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Article

Relative Vulnerability of Indian Coastal Districts to Sea-Level Rise and Climate Extremes

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This study estimates the relative vulnerability of coastal districts of India using an integrated vulnerability index, which is defined as a function of the exposure, sensitivity, and adaptive capacity of the districts to present and future climate risks. The study also ranks districts in terms of the likely number of human casualties due to potential surge associated with cyclonic storms. The results indicate that the districts on the east coast are relatively more vulnerable than those on the west coast. Relative rankings of the coastal districts based on predicted storm-induced casualties are similar to the rankings based on the integrated vulnerability index, indicating the robustness of the findings. The primary purpose of the relative vulnerability measures developed in this study is to provide insights on prioritizing adaptation for specifically vulnerable regions. The study discusses policy issues with reference to the "adapt to what" and "how to adapt" aspects of adaptation and argues in favor of avoiding maladaptation to present-day extreme climate events and harmonizing climate-change adaptation with integrated coastal-zone management practices.

Keywords: Climate change, Coastal zones, Vulnerability, Adaptation

1. Introduction

Climate change and associated sea-level rise (SLR) are believed to be inevitable, and the Intergovernmental Panel on Climate Change (IPCC) observes in its third assessment report (2001, p.10) that "there is new and stronger evidence that most of the warming observed over the last 50 years is attributable to human activities." While changing climate poses challenges to humanity as a whole, the available evidence suggests that the developing countries are particularly vulnerable. Most of the available impact estimates, however, do not account for impacts due to extreme climate events such as cyclones and droughts, whose frequency and intensity could also increase under changed climatic conditions. These natural disasters currently cause significant damage in developing countries. Asia, for example, accounted for almost 38 percent of hydrological and meteorological disasters that occurred during the period 1991 and 2000 around the world. Of those reported killed by natural disasters, 83 percent lived in Asia, while 67 percent lived in nations with low Human Development Indexes (IFRC 2001).Thus, from the developing country perspective, present-day vulnerability due to natural disasters, the possibility of increase in frequency and intensity of such events with climate change, and the

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potential high impact of climate change on the performance of climate-sensitive sectors make a strong case for focus on adaptation options as part of climate-change policy. A fundamental input necessary for formulating adaptation policy is knowledge about impacts induced by climate change on, and the vulnerability of, climate-sensitive sectors.

The threat of rising sea levels as a result of climate change makes coastal resources, coastal infrastructure, and population living in coastal areas highly vulnerable. At the same time, as the rise in sea levels is likely to be a gradual process, numerous adaptation options, such as building dikes and floodwalls, wetland restoration, afforestation, and relocation of threatened buildings, also exist. Moreover, climate change could manifest itself through extreme events such as cyclones, and hence a proper understanding of current management practices for coastal zones, such as early-warning systems and hazard insurance, could provide useful insights about potential adaptation strategies.

India, with more than 7,500 km of coastline covering the Gujarat, Konkan, and Malabar coasts in the west and Tamil Nadu, Andhra Pradesh, Orissa, and West Bengal coasts in the east, is the specific focus of this study. There are a total of 53 coastal districts and six union territories, and a large proportion of the total population lives in these areas. The objective of this study is to assess the relative vulnerability of coastal districts of India to present-day and future climate threats. The paper is organized as follows: the rest of this section briefly reviews the related literature; section 2 describes the methodology adopted and data used; section 3 presents the results; and the last section discusses the policy implications of the results.

Literature on SLR impacts is vast and well advanced. However, given that the focus of the present study is on assessing the relative vulnerability of coastal regions, the discussion here is limited to only a few aspects of this literature. After providing a brief overview of evidence for SLR and extreme climate events in India, this section outlines the literature on SLR impact assessment and India-specific studies.

The studies by Emery and Aubrey (1989) and Mahadevan (1992) have established weak evidence for rise in the mean sea level along the Indian coast. Analysis of historical tide-gauge data along peninsular India shows an average rise of sea level by 0.67 mm/yr as against the global average of 1.8 mm/yr (Asthana 1993). There are also studies refuting the link between sea-level rise and climate change and arguing that interdecadal changes in sea level along the Indian coast can be linked to the variability of the monsoon (for example, Shankar 1998).

Table 1 shows the occurrence of cyclonic storms in the Bay of Bengal during the period 1877 to 1995. According to Ali (1999), India is hit by 3.34 percent of the world's total tropical cyclonic storms; India and Bangladesh together are hit by only 4.27 percent of the world storms but suffer most, with 76 percent of total storm-related deaths occurring in the two countries. One necessary but insufficient condition for tropical cyclone formation is that the sea's surface should have a minimum temperature of about 26 to 27^{o}C. This leads to speculation that any rise in sea surface temperature (SST) due to climate change is likely to be accompanied by an increase in cyclone frequency. However, evidence from the Bay of Bengal region suggests that even though there has been an increase in the SST since 1950, no corresponding increase in the frequency of cyclones can be established.

Table 1. Cyclonic storms in the Bay of Bengal, 1877–1995

	India	Bangladesh	Dead	Total
All types	848	154	115	1,223
Depressions	539	68	69	715
Cyclonic storms (CS)	197	43	35	310
Severe cyclonic storms (SCS)	112	43	11	198
CS + SCS	309	86	46	508
% of global total (CS + SCS)	3.34	0.93	0.5	5.5

Source: Ali 1999.

Besides evidence from historical records, predictive climate models can also be used to analyze extreme climate events. In a recent study, Palmer and Raisanen (2002) analyzed the output of 19 climate models and estimated that the Asian monsoon region would experience a fivefold increase in amount of summer rainfall, escalating the risk of flooding in already flood-prone areas. On the other hand, there are reasons to expect the storm-surge height to increase, both due to climate change (and hence increase in SST) and to SLR. Using a numerical storm-surge model, Ali (1999) showed that the surge height of a cyclonic storm that hit the Bangladesh coast in April 1991 would be increased by as much as 40 percent if SST were to increase by 4^{o}C and the sea level were to rise by 1 m.

The impact assessment studies can be classified into four generations of models (West and Dowlatabadi 1999). The first-generation models overlaid SLR scenarios onto topographical maps of coastal regions to assess the physical and economic impacts (Yohe 1990), whereas the second-generation models accounted for the possibility of human adaptation (Titus et al. 1991). The third-generation models brought in the possibility of perfect foresight of the markets while assessing the value of property at risk of inundation (Yohe et al. 1996). Fourth-generation models share the features of third-generation models but also take into consideration the present-day influence of extreme climate events such as cyclones (West, Dowlatabadi, and Small 2000).

The study coordinated by Jawaharlal Nehru University for Ministry of Environment and Forests, Government of India (Asthana 1993) is by far the most comprehensive effort undertaken to assess potential land loss due to SLR and the associated population at risk in India. Using the methodology of the first generation of impact models, this study estimated that a total area of 5,763 km^2 (i.e., 0.4 percent of the total area of the coastal states) would be affected, and that about 7.1 million people (some 4.6 percent of the total coastal population) would be at risk. ADB (1994) expressed these physical impacts in value terms by making some broad assumptions about the land value and population displacement costs. The overall economic damage was estimated to be as high as 43 percent of India's 1988 gross domestic product (GDP), while the annualized costs spread over a period of 40 years are estimated at 0.18 percent of GDP.

In a more recent study, TERI (1996) assumed that changes in GDP could be used as a proxy for land and capital losses due to SLR. An interesting observation of this study is that the cost of protection is relatively low in districts that are prone to high economic impacts such as Mumbai, whereas the protection costs are higher in districts like Balasore and Goa where the impacts are likely to be less.

2. Methodology and data

To assess economic impacts due to SLR in accordance with the third- and fourth-generation models mentioned above, more precise estimates of the physical impacts than those available from Asthana (1993) would be required. In the absence of such information, the present study adopts two distinct but related strategies to assess the relative vulnerability of Indian coastal districts: First, given that the impacts due to sea-level rise are likely to be varied across different parts of the country, a district-level composite vulnerability index is developed to identify the most vulnerable coastal districts. Also, the vulnerability index would take both climate and non-climate factors into consideration and hence the analysis is a step forward from impact assessment. Second, Indian coastal districts are often affected by cyclonic storms. However, there are significant differences across districts in terms of their exposure and vulnerability to such storms. Hence, using human casualties—which are the most significant impacts due to the storms—it is possible to study the relative vulnerability of coastal districts.

2.1. Coastal vulnerability index

Two aspects of index computation that deserve attention, namely the choice of components and the method of computation, are discussed in detail here. Use of the term *vulnerability* here is in accordance with the broad definition used in IPCC literature: vulnerability of a system is a function of its exposure and sensitivity to climate change, and its adaptive capacity. A wide range of characteristics of the system, including ecological, economic, social, demographic, technological, and political factors, is considered here to assess vulnerability. District-specific data on the following parameters (which are considered to influence vulnerability) is assembled:

Demographic: (a) population density based on the 2001 census (GoI 2001); (b) annual growth rate of population; (c) population at risk due to sea-level rise.

Physical: (a) coast length; (b) insularity (defined as ratio of coastal length to the area of the district); (c) frequency of cyclones (weighted to account for cyclones of different intensities) based on historic data; (d) probable maximum surge height; (e) area at risk of inundation due to SLR; (f) number of vulnerable houses—both those at risk of damage and of destruction (based on the 1991 census).

Economic: (a) agricultural dependency (expressed in terms of population dependent on agriculture and other primary sectors); (b) income and/or infrastructure index.

Social: (a) literacy; (b) spread of institutional set-up.

In terms of the IPCC definition of vulnerability, indicators like coastal length and frequency of cyclones represent the region’s exposure, whereas population density and its growth rate, insularity, agricultural dependency of the population, area and population at risk due to SLR, probable maximum surge height, and number of vulnerable houses represent the region’s sensitivity. Together these two sets characterize the potential impacts on the region. Socio-economic indicators like literacy and income represent the adaptive capacity of the region, and the vulnerability is the net result of potential impacts and adaptive capacity. It may be noted that income can be considered both as a measure of adaptive capacity and as an indicator of sensitivity.

Table 2 shows district-specific data on the above parameters. It may be noted that some of the districts are clubbed for data consistency.[1] Income data at district level is not readily available and state-level value added in primary, secondary, and tertiary sectors is allocated across districts using the following procedure:

Income for k^{th} district is estimated as:

$$\text{Income}_k = \text{Agricultural NDDP}_k + \text{Industrial NDDP}_k + \text{Services NDDP}_k$$

where, NDDP is net district domestic product and NSDP is net state domestic product. Sector-wise NDDP for k^{th} district is calculated as:

$$\text{Agricultural NDDP}_k = \left[\frac{\text{Net sown area in the district}}{\text{Total net sown area in the state}}\right] \times \text{Agricultural NSDP}$$

$$\text{Industrial NDDP}_k = \left[\frac{\textit{Population employed in industrial sector in the district}}{\textit{Population employed in industrial sector in the state}}\right] \times \text{Industrial NSDP}$$

$$\text{Services NDDP}_k = \left[\frac{\textit{Population employed in service sector in the district}}{\textit{Population employed in service sector in the state}}\right] \times \text{Services NSDP}$$

Since the components of the index are often measured in different units, the observations have to be standardized or normalized to enable their use in index computation. The normalization procedure most commonly used is one that adjusts the observation to take a value of between 0 and 1, using the formula

$$V_{ij} = (X_{ij} - \min X_i) / (\max X_i - \min X_i)$$

where, V_{ij} stands for the standardized observation associated with the i^{th} component for region j; X_{ij} stands for the value of the i^{th} component in the vulnerability index, for region j; max X_i and min X_i stand for the maximum and minimum values of the i^{th} component for all regions in the index. The method is further refined to reduce the undue impact of outliers on the distribution of the observations, by

1. In Andhra Pradesh, Prakasam District is clubbed with Nellore District, and Vizianagaram District is clubbed with Vishakapatnam District. In Tamil Nadu, Pudukottai District is clubbed with the Thanjavur District, and Chidambaranar District is clubbed with Tirunelveli-Kattabomman District.

Table 2. Characteristics of coastal districts

Serial No.	District	State	Population 2001	Pop. growth rate 1991–01	Pop. density 2001	Literacy rate 2001	Coast length (km)[a]	Agri. labor force 1991	Share of agri. in value added	Income[b]	Cyclone freq.[c]	PMSH[d]	Area affected (ha.)[e]	No. of vulnerable houses[f]	
														Damaged	Destroyed
1	East Godavari	Andhra Pradesh	4,872,731	7.30	451	58	195.7	67.89	25.51	185,078	8	3.50	211,265	116,369	263,149
2	Guntur	Andhra Pradesh	4,405,578	7.27	387	56	59.8	73.29	41.51	177,144	3	6.00	2,896	94,858	116,098
3	Krishna	Andhra Pradesh	4,218,519	14.05	483	62	124.8	66.27	33.96	178,417	14	5.50	9,081	79,694	221,357
4	Nellore[g]	Andhra Pradesh	5,714,663	10.93	186	54	192.5	75.90	48.51	227,115	21	5.00	5,574	102,039	265,090
5	Srikakulam	Andhra Pradesh	2,499,992	7.71	386	47	199.1	76.53	30.01	235,801	14	3.00	20,069	44,642	267,657
6	Visakhapatnam[h]	Andhra Pradesh	6,224,866	15.36	340	52	129.8	62.24	21.36	148,988	8	3.00	4,896	93,664	275,456
7	West Godavari	Andhra Pradesh	3,796,159	7.92	490	65	13.7	71.99	35.35	144,176	0	4.00	1,219	80,970	145,852
8	North Goa	Goa	757,411	13.93	442	76	41.5	27.63	18.12	59,482	0	3.40	9,645	16,104	0
9	South Goa	Goa	586,595	16.16	301	71	67.2	28.53	15.54	42,902	0	3.40	6,042	12,516	0
10	Ahmedabad	Gujarat	6,079,574	26.61	667	70	35.0	26.59	11.99	401,289	0	4.00	16,425	67,187	62,223
11	Amreli	Gujarat	1,333,381	6.45	206	58	57.9	67.20	48.60	81,943	0	4.00	31,828	17,689	37,485
12	Bharuch	Gujarat	1,823,464	17.94	208	61	127.8	68.74	41.44	83,100	0	4.80	8,346	38,870	0
13	Bhavnagar	Gujarat	2,734,158	19.29	221	57	155.9	55.97	32.72	154,482	2	4.70	11,327	41,666	111,006
14	Jamnagar	Gujarat	1,913,639	22.39	135	55	285.1	57.58	42.44	114,594	3	2.50	11,421	42,806	121,301
15	Junagarh	Gujarat	2,791,914	16.58	281	59	241.0	67.43	38.86	126,270	10	2.80	3,002	47,822	221,774
16	Kachchh	Gujarat	1,526,371	20.90	33	61	472.2	57.68	52.52	110,740	3	2.50	37,774	56,868	71,767
17	Kheda	Gujarat	3,893,011	13.14	539	64	27.8	70.43	29.87	143,548	0	4.80	33,872	38,759	0
18	Surat	Gujarat	4,996,272	47.04	653	65	51.5	44.84	14.45	226,995	0	4.80	12,526	75,750	0
19	Valsad	Gujarat	2,639,894	21.45	503	63	74.5	62.18	22.27	108,127	0	5.00	14,479	62,325	0
20	Dakshin Kannad	Karnataka	3,005,994	11.57	356	73	151.1	42.53	11.06	144,389	2	3.40	19,209	49,834	0

Table 2. —*continued*

Serial No.	District	State	Population 2001	Pop. growth rate 1991–01	Pop. density 2001	Literacy rate 2001	Coast length (km)[a]	Agri. labor force 1991	Share of agri. in value added	Income[b]	Cyclone freq.[c]	PMSH[d]	Area affected (ha.)[e]	No. of vulnerable houses[f]	
														Damaged	Destroyed
21	Uttar Kannad	Karnataka	1,353,268	10.90	132	67	142.3	65.45	18.10	44,401	0	3.70	9,321	21,125	0
22	Alappuzha	Kerala	2,105,480	5.21	1,676	84	82.0	40.13	22.45	72,704	0	3.00	1,148	45,354	0
23	Ernakulam	Kerala	3,073,323	9.09	1,287	84	46.0	32.21	24.15	116,966	1	3.00	320	48,226	0
24	Kannur	Kerala	2,412,275	7.13	805	82	82.0	39.74	32.17	93,263	1	3.00	952	43,075	0
25	Kasaragod	Kerala	1,203,303	12.30	614	74	70.0	48.21	44.67	47,740	1	3.00	1,820	24,306	0
26	Kollam	Kerala	2,584,041	7.33	1,002	81	37.0	46.28	27.17	83,213	0	2.40	2,358	52,933	0
27	Kozhikode	Kerala	2,878,529	9.87	1,228	82	71.0	32.26	23.97	107,312	2	3.50	1,430	57,123	0
28	Malappuram	Kerala	3,629,518	17.22	1,023	76	70.0	53.16	32.52	97,986	1	3.40	999	54,658	0
29	Thiruvananthapuram	Kerala	3,234,832	9.78	1,476	80	78.0	46.98	24.06	94,122	1	2.30	2,004	60,353	0
30	Thrissur	Kerala	2,975,457	8.70	981	83	54.0	38.45	23.92	103,191	0	3.40	968	53,588	0
31	Greater Mumbai	Maharashtra	11,914,276	20.03	11,879	77	58.3	0.67	0.00	1,377,002	3	4.20	8,675	69,429	0
32	Raigarh	Maharashtra	2,206,020	20.89	309	67	127.7	85.53	50.94	76,459	2	4.10	4,908	43,139	0
33	Ratnagiri	Maharashtra	1,696,455	9.87	206	65	184.7	76.14	24.68	69,367	2	3.00	1,808	4,208	0
34	Sindhudurg	Maharashtra	861,693	3.55	165	71	110.9	75.76	21.25	36,320	0	2.90	3,241	22,852	0
35	Thane	Maharashtra	8,128,797	54.86	850	70	184.0	32.81	3.68	528,680	0	4.20	22,727	93,622	0
36	Baleshwar	Orissa	3,355,204	19.73	532	62	130.3	77.91	40.62	70,386	19	9.80	11,800	9,128	390,930
37	Cuttack	Orissa	6,273,724	13.60	422	68	150.6	65.99	24.97	172,137	17	5.50	17,700	56,651	564,168
38	Ganjam	Orissa	3,664,482	16.01	250	54	62.0	76.95	37.41	80,987	7	2.70	100	64,403	138,449
39	Puri	Orissa	4,313,232	20.14	331	70	147.2	64.63	16.02	103,205	10	3.20	17,600	49,549	216,519
40	Chengalpattu	Tamilnadu	5,608,905	20.53	714	68	152.9	51.20	11.58	258,011	15	3.00	13,440	100,471	366,459
41	Kanniyakumari	Tamilnadu	1,669,804	4.34	992	79	65.0	58.82	10.74	73,601	2	2.70	117	25,134	0
42	Madras	Tamilnadu	4,216,316	9.76	24,231	73	17.0	0.94	0.00	376,698	15	5.45	3,378	86,650	91,635
43	Ramanathapuram	Tamilnadu	1,209,593	5.73	280	64	186.2	74.21	40.48	48,915	3	11.00	9,908	22,111	1,725
44	South Arcot	Tamilnadu	5,224,367	7.09	480	60	79.4	80.16	37.32	153,419	5	3.00	4,272	94,603	219,049
45	Thanjavur[i]	Tamilnadu	6,309,967	7.70	488	67	225.9	73.03	30.49	224,617	13	7.00	14,300	259,674	62,062

Table 2. —*continued*

Serial No.	District	State	Population 2001	Pop. growth rate 1991–01	Pop. density 2001	Literacy rate 2001	Coast length (km)[a]	Agri. labor force 1991	Share of agri. in value added	Income[b]	Cyclone freq.[c]	PMSH[d]	Area affected (ha.)[e]	No. of vulnerable houses[f]	
														Damaged	Destroyed
46	Tirunelveli[j]	Tamilnadu	4,366,995	10.34	382	70	163.3	55.64	17.95	216,787	2	6.00	21,585	56,973	0
47	Medinipur	W. Bengal	9,638,356	15.68	685	65	107.1	69.30	48.49	348,638	12	12.50	20,700	64,721	1,237,475
48	North 24 Parganas	W. Bengal	8,930,499	22.64	2,181	70	74.2	35.74	14.56	382,458	23	12.00	29,567	136,002	570,240
49	South 24 Parganas	W. Bengal	6,908,900	20.89	694	60	118.0	59.58	31.00	233,973	23	12.25	71,933	67,086	599,244

Notes: a. Author's calculation using GIS; b. Based on the author's estimations, using 1990–91 SDP data, in hundred-thousands (*lakh*) of rupees; c. Based on data from the India Meteorological Department in various issues of *Mausam* magazine. No specific references provided. d. Probable maximum surge height; from data BMTPC 1997, in meters; e. The figures are from JNU 1993 and are for 1 m SLR; f. Data from BMTPC 1997, based on 1991 census data.

assigning the value of 1 to the top decile of values in the observations of a particular variable and a value of 0 to the bottom decile.

The averaging procedure to compute the final index can be based on assigning equal or varying weights to each component. Briguglio (1995) experimented with varying weights for each component, but the preferred method was that involving equal weights. Many index-based studies have followed this procedure (for example, Brenkert and Malone 2004; Briguglio 1995, 1997; O'Brien et al. 2004; Wells 1996).[2]

In this study, the composite index for each district is calculated by taking the average of all the standardized observations over all the components. The averaging procedure implies that equal weights are assigned to each component. The procedure is similar to that followed in the construction of the Human Development Index by the UNDP (see UNDP 2002). The index computations are made for a range of combinations of the parameters listed above. The components of the different indices are as follows:

V1 = Insularity, population density, population growth, population dependent on agriculture, literate population, vulnerable houses (total), probable maximum surge height, and cyclone frequency.

V2 = Insularity, population density, population growth, population in agriculture, literate population, vulnerable houses (at risk of being destroyed), probable maximum surge height, and cyclone frequency.

V3 = Insularity, population density, population growth, population in agriculture, literate population, vulnerable houses (at risk of being damaged), probable maximum surge height, and cyclone frequency.

V4 = V1 + income as vulnerability indicator.

V5 = V1 + income as resilience indicator.

V6 = V1 – insularity + area affected due to sea-level rise.

V7 = V6 + income as vulnerability indicator.

V8 = V6 + income as resilience indicator.

The indices V3, V2, and V1 differ in terms of categories of vulnerable houses: V2 includes houses at risk of being destroyed, V3 includes houses at risk of being damaged but not destroyed, and V1 includes houses in both categories. Three different indices are considered because in some coastal districts, more houses are at risk of damage, whereas in other districts, more houses are at risk of destruction. The indices V4 and V5 are more complete indices (in comparison to V1), as they include an income component also. However, they differ in terms of considering income as an indicator of adaptive capacity (or resilience) and as an indicator of sensitivity. The index V6 is a variant of index V1 but

2. Other methods include: (a) mapping on a categorical scale, which is suitable for qualitative data and involves mapping the scores on a categorical scale ranging from the lowest possible incidence to the highest (see Kaly et al. 1998); and (b) the regression method, which lets the data produce the weights and does not require normalization of the observations. However, the regression method has a number of methodological problems that limit the operationalization and reliability of the index, the most important limitation being the need to identify a proxy for vulnerability to serve as a dependent variable (see ; Atkins, Mazzi, and Ramlogan 1998; Wells 1996).

replaces the insularity indicator with the estimated potential area affected due to SLR. Finally, indices V7 and V8 again represent improvements over V6 as they include an income component. Different indices are constructed to check whether relative ranking across districts varies with the choice of components for the index.

2.2. Storms and human casualties

Given sufficient warning and resources, it is always possible to minimize the human loss during cyclonic storms. Broadly, the loss of human lives would depend on the risk level of the region, warning time, and compliance with the evacuation plan. Compliance with a warning would further depend on the preparedness of the region to evacuate the affected population to cyclone shelters as well as the confidence of the people in the reliability of the warning. Due to high levels of literacy and the credibility of the forecasts, in developed countries non-compliance factors would typically be low, whereas they would be high in a developing country.

The loss of human lives in any region can be estimated using the formula

$$H = \sum_i P\, C\, \alpha_i\, r_i$$

where P is the population of the region, C is the non-compliance factor, α_i is the fraction of the region's area related to a given hazard level, and r_i is the risk coefficient for the hazard level.

For each coastal district, the area with different hazard levels—which are defined based on wind velocities that would prevail during a storm and the storm penetration—is assessed using the *Vulnerability Atlas of India* (BMTPC 1997). The *Vulnerability Atlas* defines the following hazard levels for various wind speeds: very high (VH): 50 to 55 m/sec; high (H): 47 to 50 m/sec; moderate (M): 39 to 47 m/sec; and low (L): 33 to 39 m/sec. Each VH hazard zone is further classified into two zones, because part of a VH zone would be at higher risk due to the influence of surge. The surge influence factor for a district is calculated by the formula

$$\text{surge influence factor} = (\text{coast length} \times \text{inland penetration})/(\text{area})$$

where the coast length and area represent the district-specific values, and inland penetration is a parameter that is changed to generate different scenarios.

Thus for the analysis, four hazard levels are considered: VH + surge, VH, H, and M. The risk coefficients for various hazard levels are gathered from disaster-management literature (Krishna and Bhandari 1999): VH + surge: 5×10^{-2}; VH: 5×10^{-3}; H: 5×10^{-5}; and M: 5×10^{-8}. These risk coefficients reflect the probability of death due to storm; estimates of human casualties during the two major cyclones that crossed the coast of Andhra Pradesh in 1977 and 1990 made using these coefficients are close to the real figures (BMTPC 1998). The surge influence factor is calculated for two different scenarios of surge penetration: 10 km and 30 km. Two different scenarios for non-compliance factors are used to represent the extent of compliance observed during the 1977 and 1990 Andhra Pradesh cyclones. Since the present analysis assumes that the non-compliance factor is linearly related to human casualties, the two scenarios merely represent the extent of impact under different confidence levels in the cyclone warnings.

Table 3. Vulnerability indices for coastal districts

Serial No.	District	V1	V1 rank	V2	V2 rank	V3	V3 rank	V4	V4 rank	V5	V5 rank	V6	V6 rank	V7	V7 rank	V8	V8 rank
1	East Godavari	0.3192	17	0.3011	17	0.3260	21	0.2967	17	0.3818	16	0.4224	6	0.3885	7	0.4736	6
2	Guntur	0.2786	30	0.2633	31	0.3012	31	0.2600	30	0.3464	33	0.2752	26	0.2569	26	0.3434	26
3	Krishna	0.3887	9	0.3749	10	0.3852	12	0.3579	11	0.4441	11	0.3772	12	0.3477	11	0.4339	12
4	Nellore	0.3872	10	0.3750	9	0.3862	11	0.3606	10	0.4388	12	0.3841	9	0.3578	9	0.4360	10
5	Srikakulam	0.3416	15	0.3301	15	0.3123	27	0.3208	16	0.3976	14	0.3343	15	0.3143	15	0.3911	15
6	Visakhapatnam	0.2875	28	0.2760	26	0.2829	41	0.2656	25	0.3566	28	0.2770	25	0.2562	27	0.3473	25
7	West Godavari	0.2718	36	0.2560	37	0.2854	39	0.2512	32	0.3431	34	0.2719	27	0.2513	29	0.3432	27
8	North Goa	0.2363	48	0.2210	49	0.2795	43	0.2127	49	0.3185	48	0.2127	48	0.1917	48	0.2975	46
9	South Goa	0.2443	45	0.2291	45	0.2871	37	0.2185	46	0.3270	42	0.2052	49	0.1837	49	0.2923	48
10	Ahmedabad	0.2352	49	0.2268	48	0.2497	48	0.2399	37	0.2894	49	0.2414	34	0.2454	31	0.2949	47
11	Amreli	0.2397	47	0.2291	46	0.2441	49	0.2175	48	0.3196	47	0.2491	33	0.2259	34	0.3280	32
12	Bharuch	0.2735	35	0.2561	36	0.3224	22	0.2477	35	0.3496	31	0.2618	31	0.2373	32	0.3392	28
13	Bhavnagar	0.2938	23	0.2801	22	0.2921	36	0.2717	22	0.3618	24	0.2841	23	0.2630	23	0.3532	23
14	Jamnagar	0.3076	20	0.2893	20	0.3030	30	0.2806	20	0.3773	17	0.2898	20	0.2648	22	0.3615	19
15	Junagarh	0.3693	14	0.3567	14	0.3384	19	0.3364	14	0.4312	13	0.3433	13	0.3133	16	0.4081	13
16	Kachchh	0.2935	24	0.2668	29	0.3334	20	0.2678	24	0.3651	20	0.3041	19	0.2772	19	0.3746	17
17	Kheda	0.2502	40	0.2429	40	0.2710	46	0.2320	41	0.3240	43	0.2670	29	0.2469	30	0.3388	29
18	Surat	0.3094	19	0.2935	19	0.3539	17	0.2914	18	0.3697	19	0.3097	17	0.2918	18	0.3700	18
19	Valsad	0.2883	27	0.2645	30	0.3549	16	0.2629	26	0.3607	26	0.2801	24	0.2556	28	0.3534	22
20	Dakshin Kannad	0.2464	43	0.2343	44	0.2804	42	0.2286	43	0.3205	45	0.2362	39	0.2196	35	0.3114	40
21	Uttar Kannad	0.2487	42	0.2362	42	0.2838	40	0.2225	45	0.3308	40	0.2380	36	0.2129	38	0.3212	35
22	Alappuzha	0.2999	21	0.2862	21	0.3385	18	0.2704	23	0.3740	18	0.2271	45	0.2056	46	0.3092	41
23	Ernakulam	0.2462	44	0.2358	43	0.2756	44	0.2262	44	0.3226	44	0.2233	47	0.2059	45	0.3022	45
24	Kannur	0.2608	38	0.2478	38	0.2976	34	0.2373	38	0.3375	39	0.2272	44	0.2074	44	0.3077	43

Table 3. —*continued*

Serial No.	District	V1	V1 rank	V2	V2 rank	V3	V3 rank	V4	V4 rank	V5	V5 rank	V6	V6 rank	V7	V7 rank	V8	V8 rank
25	Kasaragod	0.2762	31	0.2609	33	0.3192	25	0.2472	36	0.3550	29	0.2334	40	0.2092	43	0.3169	36
26	Kollam	0.2398	46	0.2275	47	0.2744	45	0.2178	47	0.3197	46	0.2236	46	0.2034	47	0.3053	44
27	Kozhikode	0.2735	34	0.2583	35	0.3162	26	0.2497	34	0.3477	32	0.2368	38	0.2170	37	0.3150	37
28	Malappuram	0.2832	29	0.2697	27	0.3211	24	0.2576	31	0.3570	27	0.2599	32	0.2368	33	0.3363	31
29	Thiruvananthapuram	0.2750	33	0.2630	32	0.3087	28	0.2499	33	0.3500	30	0.2317	42	0.2115	40	0.3116	39
30	Thrissur	0.2502	41	0.2373	41	0.2865	38	0.2287	42	0.3273	41	0.2294	43	0.2102	42	0.3088	42
31	Greater Mumbai	0.3835	13	0.3800	8	0.3934	8	0.4520	6	0.3409	36	0.2649	30	0.3466	12	0.2355	49
32	Raigarh	0.3153	18	0.3001	18	0.3581	15	0.2843	19	0.3873	15	0.3071	18	0.2770	20	0.3800	16
33	Ratnagiri	0.2595	39	0.2590	34	0.2607	47	0.2341	39	0.3383	38	0.2330	41	0.2106	41	0.3148	38
34	Sindhudurg	0.2614	37	0.2448	39	0.3079	29	0.2331	40	0.3427	35	0.2374	37	0.2117	39	0.3213	34
35	Thane	0.3285	16	0.3175	16	0.3593	14	0.3332	15	0.3618	25	0.3186	16	0.3245	14	0.3531	24
36	Baleshwar	0.5734	1	0.5734	1	0.4542	5	0.5133	3	0.6173	1	0.5553	2	0.4972	4	0.6012	2
37	Cuttack	0.4614	6	0.4545	6	0.3907	9	0.4220	7	0.5093	6	0.4560	5	0.4172	5	0.5045	5
38	Ganjam	0.2900	25	0.2773	25	0.2955	35	0.2622	27	0.3645	22	0.2854	22	0.2581	24	0.3603	20
39	Puri	0.3844	12	0.3732	11	0.3599	13	0.3480	12	0.4466	10	0.3778	11	0.3421	13	0.4407	8
40	Chengalpattu	0.4063	7	0.3908	7	0.3875	10	0.3802	8	0.4533	7	0.3907	8	0.3663	8	0.4394	9
41	Kanniyakumari	0.2894	26	0.2777	24	0.3223	23	0.2611	28	0.3645	21	0.2411	35	0.2181	36	0.3216	33
42	Madras	0.5349	4	0.5135	5	0.5708	1	0.5042	4	0.5578	4	0.4118	7	0.3948	6	0.4484	7
43	Ramanathapuram	0.3853	11	0.3716	12	0.4221	7	0.3443	13	0.4518	8	0.3358	14	0.3003	17	0.4078	14
44	South Arcot	0.2942	22	0.2798	23	0.2982	33	0.2719	21	0.3622	23	0.2890	21	0.2672	21	0.3576	21
45	Thanjavur	0.3957	8	0.3628	13	0.4796	4	0.3680	9	0.4466	9	0.3832	10	0.3569	10	0.4355	11
46	Tirunelveli	0.2760	32	0.2677	28	0.2992	32	0.2609	29	0.3408	37	0.2719	28	0.2573	25	0.3372	30
47	Medinipur	0.5256	5	0.5225	4	0.4263	6	0.4937	5	0.5519	5	0.5297	4	0.4973	3	0.5555	4
48	North 24 Parganas	0.5467	3	0.5327	3	0.5205	2	0.5152	2	0.5678	3	0.5424	3	0.5114	2	0.5640	3

Table 3. —*continued*

Serial No.	District	V1	V1 rank	V2	V2 rank	V3	V3 rank	V4	V4 rank	V5	V5 rank	V6	V6 rank	V7	V7 rank	V8	V8 rank
49	South 24 Parganas	0.5633	2	0.5550	2	0.4932	3	0.5177	1	0.5948	2	0.5921	1	0.5434	1	0.6204	1

3. Results and discussion

Computed vulnerability indices for the coastal districts along with their ranks according to each of the specifications described in the previous section are shown in table 3, while figure 1 shows the vulnerability index as per specification V1. The rank correlation between various vulnerability indices is shown in table 4. The correlations are significantly high between various indices, indicating that the relative ranking of the districts across different index specification is robust. Discussion here focuses on the highlighted rank correlations shown in table 4. Very high (0.99) and high (0.91) rank correlation between indices V1 and V2 and between V1 and V3, respectively, suggest that including either total vulnerable houses or houses that are at risk of destruction or damage may not change the overall ranking. Interestingly, the very high correlations between V1 and V4 and between V1 and V5 indicate that including income as either a resilience indicator or a sensitivity indicator does not influence the vulnerability rankings. One may argue, based on this result, that vulnerability across the Indian coastal districts is mainly determined by the potential physical impacts. However, rankings change significantly when the literacy component is taken out of the overall index calculation, justifying a role for adaptive capacity in the definition of vulnerability. High correlation between indices V4 and V5 (and also between V7 and V8) is surprising because these indices treat income in opposite ways. A careful look at the rankings in table 3 shows that the ranking of Greater Mumbai is reversed across these indices, in accordance with the hypothesis. However, it does not translate into the overall rank correlation because of the large difference between income levels of Greater Mumbai (which includes the commercial hub of India) and other districts.

Table 4. Rank correlation between various vulnerability indices

	V1	V2	V3	V4	V5	V6	V7	V8
V1	1.00	-	-	-	-	-	-	-
V2	0.99	1.00	-	-	-	-	-	-
V3	0.91	0.89	1.00	-	-	-	-	-
V4	0.98	0.98	0.89	1.00	-	-	-	-
V5	0.96	0.94	0.87	0.92	1.00	-	-	-
V6	0.89	0.87	0.75	0.90	0.87	1.00	-	-
V7	0.90	0.89	0.77	0.92	0.83	0.98	1.00	-
V8	0.86	0.83	0.72	0.83	0.90	0.96	0.89	1.00

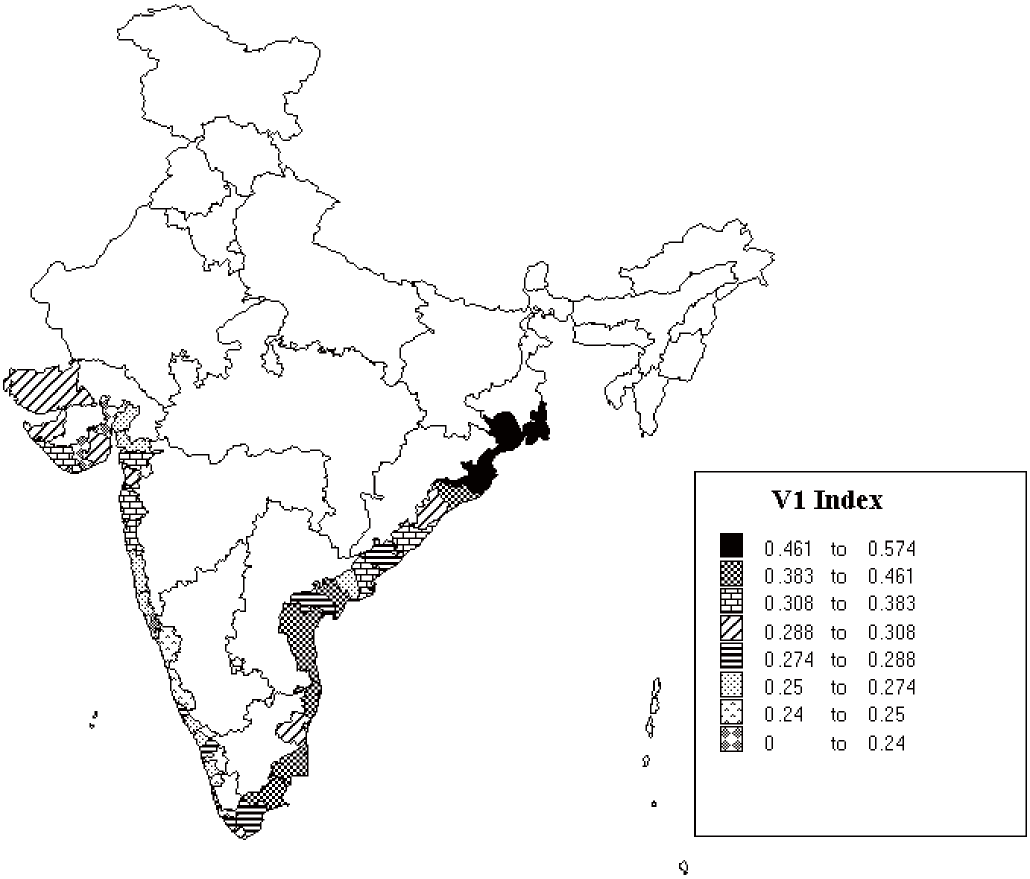

Figure 1. Map of Indian coastal districts showing vulnerability index (using index V1)

The vulnerability index indicates that:

- The districts along the east coast are relatively more vulnerable than those on the west coast.
- The coastal districts in the states of West Bengal, Orissa, Andhra Pradesh, and Tamil Nadu are only marginally different from each other in terms of their vulnerability.
- The districts that are frequently affected by cyclonic storms are relatively more vulnerable—these include districts like 24 Paraganas, Baleshwar, and Krishna.

As well as districts on the east coast of India being more vulnerable compared to those on the west coast, more cyclones hit the east coast than hit the west coast. The estimated human casualties for the coastal districts along the east coast under different scenarios are presented in table 5. The last two columns show the likely losses due to more-severe cyclonic storms with higher inland surge penetration, which are expected under climate-change conditions. As mentioned in the previous section, the non-compliance factors are chosen merely to reflect the extent of damage observed in the two earlier cyclones that crossed the coast of Andhra Pradesh. In 1977, the early warnings were not sufficiently credible and compliance was very low. Added to that, the cyclone surge was very severe and the damage was some of the worst in India's history. In contrast, the 1990 cyclone, while comparable in severity to that of 1977, was marked by credible early warning and, as a result, high compliance. Table 5 shows damage corresponding to non-compliance factors of 0.1 and 0.0065 (adapted from BMTPC 1998), reflecting these two extreme scenarios.

Comparison of the results shown in table 5 with those presented under the vulnerability index shows that the relative ranking of districts remains more or less similar between the two analyses. This is an important result because the two analyses address vulnerability from two related but different perspectives and their similarity shows the robustness of the findings.

4. Conclusions and policy implications

This study estimated the relative vulnerability of coastal districts of India using an integrated vulnerability index that takes into account impact—induced by present-day and future climate pressures,

Table 5: Expected Casualties due to Storms

NCF / District	Surge Penetration – 10 km		Surge Penetration – 30 km	
	0.1	0.0065	0.1	0.0065
East Godavari	167	334	374	747
Guntur	34	68	56	112
Krishna	105	211	224	448
Nellore	79	158	136	273
Srikakulam	218	436	476	952
Visakhapatnam	94	187	168	336
West Godavari	33	66	42	84
Baleshwar	192	384	441	882
Cuttack	186	372	390	780
Ganjam	36	71	57	115
Puri	98	196	209	417
South Arcot	71	142	127	254
Medinipur	310	620	562	1124
N 24 Parganas	470	940	1053	2105
S 24 Parganas	286	571	580	1160

Note: NCF – non-compliance factor, value 0.1 represents the extent of non-compliance observed during 1970 cyclone in Andhra Pradesh and 0.0065 represents the same during 1990 cyclone in Andhra Pradesh.

as well as the adaptive capacity of the districts, characterized by a range of physical, economic, social, and demographic parameters. Using information on areas with different hazard levels in the coastal districts, the study also estimated the number of human casualties across coastal districts due to potential surge associated with cyclonic storms.

Relative rankings of Indian coastal districts based on the integrated vulnerability index indicate that districts on the east coast are relatively more vulnerable than those on the west coast. Relative rankings of the coastal districts based on predicted storm-induced casualties are similar to the rankings based on integrated vulnerability index, indicating the robustness of the findings.

The primary purpose of the relative vulnerability measures developed in this study is to provide insights to guide prioritization of adaptation strategies for specially vulnerable regions. Given that adaptation is an important policy response, this section looks a little more closely at two important aspects of adaptation, namely what to adapt to and how to adapt.

4.1. Adapt to what?

As climate change may actually be experienced as a change in the frequency and/or intensity of extreme climatic events, disaster preparedness is an important component of climate-change action plans. Understanding vulnerability to present-day climate extremes such as cyclones would provide useful insights about the adaptive capacity of a region. Adaptation measures taken in anticipation of climate change can and usually should be harmonized with responses to current extreme climatic events. However, human activities are not always as well adapted to the current extreme events as one would want them to be. As argued by Burton, Kates, and White (1993), the losses suffered due to climate extremes cannot be ascribed to the events alone, because lack of appropriate human adaptation and sometimes maladaptation account for significant losses.

In this context it may be worth noting the experiences with the super-cyclone in 1999 that devastated the state of Orissa. There is general agreement that the cyclone’s devastating impacts were worsened significantly by deforestation on the coast. Satellite pictures show that 2.5 km^2 of mangrove forest was lost every year during the 1970s. Without the protection of forests, the super-cyclone was believed to have traveled as far as 50 km inland. Mangrove forests make ideal places for conversion into ponds for shrimp farming, and India is one of the top four shrimp exporters in the world, with production growing by 15 percent a year. Orissa, a major center for the business, specializes in raising tiger prawns.

A rough estimate by the UN Food and Agriculture Organization (FAO 1999) indicates that in the past three decades, Andhra Pradesh has lost 40 percent of its mangrove forest to shrimp farming, while the corresponding losses in Orissa, Tamil Nadu, and West Bengal are 26 percent, 26 percent, and 1.25 percent respectively. It may be noted that the majority of the highly vulnerable districts according to the estimations in this study are located in these four states. An important policy lesson is to avoid these maladaptations and aim for sustainable resource-management practices.

4.2. How to adapt

Coastal zone management is about making trade-offs aimed at resolving competing sectoral demands, rather than optimizing the output of a single resource. Solving such problems requires integration of management objectives and hence there is increasing interest in integrated coastal zone management (ICZM). In terms of responding to climate change, ICZM can be seen as an essential institutional mechanism that can deal with all competing pressures on a coast, including short-, medium-, and long-term issues. Vulnerability assessment of the type addressed in this study is often described as one possible trigger for ICZM; at the same time, ICZM will increase the need for more sophisticated and detailed assessment of the implications of climate change—while accounting for other climatic and non-climatic stresses on the coastal zones. Thus, an interactive evolution of vulnerability assessment within the ICZM framework can be envisaged, progressively contributing to an improved knowledge base for decision making. In India, ICZM plans are being drawn up for more and more coastal regions. The coastal zone regulations can be cited as an early manifestation of the ICZM plans.

Though risk management is well developed in the Indian context, with early warning systems and post-disaster management systems firmly in place, use of effective mechanisms for enabling people to better manage their own catastrophe risks are still lacking. While government's role in disaster management cannot be eliminated entirely, efforts should be made to reduce the burden substantially. Once disaster assistance is institutionalized, as it is in the Indian context, then it has many of the longer-term effects of an insurance subsidy that inadvertently worsens future problems by encouraging people to increase their exposure to potential losses. For example, compensation for cyclone damage to homes can lead to construction of more houses in cyclone-prone areas. Insurance against natural disasters should have little or no government subsidy, to avoid the problems of moral hazard and adverse selection. New approaches like index-based or area-based contracts to insure against natural disasters should be attempted, and these approaches, in conjunction with developments in micro-finance, could make insurance an increasingly viable proposition for poor people to better manage risk.[3]

The insurer often faces high exposure because of the covariate nature of the insured risk. When a payment is due, then all those who have purchased insurance against the same risk must be paid at the same time. To hedge against this risk, the insurer can sell part of it on the international reinsurance and financial markets. Even though the global reinsurance market is well developed, its benefits are reaped almost entirely by the developed world. While the United States, the United Kingdom, and Japan account for almost 55 percent of the total reinsurance market, the developing countries in Asia, where most natural-disaster-related damage is borne, accounts for less than 8 percent of the global market. It is into this area that government should put most of its efforts, rather than into actual disaster assistance.

3. Area based (or index-based) insurance is specific to an area instead of each individual. Since buyers in a region pay the same premium and receive the same indemnity per standard unit contract (SUC), it avoids all adverse selection problems. Moreover, the insured's management decisions will not be influenced by the index contract, eliminating moral hazard. A farmer with rainfall insurance, for example, possesses the same economic incentives to produce a profitable crop as the uninsured farmer. It could be very inexpensive to administer, since there are no individual contracts to write, no on-site inspections, and no individual loss assessments. It uses only data on a single regional index, and this is based on data that is available and generally reliable. It is also easy to market—SUCs are sold rather like travelers' checks, and presentation of the certificate is sufficient to claim a payment when one is due.

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References

Ali, A. 1999. Climate change impacts and adaptation assessment in Bangladesh. *Climate Research* 12: 109–116.

Atkins, J., S. Mazzi, and C. Ramlogan. 1998. A study on the vulnerability of developing and island states: A composite index. London: Commonwealth Secretariat.

Asian Development Bank (ADB). 1994. *Climate change in Asia: India country report.* Manila: ADB.

Asthana, V. 1993. *Impacts of Greenhouse Induced Sea-level Rise on the Islands and Coasts of India*, Project report submitted to Ministry of Environment and Forests, Government of India, Delhi: JNU.

Brenkert, A.L. and E.L. Malone..2004. Modeling Vulnerability and Resilience to Climate Change: A Case Study of India and Indian States, *Climatic Change*, 72(1):57-102.

Briguglio, L. 1995."Small island states and their economic vulnerabilities. *World Development* 23: 1,615–1,632.

———. 1997. *Alternative economic vulnerability indices for developing countries*. Report prepared for the Expert Group on Vulnerability Index, UN (DESA), 17–19 December.

Building Materials and Technology Promotion Council (BMTPC). 1997. *Vulnerability atlas of India: Earthquake, windstorm and flood hazard maps and damage risk to housing*, report of Expert Group on Natural Disaster Prevention, Preparedness and Mitigation. New Delhi: BMTPC, Ministry of Urban Affairs and Employment, Government of India.

———. 1998. *Techno-legal aspects of earthquake, windstorm and flood hazards and land use zoning*, report of Expert Group on Natural Disaster Prevention, Preparedness and Mitigation. New Delhi: BMPTC, Ministry of Urban Affairs and Employment, Government of India.

Burton, I., R. W. Kates, and G. F. White. 1993. *The environment as hazard.* 2nd ed. New York: Guilford Press.

Emery, K. O., and D. G. Aubrey. 1989. Tide gauges of India. *Journal of Coastal Research* 5(3):489–501.

Food and Agriculture Organization (FAO). 1999. *Rural aquaculture in India.* RAP publication 1999/21. Bangkok: FAO Regional Office for Asia and Pacific.

Government of India (GoI). 2001. *Census of India 2001: Series I (India)*. New Delhi: Office of the Registrar General.

Intergovernmental Panel on Climate Change (IPCC). 2001. *Climate change 2001: The scientific basis. Cambridge, UK:* Cambridge University Press.

International Federation of the Red Cross and Red Crescent Societies (IFRC). 2001. *World Disaters Report, Geneva, Switzerland*: IFRC.

Kaly, U., L. Briguglio, H. McLeod, A. Schmall, C. Pratt, and R. Pal. 1999. Environmental vulnerability index (EVI) to summarise national environmental vulnerability profiles. South Pacific Applied Geoscience Commission (SOPAC) Technical Report 275. Suva, Fiji: SOPAC.

Krishna, P., and N. M. Bhandari. 1999. Vulnerability and risk assessment for regions prone to cyclones. Paper presented at the Special Unit for Technical Cooperation among Developing Countries Workshop on Natural Disaster Reduction—Policy Issues and Strategies, December 21–22, Structural Engineering Research Council, Chennai.

Mahadevan, R. 1992. *Impact of Sea-level Rise due to Greenhouse Effect: Statistical Analysis of the Past Tide Gauge Data along the East Coast of India*, Project report submitted to Ministry of Environment and Forests, Government of India, Delhi.

O'Brien K L, R.M. Leichenko, U. Kelkar, H. Venema, G. Aandahl, H. Tompkins, A. Javed, S. Bhadwal, S. Barg, L. Nygaard, and J. West. 2004. Mapping vulnerability to multiple stressors: climate change and globalization in India. *Global Environmental Change* 14(4):303-313.

Palmer, T. N. and J. Raisanen 2002. Quantifying the risk of extreme seasonal precipitation events in a changing climate. *Nature* 415: 512–514.

Shankar, D. 1998. Low-frequency variability of sea-level along the coast of India. PhD thesis, Goa University.

Tata Energy and Resources Institute (TERI). 1996. The economic impact of a one metre sea-level rise on the Indian coastline: Method and case studies. Report submitted to Ford Foundation. New Delhi: TERI.

Titus, J.G., R. A. Park, S. P. Leatherman, J. R. Weggel, M. S. Greene, P. W. Mausel, S. Brown, C. Gaunt, M. Trehan, and G. Yohe. 1991. Greenhouse effect and sea-level rise: The cost of holding back the sea. *Coastal Management* 19(2):171–204.

United Nations Development Programme (UNDP). 2002. *Human development report* 2002. Oxford, UK: Oxford University Press.

Wells, J. 1996. Composite vulnerability index: A preliminary report. London: Commonwealth Secretariat.

West, J .J. and H. Dowlatabadi. 1999. Assessing economic impacts of sea-level rise. In *Climate change and risk*, ed. T. E. Downing, A. A. Olsthoorn, and R. Tol, 205–220. London: Routledge.

West, J. J., H. Dowlatabadi, and M. J. Small. 2000. Storms, investor decisions, and the economic impacts of sea-level rise. Working paper, Center for Integrated Study of the Human Dimensions of Global Change, Carnegie Mellon University.

Yohe, G. 1990. The cost of not holding back the sea: Toward a national sample of economic vulnerability. *Coastal Management* 18: 403–431.

Yohe, G., J. Neumann, P. Marshall, and H. Ameden. 1996. The economic cost of greenhouse induced sea-level rise for developed property in the United States. *Climatic Change* 32(4): 387–410.