Sustaining mangrove forests to reduce vulnerability of coastal villages from climate change

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ABSTRACT

Mangrove forests provide a range of welfare enhancing services to humans, but they also provide life support during calamities like tropical storms by reducing the probability of death. The coastal regions of India face a maximum threat from tropical cyclones due to climate change as these areas are situated at the coast of one of the core areas of cyclogenesis, namely, the Bay of Bengal. Studies on vulnerability indexing of these areas to cyclone and storm surge risks have identified Kendrapada district of East Coast of India to be either the most or the second most vulnerable district of the country. We study the 262 villages lying within a 10 km distance from the coast of the Kendrapada district and compare the relative vulnerability of these villages by estimating the village wise probability of facing human fatality due to severe storms. We calculate such probability from a cyclone impact (human deaths) function where a wide range of factors including natural ecosystems like presence of mangrove forest are used to control for the exposure and adaptive capacity of the villages. Presence or absence of mangroves comes out as an important factor impacting vulnerability. Villages established after clearing the forest in mangrove habitat areas and those with more marginal workers are found to face a very high death risk and villages situated in the leeward side of existing mangrove forest are seen to be facing a much lower risk of deaths. The results have important implications for conservation of mangrove forests in cyclone prone areas and also in the design of development policies for villages established in the mangrove habitat.

Key Words: Coastal vulnerability, Human mortality, Mangrove forests, Mangrove habitat, Orissa, Super cyclone

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1. INTRODUCTION

Coastal vulnerability and a ranking of the costal regions in terms of their exposure to different climatic extreme events are prominent research areas following the predictions of climate change theories (Gormitz et al. 1994; IPCC CZMS 2002; Shaw et al. 1998; Turner et al. 1993; UNEP 2005). The IPCC Working Group II Report on vulnerability assessment gives a comprehensive summary of the degree of vulnerabilities faced by different coastal regions of the world due to sea level rise and increased storm surge threats (IPCC 1997, 2007). The coastal regions of India face a maximum threat from tropical cyclones as these areas are situated at the coast of one of the core areas of cyclogenesis,[2] namely, the Bay of Bengal. Vulnerability indexing of these areas to cyclone and storm surge risks has been attempted (Jayanthi 1998; Kavi Kumar 2003; Patwardhan et al. 2003; and Sharma and Patawardhan 2007). However, some common limitations of the studies on coastal vulnerabilities are as follows: (i) vulnerability is accessed for larger spatial units like districts whereas evacuation and rescue are undertaken at village level; (ii) the factors used for calculating the vulnerability indices are averages over the districts and thus, the micro or local-level discrepancies are not reflected in the indexes; (iii) indexes being either the multiplicative or average values, do not show the importance of individual factors impacting vulnerabilities; (iv) the socio-economic factors are represented by population density or total population and the characteristics of the population are ignored; (v) there is an underlying assumption of uniform distribution of population and linear response of different population groups over the macro region and it may not be true, at least for developing countries where population is widely non-homogeneous. Finally, the presence of wide spread water channels, sand dunes or the presence of natural environment like mangrove forests that can act as a deterrent to the impacts of natural calamities (Das 2007b) and add to the resilience of the region (Carmen et al. 2006) is hardly been taken into account in developing the indexes.

Studies on the cyclone vulnerability of the Indian coastal areas have measured vulnerability either at the district level or for the coastal regions of the state as a whole and have considered factors like cyclone frequency, population density, coast line length, some measures of cyclone damages witnessed, etc. in vulnerability assessment. The east coast districts of India have been ranked as being more vulnerable to cyclones than the west coast districts while the Kendrapada district of the east coast has been identified as being the most vulnerable (Patwardhan et al. 2003; Sharma and Patawardhan 2007) or the second most vulnerable district (Jayanthi 1998; Kavi Kumar 2003) of the country. The present paper studies the coastal villages of the Kendrapada district and tries to address some of the above concerns by analysing the role of multiple factors on cyclone impacts.

We use data generated from 262 villages lying within a 10 km area of Kendrapada district coastline in the state of Orissa and calculate the death risk

[2] Cyclogenesis is the origination of cyclones in the given basin of the sea. Bay of Bengal, North Pacific Ocean and South China Sea are the three core areas of cyclogenesis (IPCC 1997).

for these villages due to cyclone and storm surge threats. We measure death risk as the probability of witnessing non-zero human casualty due to severe cyclones hitting these areas and the probabilities are estimated from a cyclone impact function that takes into account the hydrological, environmental, meteorological, infrastructural and socio-economic factors related to the villages. We use cross section data on village-level human casualties witnessed in these areas during the super cyclone of October 1999, and other data of the area for the same year to do our analysis.[3]

2. STUDY AREA

Kendrapada is a highly cyclone prone district of peninsular India which on an average weathers one cyclone of different intensity each year (Das 2007a). Every cyclone originating in the Bay of Bengal during the monsoon months (June, July, August), usually passes through this part of the Indian coast, although the tracks of cyclones during the other periods follow no such fixed pattern (IMD 2000). The cyclone record of the state of Orissa reveals that the frequency of very severe cyclonic storms (T=5.0 to 6.0) and super cyclones ($T \geq 6.5$)[4] have increased in recent decades over this area; the annual probability being 0.00 for 1900 – 1920, 0.10 for 1921 – 1940, 0.05 for 1941 – 1960, 0.15 for 1961 – 1980 and 0.15 for 1981 – 2000 (Chittibabu et al. 2004).

In October 1999 Kendrapada was battered by a super cyclone that had its landfall at 20 km south west to it and the entire district was severely affected by cyclonic wind and heavy rain. Of its seven *tahasils*[5], only four (Mahakalpada, Rajnagar, Patamundai and Marshaghai) were affected by saline inundation due to storm surge (Gupta and Sharma, 2000). The villages of the present study are from Mahakalpada, Rajnagar and Patamundai *tahasil.* Before the landfall of the cyclone, the state government issued a cyclone warning and evacuated people. However, 136 persons from these villages died within a range of 0 to 13 per village. The study area being north to the cyclone landfall as well as to the position of the cyclone eye throughout, the direction of both wind and storm surge was sea to land over the study area.[6]

Kendrapada district was economically backward, predominantly agricultural with 78 per cent of its population dependent on the primary sector, with more than 50 per cent living below the poverty line before 1999 (District Statistical Handbook 2001). Infrastructural facilities were scanty for the near-

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[3] Detailed village wise human casualty data for other cyclones hitting the study area being unavailable, we did the analysis using the casualties figures of a single cyclone.

[4] Cyclonic disturbances over the Arabian Sea/Bay of Bengal are categorised as follows: Deep Depression (T=2.0, wind speed= 50-61kmh^{-1}); Cyclonic Storm (T=2.5 to 3.0, wind speed=61-88 kmh^{-1}); Severe Cyclonic Storm (T= 3.5, wind speed=88-117 kmh^{-1}); Very Severe Cyclonic Storm (T=5.0 to 6.0, wind speed=117-220 kmh^{-1}); and Super Cyclone (T=6.5 and above, wind speed > 221 kmh^{-1}).

[5] Administrative unit between district and villages.

[6] In the northern hemisphere, cyclonic wind moves anti-clockwise and thus, the wind direction over areas south of the cyclone eye are from land to sea and opposite to the direction of storm surge.

coast areas, though, there were dikes to facilitate agriculture and these were also used as village roads. As per the forest map of the area that existed prior to 1952, [7] the district had vast stretches of mangrove forests along the coast line of its Mahakalpada and Rajnagar *tahasils.* With the exception of the mangroves in the Bhitarkanika region of Rajnagar tahasil which is a Ramsar site and National park, the mangroves of other areas witnessed massive destruction over the years. However, thinner strands of mangroves were present before the cyclone (average width of mangrove forest per village declining from 1.97 km in 1940s to 0.63 km in 1999). These areas were planted with casuarinas under the coastal shelterbelt plantation scheme of the state government in 1974 after a very severe cyclone caused a massive loss of lives and properties in 1971. However, casuarinas are found only in some limited patches with a near uniform width (0.2 to 0.4 km) and this may be due to the unsuitability of a large part of the coastline for casuarinas (Mohanty 1992). In 1999, natural cyclone barriers in coastal Kendrapada were formed by the mangroves and the casuarinas.

3. METHODS

Following the IPCC Third Assessment Report (McCarthy et al. 2001), the vulnerability to cyclone risk is defined as the net impact or the residual effect of the cyclone on a village after controlling for the hazard intensity, exposure and the adaptive capacity of the village. We define the net impact as the occurrences of human deaths in the village due to cyclone[8] and approximate hazard intensity by velocity of cyclonic wind and storm surge over the village; exposure by total population and physical features of the village; and adaptive capacity by economic well-being (infrastructure), governmental help and the population characteristics of the village. Thus we define vulnerability of the ith village to be same as cyclone impact measured in terms of human casualties witnessed in the village during the cyclone after controlling for factors determining the hazard intensity, exposure and adaptive capacity of the village. Equation 1 below explains these relationships as follows:

$Vulnerability_i = Cyclone\ Impact_i\ (=human\ death_i) = f\ (hazard_i,\ exposure_i,\ adaptive\ capacity_i) = f\ (cyclonic\ wind_i,\ maximum\ storm\ surge_i,\ population_i,\ physical\ features_i,\ infrastructure_i,\ population\ characteristics_i,\ governmental\ institutions_i),$ (1)

where subscript i represents the ith village. First, we estimate this impact (human casualties) function and then in step 2, we calculate the probability of facing non-zero deaths for villages with the help of the estimated coefficients and rank the villages. The probabilities are expected to reflect the degree of vulnerability of the villages due to cyclones.

[7] Mangrove destruction is reported to have started after the abolition of princely states in 1952 (Mohanty 1992; Orissa District Gazetteer, Cuttack 1996).

[8] A more appropriate measure of cyclone impact would have been the sum of different damages witnessed in the village during the cyclone, but getting village-level estimates of different damages other than human deaths was also difficult.

The above specification is also justified as human casualties depend on the intensity of the cyclone (velocity of wind, storm surge, etc), as well as on the total population, geo-physical factors surrounding the village, socio-economic well-being and also on the efficiency of cyclone warning and evacuation efforts of the government.[9]

We further simplify this equation by including the various determinants of the explanatory variables to estimate it (the name of the determining variables are put in italics and further, their definitions and expected roles in impacting human death during cyclones are tabulated in Table 1 below). Following Das (2007b), we approximate cyclonic wind by the minimum distance of a village from cyclone eye ($dcypath_i$); storm surge velocity by the height of sea elevation at the coastline nearest to the village ($surge_i$) and the distance between the coastline and the village (*dcoast).* Physical features are approximated by the following variables: $topodumy_i$ (a dummy variable for topography equaling 1 if the village is situated in a mangrove habitat area after clearing the forest, a control for elevation as mangroves come up in low lying areas), $mangrove_i$ (the width of mangrove vegetation in between the village and the coast), $mhabitat_i$ (the width of mangrove habitat area in between the village and the coast), $casurinadummy_i$ (a dummy variable equalling 1 if casuarinas plantation exists between the village and the coast), $dmajriver_i$ (minimum distance of the village from a major river), and $dminriver_i$ (minimum distance of the village from a minor river); infrastructure by $droad_i$ (minimum distance of village from a metallic road) and $roadumy_i$ (dummy variable equalling 1 if the village has a village road). Other village wise socio-economic factors and population characteristics are denoted by $scheduledcaste_i$ (percentage of scheduled caste population who are economically and socially very backward in the village), $literate_i$ (percentage of literate people), $cultivator_i$ (percentage of cultivators), $aglabour_i$ (percentage of agricultural labours), $hhworker_i$ (percentage of workers in own household industries), $otworker_i$ (percentage of workers in profession other than agriculture and household industries), and $margworker_i$ (percentage of marginal workers who have no regular job and have worked only for less than six months in the previous year), and lastly, governmental institution by $tahasildar_i$ dummy (a dummy variable for the administrator in charge of evacuation, relief and rescue for the villages falling under his *tahasil*).[10]

Table 1: List of Variables, Definitions and Expected roles during cyclone

[9] We have ignored proximity to cyclone shelters as an explanatory variable as the study area with an 80 km long coastline had only nine cyclone shelters with a capacity of 1200 each before the cyclone and as reported by survivors, people took shelter in concrete houses in the neighbourhood.

[10] Our study area included villages falling under three different *tahasildars.*

Category of Variable	Name of Variables	Definition of variables (all distances in kilometres).	Expected roles in cyclone impact (human death) function.
Cyclone impact (damages)	*Death*	Number of human casualties in a village due to cyclone.	Dependant variable.
Government Institution	*Tahasildar*	Dummy variable for local administrator in charge of cyclone warning, evacuation, rescue and relief works.	Capture differences in administrative efficiency of different tahasildars.
Variables controlling for Cyclone Intensity	*Dcypath*	Minimum distance of a village from the centre of the eye of the cyclone or from the cyclone path.	This is a proxy for cyclonic wind at village level.
	Surge	Height of sea elevation (in metres) at the coastal point nearest to the village.	*Surge* along with *dcoast* will capture the intensity or severity of storm surge at an interior village.
	Dcoast	Minimum distance of the village from the coast.	
Variables controlling for physical features of villages	*Topodmy*	Topography dummy for low elevation (=1 for villages that have come up in mangrove habitat areas and = 0 for others).	Captures the impact of low elevation of villages (as situated in mangrove habitat areas) on deaths.
	Mhabitat	Width of the historical mangrove forest or the mangrove habitat (as existed before 1950) in between a village and the coast.	Captures the impact of other unobserved features of mangrove habitat areas on storm damages.
	Mangrove	Width of existing mangrove forest in between a village and the coast.	Captures the impact of mangrove vegetation on storm damages.
	Casurina dumy	Dummy variable for the presence of casuarinas plantation in between a village and the coast.	Captures the impact of casuarinas trees and the topography of casuarinas plantation area.
	Dmajriver	Minimum distance of a village from a major river (directly connected to sea).	Major rivers have large carrying capacity, carry away surge water and help in reducing the surge velocity to flooding. Nearness to major river should reduce death.
	Dminriver	Minimum distance of a village from a minor river (a tributary of major river).	Minor rivers get inflated and bring in more water to interior areas during storm surge and can cause more death in nearby areas.
Infrastructural variables	*Droad*	Minimum distance of a village from a metallic road.	Proximity to metallic road increases economic well being by providing better accessibility, thus good health, good houses and less death.
	Roadumy	Dummy variable for the presence	Same impact as *droad* on

Thus equation 1 is re-written as the following:

$$Y_i = f(population_i, dcypath_i, surge_i, dcoast_i, topodymy_i, mangrove_i, mhabitat_i, casuarinadummy_i, dmajriver_i, d\min river_i, droad_i, roadumy_i, scheduledcaste_i, literate_i, cultivator_i, aglabor_i, hhworker_i, otworker_i, m\arg worker_i, tahasildar_i) \quad (2)$$

In equation 2, Y_i is the village wise number of human casualties and we expect the variable Y_i either to be a count (if a detailed death figure is available) or a dichotomous variable and thus, equation 2 is expected to take either a Poisson [11] (or some other count model) or a Logit approximation. Once the estimates are obtained, the probabilities of non-zero deaths, $P(Y_i > 0)$ are calculated in the next step either directly or as $1 - P(Y_i = 0)$, where P is the probability and Y_i is the expected mortality due to cyclones in the ith village, depending on the statistical specification used. For a Logit specification of equation 2, the degree of vulnerability ($P(Y_i > 0)$) will be the same as estimated or fitted probability if we assume Y_i to take value 1 for non-zero deaths and 0 for zero deaths. However, for a count specification, the fitted values are the mean values and the degree of vulnerability or the probability of non-zero deaths can be calculated from the probability density function[12] as 1 – P (Y_i = 0).

In order to identify the variables impacting the probability of death strongly, we calculate the marginal effect of the variables of eq.2 on the probability of non-zero deaths. This marginal effect in the Logit model is defined by,

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[11]The Poisson specification has a single parameter which is taken as the mean as well as the variance of the distribution. This assumption of equality between the mean and the variance results in lower standard errors and inflated z-values and if the sample mean is different than the variance, then the test of inference becomes unreliable. To check the presence of over dispersion (mean ≠ variance), negative binomial estimates should also be calculated along with Poisson. Negative binomial specification controls for over dispersion and provides the results for the tests of specifications for Poisson versus negative binomial.

[12] The probability density function for Poisson distribution is given by,

$$P(Y_i = y_i) = \frac{e^{-\lambda_i} \lambda_i^{y_i}}{y_i!}, \; y_i = 0,1,2,...,$$

where $P(Y_i = y_i)$ is the probability that the variable Y_i takes the non negative integer value y_i and λ_i is the mean (and the variance) of the Y_i variable which is assumed to be having a Poisson distribution. λ_i is estimated with the help of an equation like: $\lambda_i = E(Y_i / X_i) = \exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + ---) = e^{X_i'\beta}$,

where the X_i's are the explanatory variables impacting Y_i.

After getting the estimated coefficients, we get $P\ (Y_i = 0)$ = exp (- $\hat{\lambda}_i$) by assuming y_i = 0, and $P\ (Y_i > 0) = 1$- exp (- $\hat{\lambda}_i$).

$$\beta_j[P_i(1-P_i)], \qquad (3)$$

where β_j is the partial co-efficient of the jth regressor and P_i is the probability of y_i taking a non-zero value. However, the average marginal effect of the jth regressor over the villages in Logit can be obtained in a straight forward manner with the help of statistical packages. In case of the Poisson model, the marginal effect of variables on the probability of non-zero deaths can be obtained as shown below:

$$\frac{\partial P(Y_i > 0)}{\partial X_j} = \frac{\partial[1 - e^{-\hat{\lambda}_i}]}{\partial X_j} = -\frac{\partial \exp(-\hat{\lambda}_i)}{\partial X_j} = \exp(-\hat{\lambda}_i)\frac{\partial \hat{\lambda}_i}{\partial X_j}, \quad \text{where} \qquad (4)$$

$\frac{\partial \hat{\lambda}_i}{\partial X_j}$ is the marginal effect of the jth variable on the expected mortality of the ith village and the average of this marginal effect over the villages can be easily calculated with the help of statistical packages. The first term, $\exp(-\hat{\lambda}_i)$, the inverse of the exponential of the expected deaths of the ith village can be calculated manually.

4. DATA

We needed village-level data on human casualties and other climatic, physical and socio-economic indicators to estimate the human casualty function defined in eq.2. Such micro information on previous cyclones being unavailable, we used the village-level cross section data on human death during the Oct 1999 super cyclone and the related information for the same year to estimate the model.

For generating the geo-physical and spatial variables, we used the GIS files on village boundary, rivers, roads, coastline, forest cover, etc. They were purchased from a private source (Digital Cartography and Services, Bhubaneswar, Orissa). The Indian Remote Sensing Satellite IRS-1D, LISS III Pan censor images of 11 October 1999 with 23.9 metre resolution was used to measure the coastal forest cover (both mangroves and casuarinas) before the cyclone. For demarcating the historical spread of the mangroves in the study area, we used the jpg image (1: 250000 scale) from the archives of US Army Corps (NF 45-14 Series U502, “Cuttack” sheet). The data were then combined with the help of the GIS Arc View 3.2. We demarcated the cyclone track by joining the cyclone landfall point with the locations over which the cyclone eye passed through as described in the National Centre for Disaster Management, Indian Institute of Public Administration Report (Gupta and Sharma 2000). Geo-referencing of all the images was done at the 1:50000 scale.

Different distances (distance from cyclone path, from coastline, from rivers, from metallic road, etc.) were measured as the minimum distances from the centre of the village to cyclone track, coast line, river, road, etc. The widths of the 1999 mangrove and the historical mangrove for each village were measured as the width (the spread of the forest vertical to coast) of these forests along the minimum distance between the village and the coast. We measure the sea elevation ($surge_i$) from the surge envelop curve that was estimated by the Indian meteorologist (Kalsi et al. 2004) for the super cyclone by taking into account all the factors that influence the generation of storm surge.

The population related variables for each village were obtained from the Primary Census Abstract of Orissa State for 1991 and 2001. The average annual compound rates of growth for the decade 1991 to 2001 were estimated for different variables and then the 1991 figures were extrapolated for the year 1999 by making use of the respective growth rates. Human casualty figures were collected from the district emergency office of Kendrapada, Government of Orissa.

5. RESULTS AND DISCUSSION

The detailed human death figures for villages being available, we estimated equation 2 using both the Logit and Poisson[13] specifications, where the dependent variable, Y_i (deaths in a village) was given value 1 for non-zero deaths in the Logit model. Of the different explanatory variables, only $surge_i$ and $dcypath_i$ had a high and significant correlation (r = -0.66, P<0.01), the distance from the cyclone eye being the main determinant of sea elevation during the cyclone and we used only $surge_i$ to capture the cyclone impact[14] in order to ease the problem due to multicollinearity that biases the marginal effects of individual predictors. Table 2 shows the estimated Logit and Poisson coefficients of the human casualty equation.

Table 2: Regression coefficient and standard error estimates of the human deaths (or cyclone impact) function
Dependant variable = *Death* (number of human deaths in a village)

Name of the independent variables	Logit coefficients	Poisson coefficients
Mahakalpada tahasil	0.8702 (0.8538)	1.3845*** (0.4189)
Patamundai tahasil	-1.6426 (1.0783)	-0.8726 (0.7760)
Surge	-0.1842 (0.4511)	0.1679 (0.1373)
Dcoast	0.2545** (0.1201)	0.1651** (0.0711)
Mangrove	-1.2539*** (0.4048)	-1.1131*** (0.3630)
Mhabitat	-0.1809 (0.1451)	-0.2208** (0.0775)
Topodumy	2.2159*** (0.7116)	1.7723*** (0.4347)

[13]The over dispersion tests were rejected and both the goodness of fit and LR test of $\alpha = 0$ favored Poisson against Negative binomial.

[14] As mentioned $dcypath_i$ and $surge_i$ were highly correlated, but retaining or dropping $dcypath_i$ along with $surge_i$ in estimating the equation brought no change either in level of significance or the coefficient of the variables.

Casurinadumy	-0.2657 (0.8397)	-0.4186 (0.3908)
Dmajriver	0.3589*** (0.1298)	0.2452*** (0.0703)
Dminriver	-0.2447** (0.1132)	-0.0413 (0.0683)
Droad	-0.0879 (0.0784)	0.0070 (0.0405)
Roadumy	0.2326 (0.5061)	0.4313 (0.3182)
Pop99	0.0017*** (0.0005)	0.0005* (0.00007)
Literate	-1.5070 (1.9613)	-1.6506* (1.0304)
Schedulcaste	0.4921 (1.3481)	-1.0062 (1.0230)
Cultivator	0.4092 (1.5931)	0.5372 (0.9335)
Aglabor	-0.5074 (2.39)	0.2898 (1.6630)
Hhworker	17.8098 (26.9029)	9.5702 (19.4007)
Margworker	3.8423** (1.9284)	3.6031*** (1.1281)
Otworker	-1.2558 (5.0519)	-2.6585 (2.6077)
Constant	-3.3905** (1.7306)	-3.1651*** (1.0146)
LR Chi 2 (20)	84.23 (P = 0.00)	362.58 (P = 0.00)
Pseudo R^2	0.32	0.53
Log likelihood	-88.43	-159.38

Notes: The second and the third columns give the estimates of the coefficients by using a Logit and a Poisson model specification respectively for the human deaths witnessed due to super cyclone in the 262 villages lying within 10 km from coast in Kendrapada district of Orissa. Figures in parenthesis are the estimates of standard errors. Significance levels: *** 1%, ** 5% and * 10% (two-tailed z test).

The variables increasing death significantly are *topodumy* (dummy for mangrove habitat villages), proximity to small rivers, village population, and the percentage of marginal workers in a village. *Topodumy* takes value 1 for villages established in the mangrove habitat areas and these villages witnessed high deaths, probably due to their low elevation. Villages nearer to small rivers had a higher toll due to the low carrying capacity of small rivers. These rivers are connected to large rivers and get highly inflated during a storm surge. However, this variable was significant only in the Logit specification. The significance of marginal workers proves that all poor people are not equally vulnerable (scheduled castes and agricultural labour are also poor), but the ones without any secure or regular job are specially so. Marginal workers do not have any fixed pattern of job and probably were out working during the cyclone.

Variables that helped reduce death significantly are width of mangrove forest, proximity to major rivers and nearness to coast (?). Mangrove forests provide protection during a cyclone (Das 2007b; Badola and Hussain 2005) and this is proved here. Major rivers carry away surge water to interior areas and thus, help reduce the velocity of surge. The significance of coastal distance with a positive sign, though against expectation, could be due to the evacuation of people from villages very near the coast before the cyclone.

5.1 Identifying the more vulnerable villages

We calculate the probability of witnessing non-zero death for each village using both Logit and Poisson coefficients and categorise the villages on the basis of such probability. Under both the specifications, the probability of positive death varies from as low as 0.0004 to as high as 0.999 for different villages. We put the 262 villages of our study area under four different categories on the basis of their risk assessment. The categories are namely: (i) least vulnerable (Pro ≤ 0.10), (ii) moderately vulnerable (0.10< Pro ≤ 0.30), (iii) vulnerable (0.30 < Pro ≤ 0.50), and (iv) highly vulnerable (Pro > 0.50). Table 3 below shows the distribution of villages under the four categories and as expected each village within the 10 km boundary from the coast is not equally vulnerable.

Table 3: Number of villages falling under different vulnerability categories

Vulnerability Category	Number of villages under Poisson specification	Number of villages under Logit specification
Least vulnerable (P≤0.1)	112	132
Moderately vulnerable(0.1<P≤0.3)	82	72
More Vulnerable(0.3<P≤0.5)	37	37
Highly vulnerable(P>0.5)	34	21

We find 112 to 132 villages qualifying as least vulnerable with a death probability of less than 0.1; 82-72 villages as moderately vulnerable with a death probability ranging between 0.1 and 0.3; 34-37 villages rated as vulnerable with a death probability in between 0.3 to 0.5; and 34 to 21 villages displaying high vulnerability with a death probability greater than 0.5. In the study area, 52 villages witnessed human casualties, but the death probability shows that around 130 to 150 villages have more than a 10 per cent chance of witnessing deaths, thus needing more attention from the administration in terms of evacuation measures before a high intensity cyclone strikes. Of these villages, the last two categories that comprised villages with a death probability of more than 0.3 should, probably, be completely evacuated before the onset of a disaster.

Next we identified those villages which are least expected to witness death during severe cyclones, even though situated within a 10 km distance from the coastline. We took these villages to be the ones with a death probability less than 0.01 and found that most of these villages, although thickly populated, lie in the leeward side of the mangrove forest of Rajnagar *Tahasil*. These villages offer ideal refuge for constructing cyclone shelters or shifting people of nearby villages temporarily during an emergency.

5.2. What impacts vulnerability more?

In order to identify the variables that have the maximum impact on the degree of vulnerability of the villages, we compare the marginal effects of the variables on the probability of positive deaths.

Table 4: Marginal effect and standard error estimates of explanatory variables on the probability of non-zero death in the villages due to severe cyclones (values based on the Logit and Poisson coefficient estimates of table 2)

Variables	Marginal effect in logit	Marginal effect in Poisson ♣
Mahakalpada tahasil	0.11 (0.1222)	0.22*** (0.1183)
Patamundai tahasil	-0.098*** (0.3777)	-0.06 (0.0509)
Surge	-0.02 (0.0458)	0.02 (0.0175)
Dcoast	0.026** (0.0124)	0.02** (0.0104)
Mangrove	-0.127*** (0.0345)	-0.111*** (0.0334)
Mhabitat	-0.018 (0.0149)	-0.022*** (0.0114)
Topodumy	0.322*** (0.1259)	0.294*** (0.1572)
Casurinadumy	-0.025 (0.0731)	-0.045 (0.0352)
Dmajriver	0.036*** (0.0133)	0.025*** (0.0105)
Dminriver	-0.025** (0.0119)	-0.004 (0.009)
Droad	-0.009 (0.0079)	0.0006 (0.0053)
Roadumy	0.023 (0.0495)	0.04 (0.0401)
Pop99	0.0002*** (0.00005)	0.00005*** (0.00002)
Literate	-0.153	-0.16 (0.1408)

	(0.2001)	
Schedulcaste	0.05 (0.1354)	-0.10 (0.136)
Cultivator	0.04 (0.1619)	0.05 (0.1221)
Aglabor	-0.05 (0.3033)	0.03 (0.214)
Hhworker	1.81 (2. 7559)	0.958 (2.5327)
Margworker	0.39*** (0.1982)	0.36*** (0.173)
Outworker	-0.13 (0.5123)	-0.26 (0.343)

Notes: - The figures in parenthesis are the standard error estimates and ***, ** and * imply significant at 1%, 5% and 10% level of significance respectively.

♣ The marginal effect on the probability of positive death for the Poisson model (column 3) was calculated by multiplying the marginal effects of variables on expected deaths (the default marginal effects in Poisson) with the average value of exp (-predicted mean value) i.e. 0.77256.

We find six variables (*dcoast, mangrove, topodumy, dmajriver, pop99* and *margworkers)* impacting the death probability of villages significantly under both the specifications (see Table 4). We ignore *tahasildar dummies, dminriver* and *mhabitat* as the results on these variables are not robust and we also ignore village population (*pop99*) and coastal distance *(dcoast)* as the marginal impact of *pop99* is very low and the significance of *dcoast* reducing vulnerability is probably due to the evacuation of people as explained before. Comparing the magnitude of marginal effects shown in Table 4 (cols 2 and 4), we find one physical factor (*topodumy*) and one socio-economic factor (*margworker*) exercising a very strong adverse impact on the vulnerability and two physical factors (*mangrove* and *dmajriver*) to have reduced the vulnerability of the villages. The marginal effect of *topodumy* is as high as 0.32 in Logit and 0.29 in Poisson and so is the marginal effect of marginal workers; a 1 per cent increase in the percentage of marginal workers in the village will increase the probability of facing death by 39 per cent as per the Logit model and by 36 per cent as per the Poisson. Thus, villages situated in the mangrove habitat areas after clearing the forests and those with more marginal workers are the most vulnerable ones when compared to others. In contrast, the presence of mangroves in between the village and coast and proximity to a major river has a negative impact on vulnerability; 1 per cent increase in width of mangrove forest reducing the probability of deaths in a village by 13 per cent as per Logit and by 11 per cent as per Poisson results. Results show mangrove forests playing significant roles impacting the vulnerability of villages; villages in the leeward side of mangrove forests being least vulnerable whereas the ones established inside the mangrove habitat after cutting down the forest to be highly vulnerable.

6. CONCLUSION

The paper did a micro-level analysis of vulnerability by looking at the degree of vulnerability of villages lying within 10 km from the coast in Kendrapada district; one of the most vulnerable districts of India. The degree of vulnerability was defined as the probability of witnessing human deaths due to severe cyclones and associated storm surge risks and a wide range of factors were taken into account to derive these probabilities for villages. Of the 262 villages, 112 to 132 villages were found least vulnerable with less than a 10 per cent chance of facing deaths, whereas 72 to 82 were found moderately vulnerable, 34 to 37 vulnerable, and 21 to 34 highly vulnerable requiring complete evacuations before a calamity. In general, villages established in the mangrove habitat areas after clearing the forest and the ones with a large number of marginal workers were found to be highly vulnerable while those situated behind mangrove forests in the leeward side or near a major river directly connected to the sea were less vulnerable. The paper helps to identify the most and the least vulnerable from among the group of vulnerable people in a coastal district. Though the findings of the paper are based on the human casualty data of a single cyclone and needs to be examined with a wider data set, the policy implications should not be undermined as we control for a wide range of variables. The results need to be replicated for other coastal areas and if found significant, can provide important guidelines to develop a compact vulnerability map of the coastal regions likely to be affected by climate change.

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