Member of group association	0.895	0.499
Access to credit facilities	0.891**	0.392
Distance to market	0.008	0.005
Exposure		
Households engaged with cropping	0.418	0.289
Households with livestock	0.018	0.119
Sensitivity		
Perception of temperature change over 20 years	–1.691***	0.258
Perception of rainfall change over the last 20 years	–2.961***	0.657
Constant	2.132	0.007
cut 1	–4.891	0.954
cut 2	–3.698	0.951
cut 3	–3.019	0.951
Number of observations	150	
LR chi^2	79.259***	
Log likelihood	–179.851***	

Source: Authors' calculation from primary data. Dependent variable is the climate change adaptation index, ***, **, * refer to statistically significant at 1%, 5% and 10% level.

Conclusions and policy recommendations

This study identifies two major issues related to impact of extreme climate events for the agricultural dependent households in Odisha. First, it tries to identify what determines vulnerability at household level and second it explains the determinants of adaptation to extreme climate events. From the results of the study, several policy-related conclusions can be derived. Climate change effects on agricultural dependent households in rural India, have direct impact on the total income loss as identified in the paper. Hence, there is an importance of increasing access to credit facilities to cope with the losses. Direct policies to address the vulnerabilities of agricultural households should include local knowledge of farmers into an informal educational package, and should also promote non-farm enterprises at village level. Since livestock keeping households are more vulnerable, there is need for more research to introduce species that are tolerant to such climate challenges and promotion of protein fortified crops to aid protein inclusion in foods and diets. From the results, it is evident that education plays an important role, not only as a determinant of loss but also as an adaptive capacity. Adaptations to climate change will be greatly improved if possible agricultural extension programmes and non-farm activities can be effectively addressed at the local level. These programmes need to be re-evaluated and repackaged to tune with realities of present challenges with respect to climate change.

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ACKNOWLEDGEMENTS. We thank the Ministry of Environment and Forests (MoEF), Government of India for funding support under the National Communications to UNFCC (NATCOM-2), and the respondents of the sample villages for their active participation during the primary survey. We also acknowledge the anonymous reviewers and the editors for the comments and suggestions in the earlier draft of this paper.

doi: 10.18520/cs/v110/i7/1240-1250