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Risk mapping of Indian coastal districts using IPCC-AR5 framework and multi-attribute decision-making approach

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FRAMEWORK

Components of risk according to IPCC AR5

Hazard | Vulnerability | Exposure

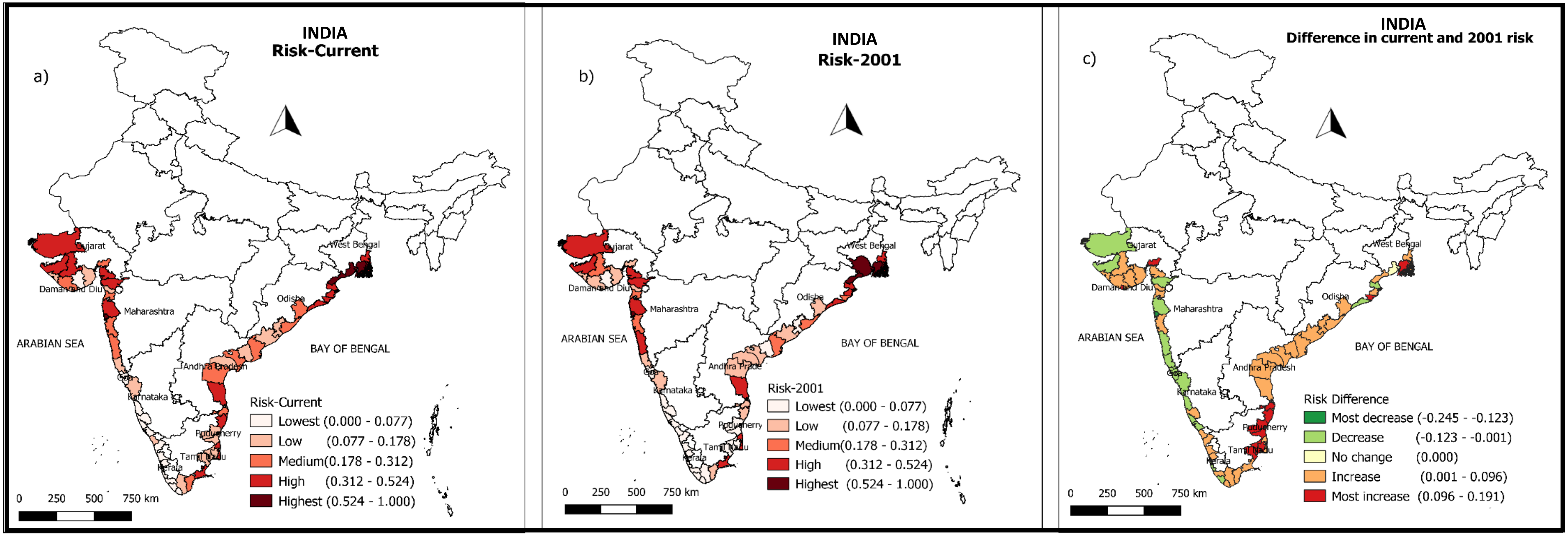
Multi-attribute decision-making to generate the components

Components multiplied to obtain Risk Index

Ranking and mapping of all indices for the a) current, b) 2001 scenarios and c) their difference

INSIGHTS

- First cartographic product representing risk and its components for entire coastline of India
- Eastern coast of India is more prone to hazard, and hazard has increased since 2001
- Eastern coast of India is more vulnerable, however vulnerability of most districts has decreased since 2001



Highlights

- Eastern coast of India is relatively more risk-prone than the west coast
- Greater risk in the east is a combined result of higher hazard and vulnerability
- Important coastal cities of India have greater exposure to hazards
- Vulnerability of coastal districts has declined since 2001
- Risk on the east coast has increased since 2001

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Abstract

Strategic location of coastal areas across the world causes them to be prone to disaster risks. In the global south, the Indian coast is one of the most susceptible to oceanic extreme events, such as cyclones, storm surge and high tides. This study provides an understanding of the risk experienced (currently as well as back in 2001) by the districts along the Indian coastline by developing a quantitative risk index. In the process, it attempts to make a novel contribution to the risk literature by following the definition of risk as a function of hazard, exposure and vulnerability as stated in the most recent (Fifth) assessment report of the Intergovernmental Panel on Climate Change (IPCC). Indicators of bio-physical hazards (such as cyclones, storm surge and tides), and socio-economic contributors of vulnerability (such as infrastructure, technology, finance and social nets) and exposure (space), are combined to develop an overall risk index at a fine administrative scale of district-level over the entire coastline. Further, the study employs a multi-attribute decision-making (MADM) method, Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), to combine the contributing indicators and generate indices on hazard, exposure and vulnerability. The product of these three components is thereafter defined as risk. The results suggest that most districts of the eastern coast have higher risk indices compared to those in the west, and that risk has increased since 2001. The higher risk can be attributed to the higher hazard indices in the eastern districts which are aggravated by their higher vulnerability index values. This study is the first effort made to map risk for the entire coastline of India — which in turn has resulted in a new cartographic product at a district-scale. Such assessments and maps have implications for environmental and risk-managers as they can help identify the regions needing adaptive interventions.

Keywords

Risk; Hazard; Exposure; Vulnerability; Index; Cyclone

1. Introduction

Coastal areas are some of the most heavily inhabited regions in the world. About 37% of the global population reside in these regions with a density twice the world's average (UNEP, 2019). These regions are also important centers of the economy. The coastal ecosystem contributed 1.5 trillion USD (<3% of the world's Gross Domestic Product) to the global economy in 2010 and it is projected to double by 2030 (OECD, 2016). However, coastal regions are prone to multiple hazards which include cyclones, storm surge and tides. In the past, cyclones have led to numerous fatalities and loss of human lives (Laurens and Bas, 2017). They have also led to substantial economic losses, for example, in 2018, tropical cyclones and storms accounted for 72 billion USD losses worldwide (Aon, 2019).

India experiences almost 10% of the world's tropical cyclones and is one of the most adversely impacted regions (Government of India, 2019). The country has an extensive coastline and has suffered several cyclones since the past century (Mohapatra, 2015). The cyclogenesis usually occurs during pre- and post- monsoon seasons at the Indian coasts, while ceasing during monsoon season because of the strong monsoon circulation along with strong wind shear (Evan et al., 2011; Evan and Camargo, 2011). During these periods though, the east coast of India usually experiences a higher frequency of cyclones than that of west coast (Figure 1a and b). Nonetheless, the recent decade shows a significant increase in the frequencies of cyclones in both the coastal regions, surprisingly slightly more in the western coast, i.e., the Arabian Sea regions (Figure 1c and d), concordant with previous studies (Balaguru et al., 2014; Evan et al., 2011; Evan and Camargo, 2011; Murakami et al., 2017). The large-scale atmospheric circulation responsible for these increases in the frequencies can be attributed to the decreased wind shear during both pre- and post- monsoon seasons (Figure 1e and f), which provides a conducive environment for the formation and genesis of cyclones (Evan et al., 2011; Murakami et al., 2017). Disagreement exists in explaining the physical mechanism associated with this decrease in wind shear, with disjoint studies crediting to the increased aerosol emission (Evan et al., 2011) and also to the increased sea surface temperature over the south Atlantic Ocean (Hari et al., 2020; Zhang and Villarini, 2019). However, all these studies culminate in the similar conclusion that the atmospheric circulations which drove these cyclones will exacerbate in the near future, mainly due to anthropogenic forcings (Hari et al., 2020; Murakami et al., 2017). Additionally, coastal populations face flooding from high tides and geomorphic characteristics. Thus, in the context of multiple and growing stress factors, it is only prudent to develop comprehensive coastal risk maps in order to design appropriate adaptation actions (IPCC, 2007, 2014a).

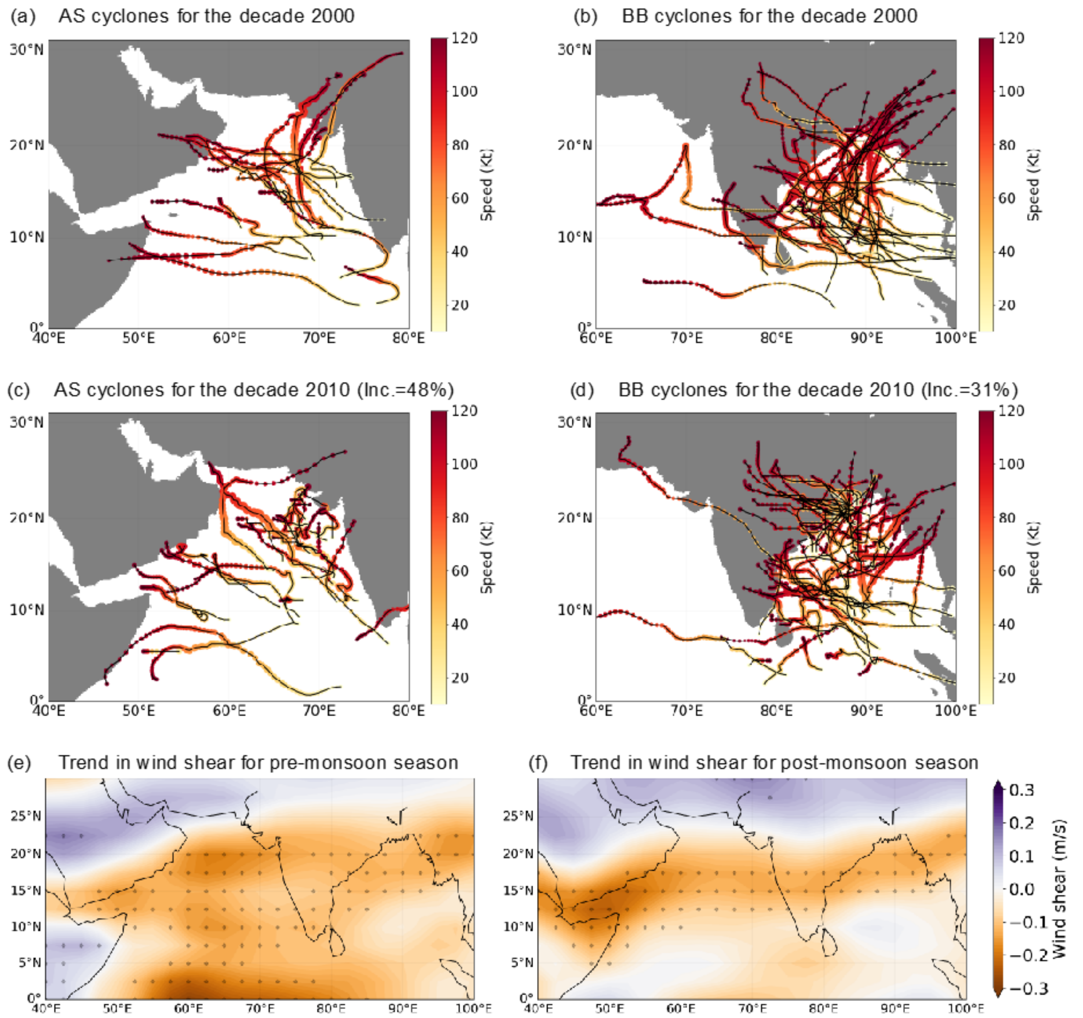

Figure 1: Recent changes in the characteristics of cyclone over the coasts of India. (a) Frequencies of cyclones over the Arabian Sea (AS) and (b) Bay of Bengal (BB) basins for the decade 2000. We notice a swift increase in these frequencies over AS (c) and BB (d). These increase in cyclone frequencies can be attributed to a significant decrease in the vertical wind shear for both pre-monsoon (e) and post-monsoon (f) seasons during 1990-2019. The black dots in the plot denotes the trends which are significant at 10% level.[1]

[1] These plots are developed using the International Best Track Archive for Climate Stewardship (IBTrACS) cyclone data (Knapp et al., 2010) and NCEP-NCAR reanalysis large-scale atmospheric circulations information (Kalnay et al., 1996).

The Third and Fourth Assessment Reports of the Intergovernmental Panel on Climate Change (IPCC) (IPCC, 2007, 2001) emphasized the need to examine the vulnerability to climate change. Hence, following their guidelines, many studies focused on assessing vulnerability of entities to climate variability and change. Vulnerability was defined as “the degree to which a system is susceptible to, and unable to cope with, adverse effects of climate change, including climate variability and extremes” (IPCC 2007, p. 883). It was also seen that indices offer a convenient quantitative representation of relative vulnerability and are quite beneficial while making policy decisions. Therefore, the literature on developing vulnerability indices is vast and various studies have proposed indices to understand vulnerability of communities and regions to environmental and climatic change (such as Cutter et al. 2003; Brien et al. 2004; Hahn et al. 2009; Malakar and Mishra 2017). Most of these regional studies are broadly based on the hazards of place model, which conceptualizes vulnerability as an interaction among characteristics of the place (Cutter, 1996).

A number of studies have also developed indices to understand vulnerability specifically of coastal areas to hazards (Ahsan and Warner, 2014; Bahinipati, 2014; Balica et al., 2012; Bjarnadottir et al., 2011; Chakraborty and Joshi, 2016; Kumar and Tholkappian, 2006; Kumar et al., 2010; Kunte et al., 2014; Mafi-Gholami et al., 2019; Mani Murali et al., 2013; Mazumdar and Paul, 2016; McLaughlin et al., 2010; Patnaik and Narayanan, 2009; Rani et al., 2018; Rehman et al., 2020; Sahana et al., 2019a, 2019b; Sahana and Sajjad, 2019; Sahoo and Bhaskaran, 2018; Saxena et al., 2013; Sekovski et al., 2020; Serafim et al., 2019; Zhang et al., 2021). These past studies on coastal vulnerability have included various climatic/hydro-geological factors indicating exposure to hazard as well as socio-economic characteristics to understand overall vulnerability and develop an index for the same. However, it is observed that the measure of vulnerability is contextual and may vary with the objective of the study. For example, while some studies considered vulnerability arising only from physical (Kumar et al., 2010; Kunte et al., 2014; Rani et al., 2018; Sahana et al., 2019a; Sekovski et al., 2020) or socio-economic factors (Mazumdar and Paul, 2016), some studies included a mix of both types of attribute (Balica et al., 2012; Bjarnadottir et al., 2011; Chakraborty and Joshi, 2016; Kumar and Tholkappian, 2006; Mafi-Gholami et al., 2019; Mani Murali et al., 2013; McLaughlin et al., 2010; Patnaik and Narayanan, 2009; Rehman et al., 2020; Sahana et al., 2019b; Sahana and Sajjad, 2019; Sahoo and Bhaskaran, 2018; Saxena et al., 2013; Serafim et al., 2019; Zhang et al., 2021). The IPCC, in its Assessment Reports, has implied that vulnerability is a result of a variety of factors, including changes in the bio-physical environment (Turner et al., 2003) and socio-economic attributes (IPCC, 2012). Hence, the studies based solely on bio-physical or socio-economic variables are considered limited, and those which aggregate both are considered to be the most holistic. Next, the IPCC in its Fourth Assessment Report provided a framework wherein the factors responsible for vulnerability can be compartmentalized into three broad themes — exposure, sensitivity and adaptive capacity (IPCC, 2007). Hence, among the studies which consider both bio-physical and socio-economic factors, many (Ahsan and Warner, 2014; Bahinipati, 2014; Chakraborty and Joshi, 2016; Sahana et al., 2019b) have adopted this approach and have built an integrated measure of vulnerability.

However, the Fifth Assessment Report of the IPCC suggests the examination of 'risk' rather than 'vulnerability' to hazards (IPCC, 2014a). Previous reports of the IPCC defined vulnerability as a function of exposure, sensitivity and adaptive capacity (IPCC, 2007). On the other hand, the Fifth report proposed risk to be a result of vulnerability, exposure, and hazard (IPCC, 2014a). The new framework was introduced to bring convergence between the literature on disaster risk and climate change vulnerability (Jurgilevich et al., 2017). Earlier risk assessments pertinent to the literature on disaster management did not consider socio-economic variables that can determine exposure and vulnerability (Adger et al., 2018). Hence, the climate change vulnerability framework was merged with that of risk in order to obtain a common assessment regime that can be applied universally to disasters, extreme events and climate change. Nonetheless, the two approaches do not drastically vary and both seek to give an understanding of the degree of possible impacts of hazards. For example, in the earlier framework, 'exposure' consisted of factors indicating the current or future hazards (cyclones, floods, sea-level rise etc.) that a system may experience. Currently, these factors are directly considered as 'hazards'. On the other hand, exposure now consists of factors indicating the presence of communities or any kind of asset which may be affected by the hazard (IPCC, 2014b). Lastly, vulnerability is driven by sensitivity and lack of adaptive capacity of the system (IPCC, 2014b).

In the near future, vulnerability studies based on the framework of earlier Assessment Reports (AR4) may soon become peripheral, and risk indices following IPCC's latest directions will be considered indispensable. However, since this approach is proposed in the most recent assessment report, a limited number of studies (Carter et al., 2018; Das et al., 2020; Satta et al., 2017, 2016) have adopted it to assess risk from hazards in regions or communities. Further, assessment of the literature shows that no study to date has adopted it for risk assessment (at district-level) for a country's entire coastline. For example, the study by Carter et al. (2018) is not specific for coastal hazards and its application is limited to European regions. The risk indices in Satta et al. (2017, 2016) are for the Mediterranean region and considers relatively few socio-economic variables (e.g., six out of nineteen). Lastly, Das et al. (2020) has limited their analysis to a small region, that is, the Indian Bengal Delta and its selected variables may not be applicable/available for the entire Indian coastline.

Following the new framework of the IPCC, this study aims to develop a comparative risk index for the coastal districts of India. It combines indicators representing hazard, exposure and vulnerability of the districts — which in turn are a mix of physical and socio-economic factors — in order to provide a comprehensive perspective of risk. As discussed earlier, previous studies focussed on calculating vulnerability rather than risk (Chakraborty and Joshi, 2016; Kumar and Tholkappian, 2006; Vittal et al., 2020). Hence, this is one of the first attempts to characterize the risk experienced explicitly by the Indian coast at the district-level.

One of the crucial steps while building indices is the choice of aggregation method. The study by Sherly et al. (2015) provides an overview of the variety of techniques used in the literature to develop vulnerability indices. The methodologies range from simple weighted averaging, factor analysis to multi-attribute decision making (MADM) approaches such as Analytic Hierarchy Process (AHP), Delphi technique, Pareto ranking and Data Envelopment Analysis (DEA). However, there is another popular MADM method called the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), whose usage has been limited in the literature on coastal vulnerability despite its advantages. TOPSIS is a useful MADM method known for its practicality and ease of application (Roszkowska, 2011). TOPSIS has been applied in various MADM scenarios such as marketing management, supply-chain operations, and environmental management. It is preferred over other MADM techniques (Yadav et al., 2019) because (i) it can efficiently accommodate a large number of criteria and alternatives; (ii) has logical and programmable actions; (iii) needs limited subjective inputs; and (iv) provides stable solution or consistency in the alternative ranking. Therefore, this study uses

TOPSIS to merge the indicators of each component, that is, hazard, vulnerability and exposure, instead of popular statistical approaches.

Finally, the risk index is calculated as a product of the three components — hazard, vulnerability and exposure (IPCC, 2014a; Satta et al., 2017). Two temporal indices and their sub-components are calculated, one representing the current risk (mostly using data from 2011) and the other characterizing the scenario back in 2001. Broadly, the index proposed in this study provides an assessment of the risk of coastal areas to multiple hazards, which can be significant for identifying the administrative zones in need of support and intervention. These indices also allow temporal comparison which enables visualization of changes in risk and its components. Further, the study can contribute to the latest literature on risk assessment which follows AR5 typology.

The next section describes the study area. Section 3 explains the methodology. The results are presented in section 4, and are followed by a discussion in section 5. The article concludes in section 6.

2. Study area

India has a coastline of about 7500 kms. Its eastern coast borders the Bay of Bengal and its western coast is along the Arabian Sea. The tip of India touches the Indian Ocean. It has 13 coastal states and union territories: Gujarat, Daman and Diu, Maharashtra, Goa, Karnataka, Kerala, Tamil Nadu, Puducherry, Andhra Pradesh, Odisha, West Bengal, Lakshadweep and Andaman and Nicobar Islands (Figure 2). Further, these states have 75 coastal districts (as per the Census of India 2011).

Coastal India has a high probability of extreme rainfall events (Vittal et al., 2020) and is classified as having 'high' coastal flood hazard (GFDDR, 2020). Around 40% of India's population are located within 100 km from the seashore and about 370 million people experience cyclones annually in India (Government of India, 2019). Table 1 shows the Maximum Sustained Wind (MSW) speed and the storm category experienced by the coastal states in India. It is seen that many eastern coastal states face high MSW speeds. Also, India's eastern coast has had greater cyclone occurrences (BMTPC, 2018), because of which almost all of its districts are said to be high-damage zones (BMTPC, 2010). Some of the most recent, extremely and very severe tropical cyclones that have impacted the eastern coast of India are Phailin and Lehar in 2013, Hudhud in 2014, Vardah in 2016, Fani in 2019 and Amphan in 2020. Further, districts with greater cyclone occurrences may also be prone to risks from storm surges as both of them are associated, and high wind speeds usually result in bigger storm surges (Government of India, 2019).

Table 1: Maximum Sustained Wind (MSW) speed and storm category in Indian coastal states (Adopted from (BMTPC, 2018))

Coast	State	Maximum Sustained Wind (MSW) speed	Storm category
East	West Bengal, Odisha and Andhra Pradesh	91 knots and more	Extremely severe cyclonic storm, and super cyclonic storm when wind speeds are beyond 119 knots (IMD, n.d.; WMO, 2015)
	Tamil Nadu	48-90 knots	Very severe and severe cyclonic storms
	Andaman and Nicobar Islands (located in the Bay of Bengal)	64-90 knots	Very severe cyclonic storm
West	Gujarat	64-90 knots	Very severe cyclonic storm
	Maharashtra and Goa	48-63 knots	Severe cyclonic storms
	Most districts of Karnataka and Kerala	34-47 knots	Cyclonic storms

It is also observed that the tidal range of many of the northern coastal states is relatively higher than those in the south (Murali and Sundar, 2017). For example, almost all districts of the southern states of Kerala and Tamil Nadu have a tidal range of less than 1 meter. Districts of northern states of Maharashtra and West Bengal have a tidal range of 4-6 meters. Few districts in Gujarat have a tidal range of 10-12 meters. Such districts with a greater tidal range are prone to flooding from high tides.

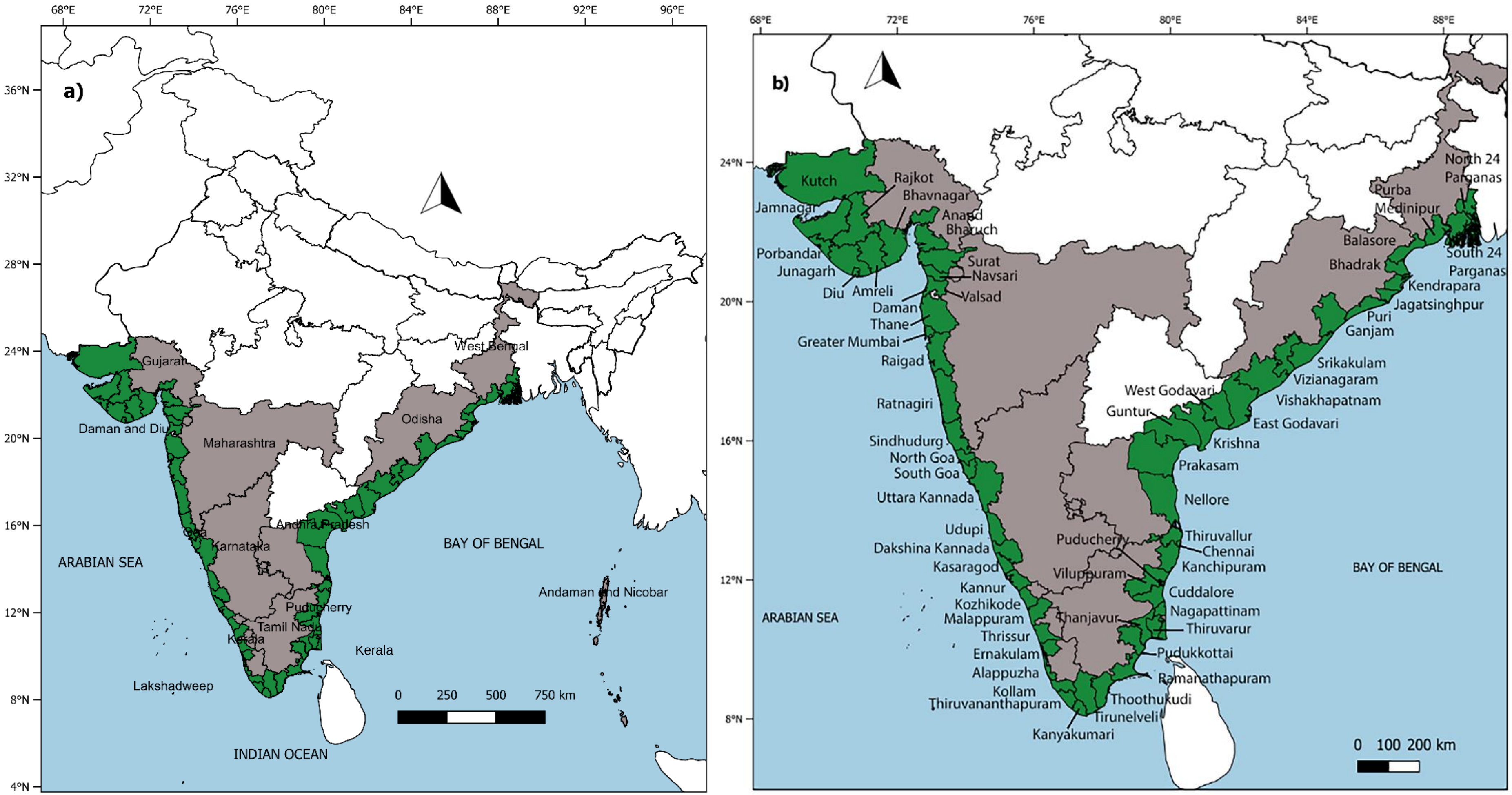

Figure 2: Map of India (a) highlighting the coastal states (in grey) and districts (in green) and (b) with names of the coastal districts considered in the study

3. Methodology

The building of the index, first, involves selecting indicators, and thereafter, their aggregation to obtain a composite value. Figure 3 provides a snapshot of the methodology of the study, and the following sub-sections present a description of the steps involved.

3.1. Indicators of risk

In this study (Figure 3), risk is considered to be a function of hazard, vulnerability and exposure in accordance to IPCC's 5th Assessment Report (IPCC, 2014a). Both physical (indicating the hazard) and socio-economic factors (indicating vulnerability and exposure) are taken into consideration to construct the risk indices — representing the current scenario as well as that in 2001. The sub-components are described in detail in the following subsections and all the indicators considered are listed in Table 2.

Hazard

The IPCC considers any natural or climate-related event which can impact life and property as hazard (IPCC, 2014b). Extreme events such as cyclones, storm surge and high tides are common hazards associated with coastal regions. Thus, the physical indicators representing hazard used in the study are number of cyclones (between 1891-2018 for the current risk index and between 1891-2001 for the 2001 risk index), Probable Maximum Storm Surge (PMSS in meter), maximum of tidal range (in meter) and extreme precipitation exceedance probability in the districts. These indicators represent the physical events that may cause loss of life and property in the coastal districts, and have been used by previous studies focussing on coastal vulnerability (Kumar and Tholkappian, 2006; Kumar et al., 2010; Kunte et al., 2014; Mani Murali et al., 2013; McLaughlin et al., 2010).

The data source of the number of cyclones, PMSS and tidal range is listed in Table 2. The fourth hazard variable, i.e., extreme precipitation exceedance probability, is calculated using the daily precipitation data at 0.25° resolution provided by the India Meteorological Department (Pai et al., 2014). To extract the precipitation extreme for the decades 1990-2000 and 2001 – 2010, we use the 95th percentile as a threshold (Vittal et al., 2013) with the baseline period of 1960-1990, based on the suggestion of the Expert Team for Climate Change Detection and Indices (ETCCDI) (Alexander et al., 2006; Donat et al., 2013). We then fit a non-parametric kernel distribution to the extracted extreme intensities individually for the decades 1990-2000 and 2001 – 2010. The choice of non-parametric distribution is made as it overcomes the assumption that the sample of observations originates from a population with a known probability density function (Adamowski et al., 1998; Vittal et al., 2015); and also, the non-parametric estimation will always reproduce the sample characteristics in a better way (Karmakar and Simonovic, 2008). Moreover, studies such as Vittal et al. (2013) and Shashikanth et al. (2018) showed that the non-parametric distribution estimates the precipitation extreme more accurately and realistically. The non-parametric kernel distribution for a univariate sample ($x_1, x_2, ..., x_n$) can be represented as:

$$f(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x-x_i}{h}\right) \quad (1)$$

where K represents a Gaussian kernel function with a bandwidth h, which is estimated by the approach suggested by Bowman and Azzalini (1997);

$$h = \left[\frac{4}{n(p+2)}\right]^{\frac{1}{p+4}} \sigma \quad (2)$$

where n is number of observations and p is number of variables (for univariate p=1) and σ is the standard deviation of the variable. Once the kernel distribution is fitted, we then estimate the cumulative distribution function (CDF; $F(x)$) for the same, and the exceedance probability is estimated for a potentially damaging event. Here, the 99.5th percentile, as obtained from the base period, is considered as the potentially damaging event for these two decades' (i.e., 1990-2000 and 2001 – 2010) extracted intensity and is represented as;

$$P\{X > x_{99.5B}\} = 1 - F(x_{99.5B}) \quad (3)$$

where $F(x_{99.5B})$ is the non-exceedance estimates of the 99.5th baseline percentile value obtained by fitting a kernel distribution to the extracted extreme precipitation intensities for the decade. All these analyses are initially performed at a 0.25° grids, which are further area-aggregated to obtain the values for each coastal district.

Vulnerability

IPCC suggests that vulnerability is a result of factors contributing to "susceptibility to harm and lack of capacity to cope and adapt" (IPCC 2014b, p. 1775). The present study follows Malakar and Mishra (2017) in selecting indicators representing vulnerability as it has provided an in-depth understanding of this construct in the Indian context. Malakar and Mishra (2017) take cue from previous studies on assessing socio-economic vulnerability to disasters (Cutter et al., 2003; Prashar et al., 2012) for proposing the contributing indicators. It shows that vulnerability may be a result of various sub-factors such as lack of infrastructure, technology, poor financial and social condition in India[2]. It argues that these indicators denote lack of adaptive capacity and sensitivity to adverse impacts of disasters, and hence contribute to vulnerability. Further, it was highlighted that the Indian Census is a rich source of information on a variety of socio-economic indicators of vulnerability for various administrative units. This can be highly useful while constructing a convenient and practical vulnerability index for regions in India. Thus, following this previous study (Malakar and Mishra, 2017), the vulnerability of the coastal districts is also measured through indicators on infrastructure, technology, finances and social set-up (Table 2). A variety of indicators are used. Among them, some, such as the percentage of dilapidated houses, population above 60 years of age and illiterates, can increase vulnerability. On the other hand, indicators such as percentage of households having water supply, electricity, internet and banking services can decrease vulnerability. Table 2 specifies whether an indicator contributes positively or negatively to vulnerability, and its data source.

Exposure

This construct consists of population and assets which may be impacted by hazards in a region (IPCC, 2014b; Qiang, 2019). Thus, indicators such as population growth rate, density, percentage of built-up area and length of coastline are taken as representative of 'exposure' in the districts. Similar indicators have also been adopted in past studies (Satta et al., 2017,

[2] Since the present study is based on the latest IPCC typology of vulnerability being functions of adaptive capacity and sensitivity (IPCC 2014a), the space index (considered in Malakar and Mishra (2017)) is excluded from the 'vulnerability' sub-index. The space index consisting of population growth rate, density and percentage of built-up area is considered to be a part of 'exposure'.

2016) as measures of exposure. Following the previous typology of the IPCC (where vulnerability is a function of exposure) (IPCC, 2007), the study by Malakar and Mishra (2017) also uses these indicators (except for coastline length) as contributors to spatial vulnerability (named as ‘space index’) of Indian cities (Data source in table 2).

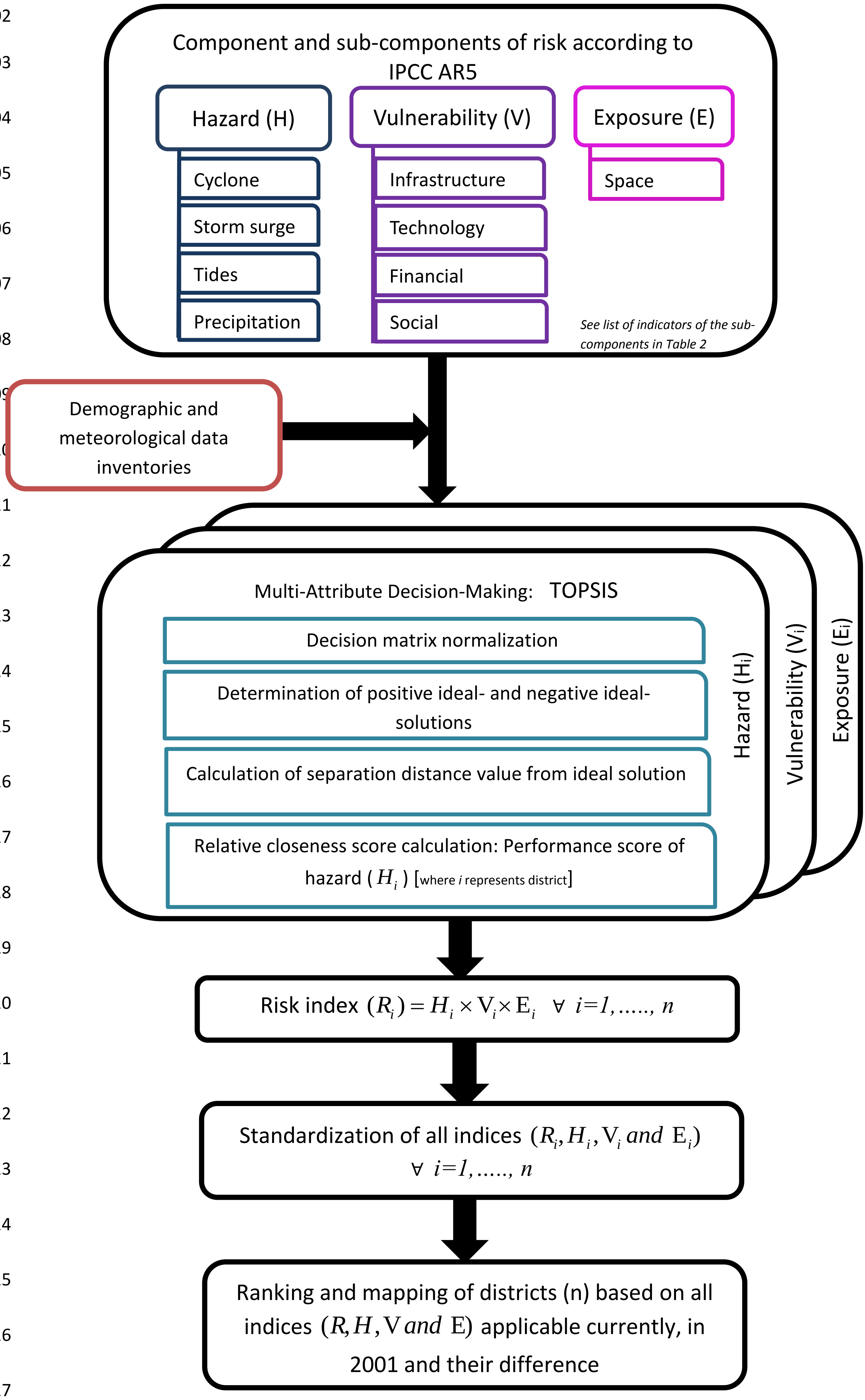

Figure 3: Methodology adopted in the study to calculate coastal risk and its components, i.e., hazard, vulnerability and exposure

Table 2: Components, sub-components and indicators used for risk analysis of the districts

Component of risk	**Sub-components**	**Indicators**	**Overall contribution to the components [Increase (+) or decrease (-)]**	**Data source**
Hazard		Cyclones since 1891 to 2001/2018	Increase (+)	Estimated based on Cyclone eAtlas of the India Meteorological Department (IMD, 2018)
		Probable Maximum Storm Surge (PMSS in meter)	Increase (+)	Mohapatra et al. (2012)
		Maximum of tidal range	Increase (+)	Murali and Sundar (2017)
		Extreme precipitation exceedance probability	Increase (+)	Derived in the present study
Vulnerability	Infrastructure	% of dilapidated houses	Increase (+)	Census of India 2001 and 2011 (Government of India, 2011, 2001)
		% of households having grass/thatch/bamboo/mud/ plastic/polythene/wood/no mortar stoned etc. wall	Increase (+)	
		% of households with drinking water facility within premises	Decrease (-)	
		% of households having electricity	Decrease (-)	
		% of households having toilet facility within premise	Decrease (-)	
		% of households having bathroom within the house	Decrease (-)	
		% of households using LPG for cooking	Decrease (-)	
		% of population having own (not rented) houses	Decrease (-)	
		Hospital beds available per lakh population#	Decrease (-)	(Gangolli et al., 2005; Indiastat, 2009)
		Per capita expenditure#	Decrease (-)	(Government of India, 2015)
	Technology	% of the households having radio	Decrease (-)	Census of India 2001 and 2011 (Government of India, 2011, 2001)
		% of the households having television	Decrease (-)	
		% of the households having internet (only applicable for 2011, data unavailable for 2001 as it was not widely used then)	Decrease (-)	
		% of the households having telephone	Decrease (-)	
		% of the households having mobile phone (only applicable for 2011, data unavailable for 2001 as it was not widely used then)	Decrease (-)	

(Table continued on next page)

		% of the households having mobile & telephone (only applicable for 2011, data unavailable for 2001 as mobile was not widely used then)	Decrease (-)	
	Financial	Per Capita Net District Domestic Product (NDDP) at Current Prices*	Decrease (-)	Economic reports of respective states
		% of households having banking services	Decrease (-)	Census of India 2001 and 2011 (Government of India, 2011, 2001)
		% of main workers i.e. % of population having employment for more than 6 months of the year.	Decrease (-)	
	Social	% of female population	Increase (+)	Census of India 2001 and 2011 (Government of India, 2011, 2001)
		% of female headed households	Increase (+)	
		% of population in SC (Scheduled Caste) category**	Increase (+)	
		% of population in ST (Scheduled Tribe) category**	Increase (+)	
		% of population below 6 yrs of age	Increase (+)	
		% above 60 years of age	Increase (+)	
		% of illiterates	Increase (+)	
		% of disabled population	Increase (+)	
Exposure	Space	Population growth rate	Increase (+)	Census of India 2001 and 2011 (Government of India, 2011, 2001)
		Population density	Increase (+)	
		% of built-up area	Increase (+)	(Bhuvan, 2013)
		Coastal length in kms	Increase (+)	District websites

% indicates percentage

#District-level data for these variables are not available, hence state-level data is used.

*Districts of Gujarat, Goa and Daman & Diu did not have NDDP values, hence per capita state domestic product are used.

Further, in case of variables not sourced from the census — If the most recent data for calculating current risk or that of 2001 are unavailable, the nearest available year's data are used.

**People belonging to SC and ST communities are considered to be the underprivileged sections of the Indian society as they have been socially and economically repressed in history.

3.2. Calculation of index

Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), an MADM approach, is adopted to generate the components of risk index based on the various indicators listed in Table 2. TOPSIS provides a relative quantitative measure based on the subject's proximity to the ideal solution. This ideal solution is according to the best and worst value of each indicator. Thus, TOPSIS is unlike other statistical methods, such as factor analysis (which is also used widely to develop indices), which extract variability in data to obtain results and hence is not inclusive of insights of decision-makers or stakeholders. TOPSIS enables decision-making based on criteria formulated by policy-makers or stakeholders, and may be more practical for aggregation of a variety of indicators with different criteria for their best/worst value. Thus, this method has been used by previous studies to develop flood vulnerability ranks of river basins (Jun et al., 2011; Lee et al., 2014, 2013; Yang et al., 2018), because of its ease of application, control and interpretation.

The steps (also presented in Figure 3) followed to obtain the components on hazard, vulnerability and exposure in this study through TOPSIS are as follows (Mathew, 2018; Yadav et al., 2019):

a) Decision matrix normalization: The indicators' values are normalized according to equation 4. This helps in comparison of indicators having heterogeneous scales.

$$V_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}} \ \forall j \tag{4}$$

where, x_{ij} is the value of i^{th} district for j^{th} indicator of the original score matrix; and V_{ij} comprises the values of the normalized matrix. In the present study, the number (n) of districts is 65, and the number (m) of indicators is 3 for hazard, 27 for vulnerability, and 4 for exposure.

The present study considers all indicators to be equally important and hence a weighted matrix is not required to be calculated hereafter. Due to the subjectivity of weightages, the literature has several studies that have given equal weightage and simply averaged the indicators to obtain vulnerability indices (Brien et al., 2004; Malakar and Mishra, 2017; McLaughlin et al., 2010). Few regional studies pertaining to coastal districts in India have also adopted this approach (Bahinipati, 2014; Kumar and Tholkappian, 2006; Patnaik and Narayanan, 2009).

b) Finding positive- and negative-ideal solutions: The positive ideal solution (ideal best) and negative ideal solution (ideal worst) of each indicator among the districts are identified. The aim of the resulting index is to represent greater hazard, vulnerability or exposure (denoted as 'component' hereafter) with its increasing value. Hence, in case of the factors which are increasing or positively (+) contributing to the component (Table 2), the ideal best or positive-ideal solution (V_j^+) is its maximum value among all the districts (n). The ideal worst or negative-ideal solution (V_j^-) is its minimum value among the districts.

On the other hand, in case of the factors which are decreasing or negatively (-) contributing to the component, the ideal best or positive ideal solution (V_j^+) is its minimum value among the districts (n). The ideal worst or negative ideal solution (V_j^-) is its maximum value among the districts.

c) Calculation of separation distance from ideal best solution: The separation measure of each district or the Euclidean distance value from the ideal best (Equation 5) and ideal worst (Equation 6) is calculated.

$$S_i^+ = \sqrt{\sum_{j=1}^{m} (V_{ij} - V_j^+)^2} \ \ \forall i \tag{5}$$

$$S_i^- = \sqrt{\sum_{j=1}^{m} (V_{ij} - V_j^-)^2} \ \ \forall i \tag{6}$$

The TOPSIS renders an optimal solution that is closest to the positive-ideal solution and farthest from the negative-ideal solution.

d) Relative closeness score calculation: A performance score, which is synonymous with the index pertaining to each component in this study, is calculated according to equation 7. Higher the value of the score, higher is the component- hazard, vulnerability or exposure.

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{7}$$

where C_i represents the individual components of risk (R_i), i.e., hazard (H_i), vulnerability (V_i) or exposure (E_i) for the n number of districts (i).

The final risk index (R_i) is calculated as a product of the components hazard (H_i), vulnerability (V_i) and exposure (E_i) according to equation 8 (IPCC, 2014a; Satta et al., 2017).

$$R_i = H_i \times \mathrm{V}_i \times \mathrm{E}_i \tag{8}$$

The indices on risk and its components are then normalized (normalized values denoted by Z_i) according to equation 9. This results in index values lying between the closed interval [0, 1] with higher values indicating greater risk and its component. This helps in eloquent comparison among the districts.

$$Z_i = \frac{Y_i - Y_{\min}}{Y_{\max} - Y_{\min}} \tag{9}$$

where Y_i represents indices on risk (R_i), hazard (H_i), vulnerability (V_i) or exposure (E_i)

The above steps are applied to obtain the risk indices and their components for the current scenario as well as that in 2001 for total n districts. These two time-points are specifically chosen because of the ease of obtaining data on variables contributing to the risk index from the Indian censuses released at the beginning of each decade. This has led to the advantage of inclusion of common indicators for both decades, and making the indices comparable. Further, past studies are in consensus on considering two consecutive decades for comparative risk analysis (Sharma et al., 2020; Vittal et al., 2020).

Next, the districts are ranked according to their index values, with districts having greater index values holding higher ranks (listed in Supplementary Material). The districts are also mapped and classified into five groups, namely, highest, high, medium, low and lowest, based on their index values (using QGIS, an open-source cross-platform desktop geographic information system application). The preferred method of classification of the indices is Jenks natural break as it can optimally classify the index values. This method enables the reduction of variance within a group and segregates groups by maximizing variance between them. However, applying this method on the current and 2001 indices separately will result in different group ranges, which will hamper comparison between the years. In order to obtain uniform group ranges, first, the average values of all contributing indicators across 2001 and 2011 are calculated for each district. Thereafter, equations 4-9 are applied to the averaged data to obtain indices. These indices are then classified using Jenks natural break. Finally, the group ranges obtained from this classification are used to categorize the current and 2001 indices.

Lastly, the differences between the current indices and those in 2001 are also calculated and mapped.

It is to be noted that, in this study, districts belonging to the islands, that is Lakshadweep, Andaman and Nicobar, had to be dropped due to the unavailability of data on some of the indicators. Smaller districts of Puducherry with few kilometers of coastline, that is, Yanam, Mahe and Karaikal, also had to be excluded for the same reason. This resulted in a total of 65 districts in mainland India for which risk indices and their components are calculated in this study.

4. Results

4.1. Indices for components of risk

The following sub-sections describe the indices generated separately for the three components of risk — hazard, vulnerability and exposure. The indices are spatially mapped and presented alongside each section. However, the numeric values of the indices for each district are presented in Supplementary Material.

4.1.1. Relative ranks of hazard prone districts

The current indices (Figure 4a) for hazard show that Balasore district of the eastern state of Odisha has the highest rank among all. This district has experienced the highest number of cyclones and high storm surges in the past, which must have contributed to its highest rank. Two eastern coastal districts, Purba Medinipur[3] (0.962) and South 24 Parganas (0.832), of West Bengal also have some of the highest hazard indices. This is a result of Purba Medinipur's

[3] This district was formed from the larger district called Medinipur in 2002

high cyclone frequency and storm surge, and South 24 Parganas's high storm surge. Thereafter, Bhadrak (in Odisha) is also classified as a 'highest' hazard district. Again, Bhadrak (in Odisha) ranks third in the number of cyclones and has high PMSS, which has resulted in its high hazard index (0.725). Thus, the districts' higher hazard ranking is mostly the outcome of high cyclone frequency and PMSS.

The high-hazard category consists of thirteen districts, mostly (ten) from the eastern states, such as West Bengal, Odisha, Andhra Pradesh and Tamil Nadu. Gujarat is the only western coastal state whose districts (Anand, Rajkot and Bharuch) have high hazard indices. This shows that the eastern coast has comparatively severer experiences of hazards than the west.

Thirteen districts are classified as medium hazard zones. This category has five districts from the western coastal states of Maharashtra and Gujarat. Out of five coastal districts of Maharashtra, four (including Greater Mumbai which is an important city and commercial center in India) are in this category.

Twenty-two districts are part of the low hazard category. A majority (fourteen) districts from the west coast are in this group. All districts of the eastern state of Karnataka and most from Kerala (except for Thrissur and Kozhikode which are in the low category) are in the lowest hazard group, with Thiruvananthapuram (in Kerala) having the lowest rank. This is because all these districts have some of the lowest frequencies of cyclones. The city of Chennai (0.144) is also classified as having 'lowest' hazard index. The southern-most district of Tamil Nadu, that is, Kanyakumari (0.024), on the east coast also has one of the lowest hazard-indices. Thus, most districts of the western coast hold the lower ranks suggesting that it is comparatively calmer and experience less extreme events than the east.

In 2001 (Figure 4b), the districts holding the highest seven and lowest two ranks were the same as the current scenario. The reasoning behind their ranking is the same as in the case of the current scenario, that is, these districts have high/low number of cyclonic events and PMSS which make their indices high/low. Balasore (1.00), Medinipur (0.929) and South 24 Parganas (0.788) were grouped in the highest category. Nine districts, again mostly (seven) from the eastern coast, were part of the high group. Fifteen districts formed the medium category, out of which ten were again from the east. Seventeen districts were in the low category, however, in this case, most districts (twelve) belonged to the west coast. Lastly, twenty-one districts were in the lowest category, again, out of which fifteen were from the west.

The hazard index of most (54 out of 65) of the districts has increased since 2001 (Figure 4c). Vishakhapatnam, Nagapattinam, Bhavnagar, Cuddalore and Amreli are the districts that have experienced the highest increase in hazard since the beginning of the century. This increase is because of various changes in the contributing indicators for the districts. Vishakhapatnam and Cuddalore have seen an increase in cyclonic and extreme precipitation events, Nagapattinam has had increased cyclones, and Bhavnagar and Amreli have had more precipitation. Two districts, Balasore and Thiruvananthapuram, has shown no change in their hazard index. This is because Balasore and Thiruvananthapuram are the districts with the highest and lowest hazard indices, respectively, both in 2001 and currently. Only nine districts have seen a reduction in their hazard indices — mostly because of their reduced probability of having extreme precipitation events. These include Uttar Kannanda, Puri, Kasaragod, Nellore, Alappuzha, Kannur, Udupi, Kollam and North Goa. Thus, districts with reduced hazard mostly belong to the western coast.

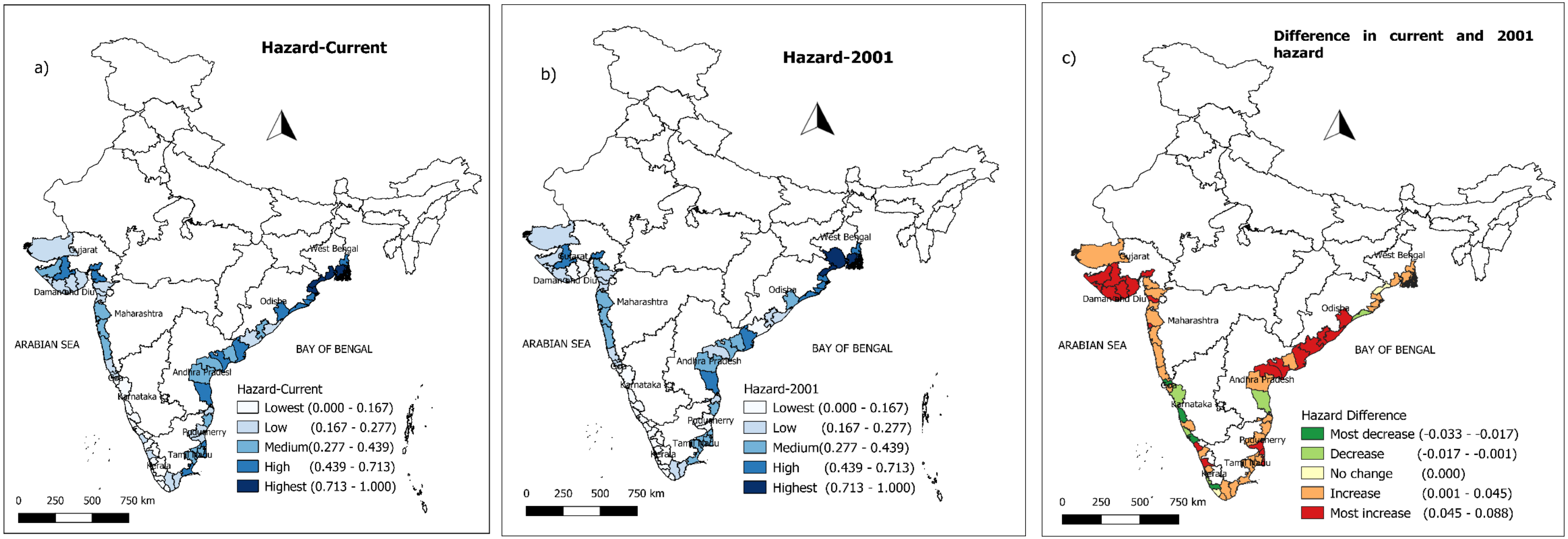

Figure 4: Map showing the hazard index of the coastal districts (a) currently, (b) in 2001 and (c) their change/difference

4.1.2. Level of vulnerability

According to the current index values (Figure 5a), a total of twelve districts are classified as having the highest vulnerability, out of which a majority (nine) of them are from the eastern coast. Balasore district of the eastern state of Odisha currently has the highest vulnerability. This is because of a number of socio-economic factors such as the district's high percentage of dilapidated houses, socially-underprivileged population (SC and ST), low number of hospital beds and low percentages of households with electricity. Valsad (0.943) and Navsari (0.899) in Gujarat on the western coast has the second and third-highest vulnerability indices, respectively. Further, all other districts of Odisha - Bhadrak, Ganjam, Kendrapara, Puri and Jagatsinghpur - are part of the highest range, highlighting the severe vulnerability of the state. The rest of the districts in this group belong to the states of Andhra Pradesh, West Bengal and Gujarat.

Twenty-five districts are part of the high vulnerability range, again majority (seventeen) belonging to the eastern coast. The medium, low and lowest vulnerability groups are populated by the western districts. It is also seen that the two of the most important metropolitan coastal cities of India, that is, Chennai (0.22) and Greater Mumbai (0.194), have low vulnerability. This shows that compared to other coastal districts of India, these cities are better equipped with the required infrastructure, technology, finance and social characteristics to adapt, which in turn reduce vulnerability.

Overall, the ranking of the districts according to their vulnerability shows that most of the eastern and western districts hold the higher and lower ranks, respectively. This suggests that the eastern coast is more vulnerable compared to the west. The higher vulnerability of the eastern states is resultant of the lack of infrastructure, technology, finance and social set-up necessary to face and be resilient towards hazards.

In 2001 (Figure 5b), a total of eleven districts were classified to be in the highest vulnerability group. Similar to the current vulnerability indices, most (eight) districts in this group were from the eastern coast. In the high vulnerability group, comprising of 27 districts, most (nineteen) were again from the eastern coast. The rest of the groups, medium, low and lowest vulnerability, comprise majorly of western districts. Further, the cities of Chennai (0.307) and Mumbai (0.287) were categorized to have low vulnerability also in 2001.

The maps show that the vulnerability of the majority (42 out of 65) of coastal districts of India has declined since 2001 (Figure 5c). The number of districts undergoing an increase/decrease in vulnerability from the east and west coast is similar. That is, eleven districts each from the east and west have experienced an increase in vulnerability. Further, the vulnerability of twenty eastern and twenty-two western districts has decreased. It is to be noted that Balasore remains the most vulnerable among all districts currently as well as back in 2001. Hence, the Balasore (in Odisha) shows no change in its index. The districts that have experienced the most decline in vulnerability are Jagatsinghpur, South Goa and North Goa. The decrease in vulnerability of the districts suggests improvement in infrastructure, technology, financial ability and social structure since 2001.

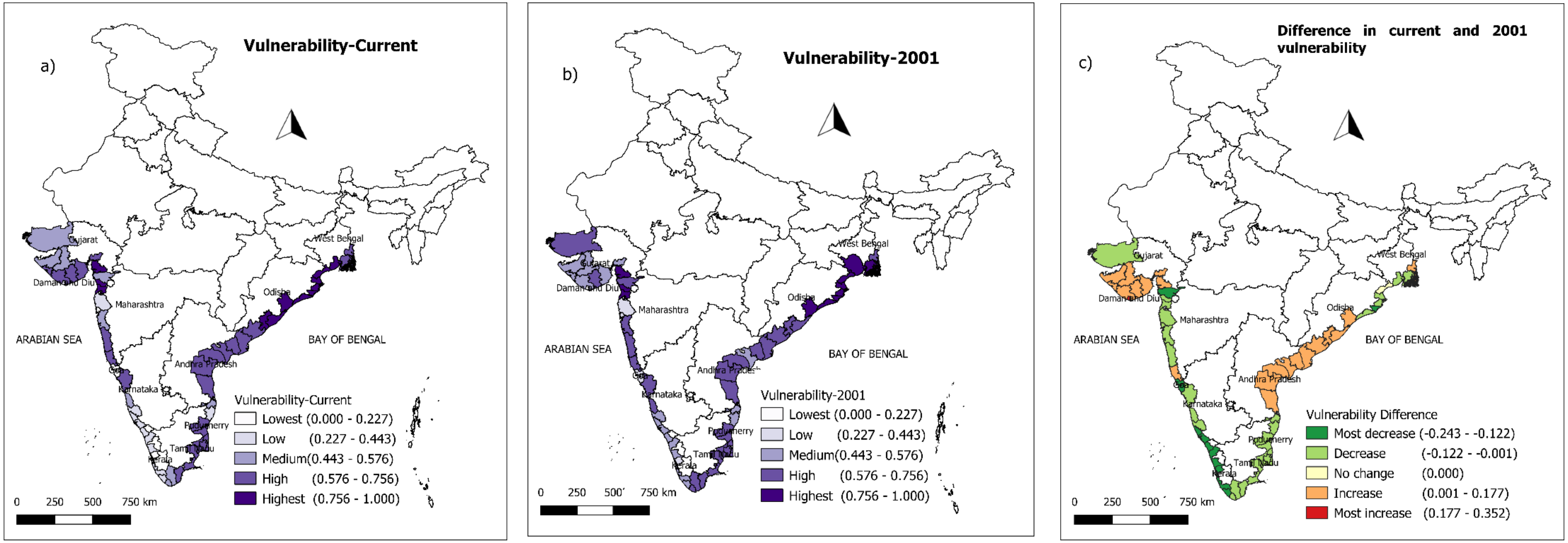

Figure 5: Map showing the vulnerability index of the coastal districts (a) currently, (b) in 2001 and (c) their change/difference

4.1.3. Level of exposure

A concerning finding emerges from the current exposure indices (Figure 6a). It shows that Chennai (1) and Greater Mumbai (0.779), which are two of the most important metropolitan cities in India, have the highest exposure indices. These two cities have the highest population density and built-up area which has resulted in their high exposure indices.

Daman (0.553) and Kutch (0.446) in Gujarat are next in order and are part of the high exposure group. They are highly exposed to extreme coastal events because of their high population growth and long coastal length, respectively. A total of nine districts are categorized to be having high exposure, out of which five (mostly from Gujarat) belong to the west coast. Next, only three districts located on the east coast have medium exposure.

A majority of the districts are part of the low (twenty-two) and lowest (twenty-nine) exposure group. The low group consists of almost an equal mix of districts from the east (twelve) and west (ten) coast. The lowest exposure group comprises mostly (17 out of 29) of western districts. However, the least exposed districts are from the east — West Godavari and Vizianagaram in Andhra Pradesh. This is an aggregate effect of the districts' low population growth, density, and built-up area and coastal length.

In 2001 (Figure 6b), Chennai, Greater Mumbai and Daman had the highest exposure and held the first three ranks. This is the same as the current ranking. The high exposure group consisted of only five districts, mostly from the western states of Gujarat and Maharashtra. Ten districts constituted the medium exposure group, mostly (seven) from the east coast. Similar to the current classification, majority of the districts were part of the low (eighteen) and lowest (twenty-nine) category in 2001. The low group comprised of ten districts from the east and eight from the west. The lowest group consisted mostly (16 out of 29) of districts from the west coast. Again, the least exposed districts belonged to the eastern states of Andhra Pradesh and Tamil Nadu.

The exposure indices of twenty-two districts have increased (Figure 6c), with Kanchipuram, Thiruvallur and Villupuram of Tamil Nadu experiencing the highest increase. This is because of the increase in the districts' population growth rate, density and built-up area. The districts of Chennai (in Tamil Nadu) and Vizianagaram (in Andhra Pradesh) show no change in their indices as they hold the highest and lowest rank for exposure currently as well as in 2001. A majority (forty-one) of districts have experienced declining exposure since 2001, with Puducherry undergoing the most decrease.

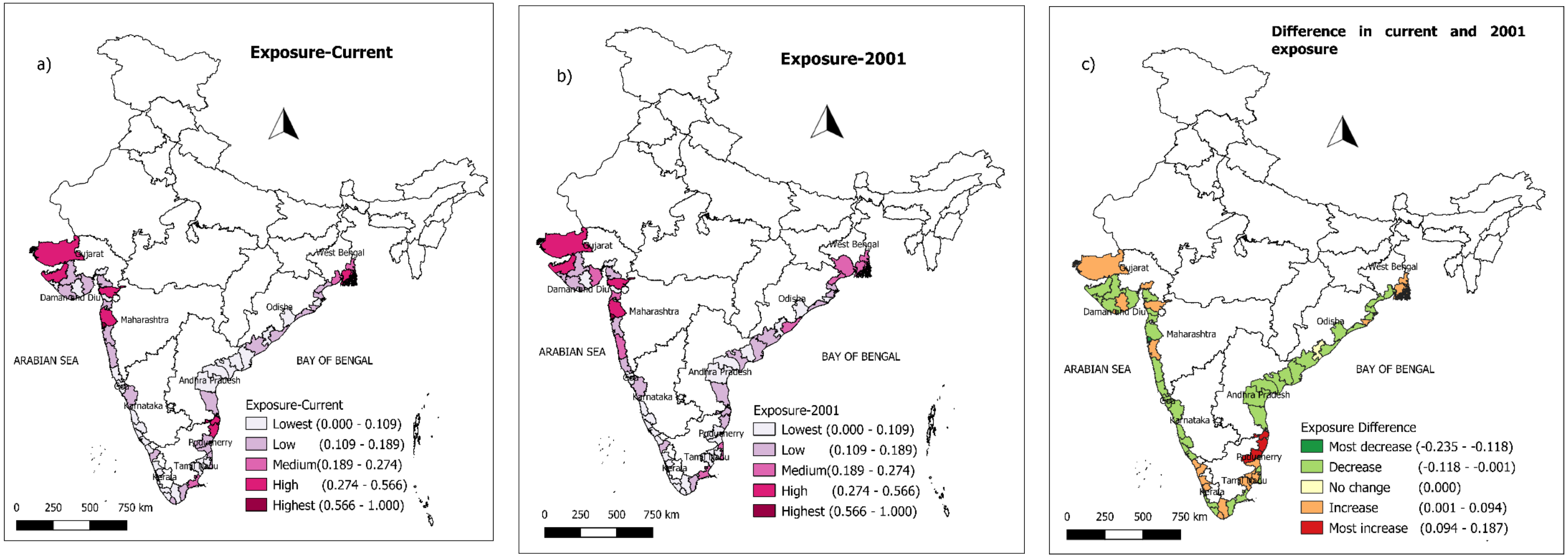

Figure 6: Map showing the exposure index of the coastal districts (a) currently, (b) in 2001 and (c) their change/difference

4.2. Risk Analysis

The current indices show that the most risk-prone districts lie on the eastern coast of India (Figure 7a, also see Supplementary Material). Four districts are categorized to have the highest risk. The eastern districts of Purba Medinipur (1) and South 24 Parganas (0.877) in West Bengal rank the highest, followed by Balasore (0.851) in Odisha. Greater Mumbai (0.693), lying on the western coast, which is the financial capital and an important metropolitan city of India, is the fourth riskiest district (mostly because of its high exposure).

Seventeen districts, again ten of which are from the east, are a part of the high-risk category. The western districts which face high risk are mostly from the state of Gujarat and other upper districts such as Daman and Thane in Maharashtra. This group also includes Chennai (0.482) which is an important city located in Tamil Nadu (eastern coast). This is again because of its high exposure index. Thirteen districts are medium-risk regions, again eight of which are from the eastern states. Further, few districts from the western states of Gujarat and Maharashtra are classified as medium zones.

Seventeen districts face low risk according to the classification, and fourteen districts have the lowest risk. It is observed that the lowest category comprises majorly (thirteen) of western coastal districts. All districts of Goa and most of Kerala are part of this category because of their low levels of hazard, vulnerability as well as exposure. Thiruvananthapuram in Kerala has the lowest risk. This must be a result of its low hazard and exposure (section 4.1). Kanyakumari in Tamil Nadu is the only eastern district in the lowest-risk category.

Overall, it may be derived that the higher ranks of risk are held mostly by districts belonging to the eastern coast. The eastern districts have a high risk because of their high hazard indices as well as vulnerability, as discussed in section 4.1. Thus, eastern districts are susceptible to natural extreme events whose impacts are aggravated by their poor socio-economic condition. Among the many western states, Gujarat experiences high hazard (Rajkot district) and exposure (Kutch and Jamnagar), making its districts prone to high risk— which is comparable to districts on the eastern coast.

In 2001 (Figure 7b), similar to current groupings, Medinipur, Greater Mumbai, Balasore and South 24 Parganas, were ranked to be the top four riskiest districts. Additionally, Chennai was a part of the highest-risk category and held the fifth place. Thus, the highest ranks of risk were held by eastern districts. The high-risk group also comparatively had more number of eastern districts (9 out of 15) than the west. The districts from the west in this group belong to the three upper coastal states of Gujarat, Maharashtra and Daman. An almost equal number of districts from the east and the west (belonging to the north-western states of Gujarat and Maharashtra) formed the medium and low-risk group. Lastly, most south-western districts belonging to Goa, Karnataka and Kerala had the lowest risk. However, the eastern district of Vizianagaram of Andhra Pradesh, because of its minimum exposure, had the least risk among all.

Most (forty-five) districts have seen an increase in risk since 2001 (Figure 7c). This can be attributed to increasing hazards, as discussed in section 4.1.1. Kanchipuram, Jagatsinghpur, Anand and Villupurum have experienced the highest increase in risk. The risk of Purba Medinipur has not changed as it ranks the highest currently as well as in 2001. It is further noticed that the increase in the risk of the districts along the eastern coast is higher than those along the west. The risk of twenty-seven eastern districts has increased compared to only eighteen in the west. On the other hand, the risk of sixteen western districts has decreased compared to only three in the east. Thus, in total, only nineteen districts have decreased levels of risk. The risk of Greater Mumbai, Puducherry and Chennai have decreased the most. This is a result of their decreasing vulnerability and exposure (values in Supplementary Material).

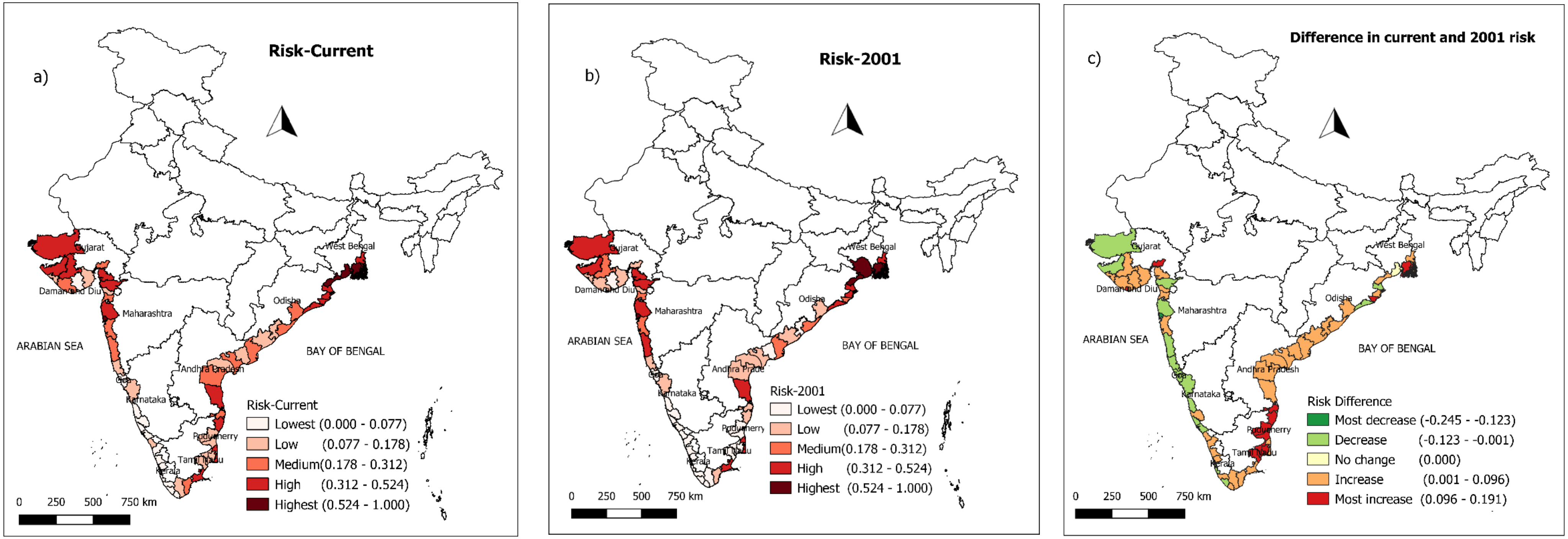

Figure 7: Map showing the risk index of the coastal districts (a) currently, (b) in 2001 and (c) their change/difference

5. Discussion

This section presents a discussion of the empirical results. The findings are compared with previous indices, and the implications and limitations of the study are discussed elaborately.

5.1. Comparison with earlier studies

The indices show that most districts of the eastern coast rank high in terms of their experiences of hazards as well as vulnerability. Similar results were obtained by Rehman et al. (2020). However, the study had followed the earlier IPCC AR4 framework to calculate vulnerability and their results may not be directly comparable. Nevertheless, they too had found higher exposure (~comparable to hazard in new AR5 framework) and low adaptive capacity (~higher vulnerability in new AR5 framework) on the eastern coast. The indices obtained in section 4.2 show that most districts in the east have higher risk. Earlier studies (Kumar and Tholkappian, 2006; Rehman et al., 2020), which used the older IPCC framework, have also concluded the eastern coast to be more vulnerable (~comparable to risk in new AR5 framework and this study) than the west. However, they (Kumar and Tholkappian, 2006; Rehman et al., 2020) did not consider the exact variables as in the present study or segregate their variables into the three components of vulnerability, that is, exposure, sensitivity and adaptation according to IPCC AR4 (Kumar and Tholkappian, 2006). Owing to different variables and methods used, identifying the component responsible for the vulnerability and comparing with current indices becomes difficult. However, in spite of differences in the methodologies followed, it is found that there is similarity in the rankings of some districts given by the previous (Kumar and Tholkappian, 2006; Rehman et al., 2020) and current study. For example, previous indices have also ranked the districts of Purba Medinipur, South 24 Parganas, North 24 Parganas and Balasore to be the most vulnerable (comparable to risk in the current study). Further, most districts of Kerala and Goa are ranked lower in the previous studies as well. This similarity in the ranking somewhat aids in substantiating the new IPCC AR5 framework for assessing risk in the coastal districts.

5.2. Implications for risk management

The states, such as West Bengal, Odisha, Gujarat and Andhra Pradesh, which have high-ranking districts in terms of hazard, need policies that can lessen the physical impacts of extreme events. Therefore, equipping the districts with infrastructures, such as early warning systems, cyclone shelters and coastal defense/sea walls, can help. Such infrastructure is partly available in many coastal areas in India, for example, the literature shows the presence of early warnings in Maharashtra (Malakar et al., 2018), early warnings and cyclone shelters in Odisha (Wangchuk, 2019) and Andhra Pradesh (Sharma et al., 2009) and sea walls in Odisha (PTI, 2016). Further, recently, a number of digital innovations have been piloted to avert disasters in parts of India. This includes usage of Artificial Intelligence (AI) to project flood maps and alert residents in an area, web and smartphone-based apps to provide real-time information and alerts, coordinate rescue activities and assess damage, AI-enabled drones to locate trapped people and social media for information dissemination (Srikanth, 2019). These initiatives, however, need to be strengthened, made reliable and extended to all risk-prone coastal areas. The National Science, Technology, and Innovation Policy should encourage and invest in the development of all such disaster-mitigating technologies. Further, policies to enable easy and wide access to these technologies by the communities and regional authorities are needed. This can significantly help in locally mitigating disaster risk.

Districts with high vulnerability, such as those primarily in Odisha, West Bengal, Andhra Pradesh and Gujarat, need developmental interventions that assist the region in accessing better housing and related infrastructure, medical services, communication and technology, financial capital and social status. This would require long-term policies that can benefit generations and communities' overall quality of life. Further, it would require collaboration and action from different government bodies responsible for these varied sectors. Programmes that can particularly improve the socio-economic well-being of coastal communities and reduce their vulnerability, such as those on providing resilient and economical housing and road connectivity, may be introduced. The SAPCCs (State Action Plans on Climate Change) of the vulnerable states of Odisha and Andhra Pradesh have also indicated similar policy measures, and have focussed on improving housing, public infrastructure and livelihoods in coastal areas (EPTRI, 2012; Government of Odisha, 2018). The vulnerability of the coastal districts may also be lowered by tweaking the current policies and programmes to accommodate their special needs. For example, current government housing programmes such as the Pradhan Mantri Awas Yojana (PMAY) may consider providing cyclone-resilient residences to poor and vulnerable coastal populations. Past studies have given similar directives (Malakar and Mishra, 2020, 2019). They have shown that the socio-economic condition of communities can influence adaptive capacity and hence, reduce vulnerability. Factors such as education, poverty and housing quality impact adaptation, and policies aimed at overall socio-economic upliftment are required in vulnerable regions. In 2021, the Government of India has introduced a draft Blue Economy Policy which envisages to holistically develop the coastal economy and livelihoods including fisheries, aquaculture, tourism, shipping, mining, offshore energy, etc. (MoES, 2021). This may significantly improve the socio-economic demography of the region and act as a co-benefit for coastal vulnerability reduction.

Districts that are high on exposure are generally those which have high population density and built-up area. These districts, especially those which simultaneously rank high on the risk index (such as the metropolitan cities of Chennai and Mumbai), need programmes that prevent further construction and population influx. This would only be possible when areas near these districts are equally developed and made attractive to the population by creating better opportunities, lifestyle and access to resources. For example, areas in suburban districts of Raigad and Thane, especially those near Mumbai, have been developed in the last few decades to provide better housing and job opportunities, thereby creating new population hubs away from the main city (Anarock, 2018; Pol, 2018; ToI, 2019). Development of such suburban areas has possibly resulted in Mumbai's lowering population growth rate (Government of India, 2011). However, as the results in this study have indicated, these cities/districts need further interventions to lower their exposure to hazards. Possibilities of relocating important businesses and commercial activities to inland areas need to be explored.

Since risk is the resultant of three components (hazard, vulnerability or exposure), districts would require policy-makers to adopt multi-dimensional approach for Disaster Risk Reduction (DRR). All states and districts would benefit by developing their local disaster management plans wherein specific actions are listed for addressing each of the three components (as described above). Further, all directives may be associated with a time horizon and described as short-, medium- or long-term plan. Such DRR plans can also become part of the currently revised SAPCC (State Action Plans on Climate Change), and following the proposed strategy-delineation will enable them to be in line with the new IPCC AR5 risk framework.

5.3. Caveats of the study

The present study, however, also has certain limitations. These include few adjustments made to the data, that is, the usage of data from nearest years (to 2001/2011) for few variables, such as NDDP, and the usage of state-level data for few districts — applicable for variables, such as hospital beds per lakh population and per capita expenditure, which are not sourced from the census. However, this is a common challenge while building data-rigorous indices (Malakar and Mishra, 2016). Next, due to lack of district-level data on loss and damages resulting from various hazards (specifically, cyclone, storm surge, tides and extreme precipitation considered in this study), the indices could not be statistically validated. Availability of such detailed data would have enabled examination of the correlation between the losses and indices, and led to tangible index-validation.

6. Conclusion

Coastal regions and their communities are prone to risks from extreme events such as cyclones, storm surge and high tides. In order to identify the regions requiring interventions for DRR, there is a need for studies that quantify such risk. The Indian coastline is one of the most vulnerable to extreme events in the world. Therefore, the present study proposes an index that quantifies the risk in the coastal districts of India. The index is developed by implementing the IPCC's most recent typology of risk, which suggests that it is a product of three components — hazard, exposure and vulnerability (IPCC, 2014a). In this study, these three components are generated by combining relevant indicators using TOPSIS, an efficient MADM technique, whose application has been limited in the coastal risk literature. The study's approach of implementing IPCC-AR5's latest typology together with TOPSIS, to study the risk of India's entire coastline at a district-scale, makes it a novel contribution to the literature on mapping risk and vulnerability to hazards. Further, the study calculates two temporal indices for all coastal districts — one quantifying the current risk and the other at the beginning of the century, i.e., in 2001. This is done to understand the changes in coastal risk and its components since the past decade. The entire exercise has enabled the ranking of the coastal districts of India based on their hazard, exposure, vulnerability and risk at two time periods. Furthermore, all the calculated indices are mapped, and hence this study also results in new cartographic products that can be useful for climate risk management.

The results show that the eastern coast is more risk-prone because of greater hazard and vulnerability indices, implying risk to be a consequence of natural as well as socio-economic factors. The ranking of the districts (eastern or western) in terms of exposure is mixed. It is also seen that increasing hazards in the eastern districts has led to an increase in risk since 2001. However, the vulnerability and exposure in the districts have declined. Such observations, characterized by hazard-driven and vulnerability-driven risk, will help in monitoring progress in disaster management policies and identify areas needing attention. One such policy initiative which may benefit from the findings of the present study is the National Cyclone Risk Mitigation Project (NCRMP) by the Government of India (GoI, 2021), which aims at improving the adaptive capacity of coastal communities and mitigate risk.

Overall, this study produces a data-intensive, comprehensive and easily reproducible coastal risk index by appropriately using publicly available data from census and other government sources (such as the India Meteorological Department). This makes it replicable in the future as and when data is available, thereby making it useful for policy-makers to make comparisons across decades and suggest risk-management interventions. The results help in identifying the risk-prone coastal districts of India, and may help policy-makers in directing initiatives towards addressing the specific factors—hazard, socio-economic attributes representing vulnerability and exposure—contributing to the risk. However, future studies may consider a different set of indicators in accordance with the type of risk it intends to measure. For example, the indicators representing risk specifically of coastal livelihoods (e.g., fishing) may differ. Lastly, the results of the current study can act as a foundation for data-intensive sub-national studies in India on assessing coastal risk. The indices can help identify the districts in need of bottom-up research regarding their drivers of risk and such regional assessments can complement the findings of the present study.

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Rank	State	District	Risk Index_Current
1	West Beng	Purba Med	1.000
2	West Beng	South 24 P	0.877
3	Odisha	Balasore	0.851
4	Maharasht	Greater Mu	0.693
5	West Beng	North 24 P	0.506
6	Tamil Nadu	Chennai	0.482
7	Odisha	Bhadrak	0.476
8	Daman & [	Daman	0.454
9	Gujarat	Kutch	0.443
10	Tamil Nadu	Ramanatha	0.436
11	Odisha	Puri	0.434
12	Maharasht	Thane	0.384
13	Tamil Nadu	Nagapattin	0.378
14	Andhra Pra	Nellore	0.376
15	Gujarat	Jamnagar	0.366
16	Tamil Nadu	Kanchipura	0.356
17	Odisha	Jagatsingh	0.347
18	Gujarat	Rajkot	0.345
19	Odisha	Kendrapar	0.341
20	Gujarat	Bharuch	0.332
21	Gujarat	Surat	0.319
22	Andhra Pra	East Godav	0.289
23	Gujarat	Anand	0.288
24	Maharasht	Raigad	0.276
25	Gujarat	Valsad	0.268
26	Maharasht	Ratnagiri	0.262
27	Odisha	Ganjam	0.257
28	Andhra Pra	Srikakulam	0.249
29	Tamil Nadu	Thiruvallur	0.238
30	Andhra Pra	Prakasam	0.237
31	Andhra Pra	Krishna	0.199
32	Tamil Nadu	Thoothukk	0.183
33	Gujarat	Junagadh	0.181
34	Puducherry	Puducherry	0.179
35	Andhra Pra	Visakhapat	0.177
36	Gujarat	Bhavnagar	0.168
37	Andhra Pra	Guntur	0.167
38	Tamil Nadu	Pudukkott	0.164
39	Tamil Nadu	Thanjavur	0.161
40	Tamil Nadu	Thiruvarur	0.157
41	Tamil Nadu	Cuddalore	0.146
42	Tamil Nadu	Viluppuram	0.144
43	Gujarat	Porbandar	0.135
44	Daman & [	Diu	0.132
45	Tamil Nadu	Tirunelveli	0.127
46	Gujarat	Navsari	0.126
47	Andhra Pra	West Goda	0.105
48	Karnataka	Uttara Kan	0.103
49	Maharasht	Sindhudurg	0.087

Rank	State
1	Odisha
2	West Beng
3	West Beng
4	Odisha
5	Gujarat
6	Gujarat
7	Odisha
8	West Beng
9	Odisha
10	Odisha
11	Andhra Pra
12	Andhra Pra
13	Tamil Nadu
14	Gujarat
15	Tamil Nadu
16	Andhra Pra
17	Odisha
18	Andhra Pra
19	Maharasht
20	Maharasht
21	Andhra Pra
22	Maharasht
23	Tamil Nadu
24	Tamil Nadu
25	Maharasht
26	Tamil Nadu
27	Tamil Nadu
28	Andhra Pra
29	Andhra Pra
30	Gujarat
31	Gujarat
32	Daman & [
33	Andhra Pra
34	Gujarat
35	Gujarat
36	Gujarat
37	Tamil Nadu
38	Daman & [
39	Gujarat
40	Gujarat
41	Tamil Nadu
42	Goa
43	Andhra Pra
44	Maharasht
45	Tamil Nadu
46	Tamil Nadu
47	Kerala
48	Tamil Nadu
49	Gujarat

50	Kerala	Kozhikode	0.082		50	Gujarat
51	Andhra Pra	Vizianagara	0.082		51	Kerala
52	Kerala	Malappura	0.076		52	Puducherry
53	Gujarat	Amreli	0.076		53	Tamil Nadu
54	Tamil Nadu	Kanyakuma	0.061		54	Karnataka
55	Kerala	Thrissur	0.057		55	Goa
56	Karnataka	Dakshina K	0.050		56	Kerala
57	Karnataka	Udupi	0.047		57	Kerala
58	Kerala	Ernakulam	0.041		58	Karnataka
59	Goa	North Goa	0.040		59	Karnataka
60	Kerala	Kasaragod	0.037		60	Kerala
61	Kerala	Alappuzha	0.032		61	Kerala
62	Kerala	Kannur	0.030		62	Kerala
63	Goa	South Goa	0.023		63	Kerala
64	Kerala	Kollam	0.010		64	Tamil Nadu
65	Kerala	Thiruvanan	0.000		65	Kerala

District	Hazard Index_Current
Balasore	1.000
Purba Med	0.962
South 24 Pa	0.832
Bhadrak	0.725
Anand	0.631
Rajkot	0.627
Puri	0.545
North 24 Pa	0.537
Jagatsinghp	0.523
Kendrapara	0.521
Nellore	0.509
East Godav	0.506
Nagapattin	0.467
Bharuch	0.455
Ramanatha	0.449
Krishna	0.445
Ganjam	0.445
West Goda	0.428
Thane	0.401
Greater Mu	0.398
Prakasam	0.394
Raigad	0.392
Pudukkotta	0.355
Thanjavur	0.352
Ratnagiri	0.333
Kanchipura	0.332
Thiruvarur	0.320
Guntur	0.302
Vizianagara	0.296
Jamnagar	0.289
Valsad	0.265
Daman	0.265
Srikakulam	0.264
Kutch	0.258
Junagadh	0.256
Porbandar	0.254
Tirunelveli	0.254
Diu	0.250
Navsari	0.248
Surat	0.245
Thoothukk	0.243
North Goa	0.241
Visakhapat	0.233
Sindhudurg	0.221
Thiruvallur	0.209
Cuddalore	0.208
Thrissur	0.195
Viluppuram	0.190
Bhavnagar	0.185

Rank	State	District
1	Orissa	Balasore
2	Gujarat	Valsad
3	Gujarat	Navsari
4	Orissa	Bhadrak
5	Orissa	Ganjam
6	Orissa	Kendrapara
7	Andhra Pra	Srikakulam
8	Orissa	Puri
9	West Beng	Purba Med
10	Andhra Pra	Vizianagara
11	Gujarat	Bharuch
12	Orissa	Jagatsinghp
13	Andhra Pra	Nellore
14	West Beng	South 24 Pa
15	Andhra Pra	Prakasam
16	Tamil Nadu	Vilupuram
17	Tamil Nadu	Thiruvarur
18	Andhra Pra	East Godav
19	Andhra Pra	Visakhapat
20	Tamil Nadu	Ramanatha
21	Tamil Nadu	Nagapattin
22	West Beng	North 24 Pa
23	Andhra Pra	West Goda
24	Maharasht	Sindhudurg
25	Andhra Pra	Guntur
26	Tamil Nadu	Pudukkotta
27	Tamil Nadu	Cuddalore
28	Andhra Pra	Krishna
29	Tamil Nadu	Thanjavur
30	Maharasht	Ratnagiri
31	Gujarat	Amreli
32	Karnataka	Uttara Kan
33	Gujarat	Bhavnagar
34	Gujarat	Junagadh
35	Gujarat	Anand
36	Gujarat	Porbandar
37	Tamil Nadu	Thoothukk
38	Gujarat	Kutch
39	Tamil Nadu	Tirunelveli
40	Tamil Nadu	Kanyakuma
41	Gujarat	Jamnagar
42	Maharasht	Raigad
43	Gujarat	Surat
44	Karnataka	Udupi
45	Gujarat	Rajkot
46	Tamil Nadu	Thiruvallur
47	Kerala	Kasaragod
48	Kerala	Malappura
49	Tamil Nadu	Kanchipura

Amreli	0.184	50	Maharasht	Thane	
Kozhikode	0.183	51	Kerala	Kollam	
Puducherry	0.178	52	Karnataka	Dakshina K	
Chennai	0.144	53	Kerala	Thiruvanan	
Uttara Kanı	0.138	54	Kerala	Alappuzha	
South Goa	0.137	55	Kerala	Kozhikode	
Alappuzha	0.132	56	Kerala	Kannur	
Malappura	0.129	57	Daman anc	Daman	
Dakshina K	0.119	58	Daman anc	Diu	
Udupi	0.117	59	Kerala	Thrissur	
Ernakulam	0.107	60	Kerala	Ernakulam	
Kollam	0.093	61	Puducherry	Puducherry	
Kasaragod	0.090	62	Tamil Nadu	Chennai	
Kannur	0.077	63	Maharasht	Greater Mu	
Kanyakuma	0.024	64	Goa	South Goa	
Thiruvanan	0.000	65	Goa	North Goa	

Vulnerability Index_Current	Rank	State	District
1	1	Tamil Nadu	Chennai
0.943	2	Maharasht	Greater Mumbai
0.899	3	Daman and	Daman
0.879	4	Gujarat	Kutch
0.87	5	Gujarat	Surat
0.866	6	Gujarat	Jamnagar
0.843	7	Tamil Nadu	Kanchipuram
0.842	8	Puducherry	Puducherry
0.836	9	Maharasht	Thane
0.808	10	West Beng	South 24 Parganas
0.798	11	Tamil Nadu	Thiruvallur
0.783	12	West Beng	Purba Medinipur
0.745	13	West Beng	North 24 Parganas
0.74	14	Tamil Nadu	Ramanathapuram
0.733	15	Tamil Nadu	Nagapattinam
0.721	16	Maharasht	Ratnagiri
0.718	17	Gujarat	Bhavnagar
0.695	18	Maharasht	Raigad
0.692	19	Orissa	Balasore
0.678	20	Tamil Nadu	Kanyakumari
0.674	21	Andhra Pra	Srikakulam
0.672	22	Gujarat	Valsad
0.672	23	Orissa	Puri
0.671	24	Tamil Nadu	Thoothukkudi
0.67	25	Andhra Pra	Nellore
0.664	26	Gujarat	Junagadh
0.662	27	Daman and	Diu
0.623	28	Gujarat	Rajkot
0.621	29	Gujarat	Bharuch
0.605	30	Andhra Pra	Visakhapatnam
0.604	31	Orissa	Jagatsinghpur
0.593	32	Karnataka	Uttara Kannand
0.591	33	Tamil Nadu	Cuddalore
0.587	34	Tamil Nadu	Vilupuram
0.584	35	Orissa	Bhadrak
0.582	36	Kerala	Malappuram
0.577	37	Orissa	Kendrapara
0.568	38	Andhra Pra	East Godavari
0.563	39	Kerala	Ernakulam
0.557	40	Andhra Pra	Prakasam
0.555	41	Kerala	Kozhikode
0.524	42	Gujarat	Porbandar
0.517	43	Andhra Pra	Guntur
0.497	44	Tamil Nadu	Tirunelveli
0.486	45	Gujarat	Anand
0.467	46	Goa	South Goa
0.44	47	Orissa	Ganjam
0.436	48	Karnataka	Dakshina Kannad
0.435	49	Goa	North Goa

0.428	50	Kerala	Kannur
0.419	51	Andhra Pra	Krishna
0.414	52	Tamil Nadu	Thanjavur
0.413	53	Tamil Nadu	Thiruvarur
0.395	54	Tamil Nadu	Pudukkottai
0.378	55	Kerala	Kasaragod
0.371	56	Kerala	Thrissur
0.365	57	Karnataka	Udupi
0.324	58	Gujarat	Amreli
0.32	59	Kerala	Thiruvananthapura
0.226	60	Gujarat	Navsari
0.223	61	Maharasht	Sindhudurg
0.22	62	Kerala	Alappuzha
0.194	63	Kerala	Kollam
0.057	64	Andhra Pra	Vizianagaram
0	65	Andhra Pra	West Godavari

Exposure Index_Current
1
0.779
0.553
0.446
0.335
0.33
0.323
0.321
0.3
0.284
0.284
0.261
0.239
0.237
0.187
0.178
0.178
0.177
0.166
0.165
0.161
0.16
0.157
0.157
0.153
0.145
0.144
0.142
0.137
0.134
0.123
0.122
0.12
0.119
0.115
0.114
0.108
0.106
0.104
0.104
0.099
0.094
0.092
0.089
0.087
0.08
0.08
0.077
0.076

0.073
0.073
0.073
0.069
0.069
0.067
0.063
0.061
0.053
0.053
0.047
0.043
0.04
0.013
0
0

Rank	State	District	Risk Index_2001	Rank
1	West Bengal	Medinipur	1.000	1
2	Maharashtra	Greater Mumbai	0.938	2
3	Odisha	Balasore	0.839	3
4	West Bengal	South 24 Parganas	0.754	4
5	Tamil Nadu	Chennai	0.577	5
6	Odisha	Bhadrak	0.486	6
7	Maharashtra	Thane	0.466	7
8	Gujarat	Kutch	0.459	8
9	Odisha	Puri	0.437	9
10	West Bengal	North 24 Parganas	0.421	10
11	Tamil Nadu	Ramanathapuram	0.420	11
12	Gujarat	Jamnagar	0.386	12
13	Puducherry	Puducherry	0.372	13
14	Andhra Pradesh	Nellore	0.362	14
15	Tamil Nadu	Nagapattinam	0.353	15
16	Maharashtra	Ratnagiri	0.350	16
17	Gujarat	Surat	0.331	17
18	Daman & Diu	Daman	0.322	18
19	Gujarat	Bharuch	0.316	19
20	Odisha	Kendrapara	0.313	20
21	Gujarat	Rajkot	0.276	21
22	Gujarat	Valsad	0.265	22
23	Andhra Pradesh	East Godavari	0.261	23
24	Maharashtra	Raigad	0.247	24
25	Andhra Pradesh	Srikakulam	0.225	25
26	Odisha	Jagatsinghpur	0.204	26
27	Odisha	Ganjam	0.178	27
28	Tamil Nadu	Thoothukkudi	0.174	28
29	Andhra Pradesh	Prakasam	0.170	29
30	Tamil Nadu	Kanchipuram	0.166	30
31	Andhra Pradesh	Krishna	0.163	31
32	Gujarat	Junagadh	0.156	32
33	Gujarat	Anand	0.150	33
34	Karnataka	Uttara Kannada	0.128	34
35	Andhra Pradesh	Visakhapatnam	0.124	35
36	Gujarat	Bhavnagar	0.117	36
37	Maharashtra	Sindhudurg	0.115	37
38	Gujarat	Porbandar	0.107	38
39	Tamil Nadu	Thiruvallur	0.106	39
40	Andhra Pradesh	Guntur	0.104	40
41	Gujarat	Navsari	0.080	41
42	Kerala	Malappuram	0.056	42
43	Karnataka	Udupi	0.056	43
44	Tamil Nadu	Pudukkottai	0.055	44
45	Tamil Nadu	Tirunelveli	0.055	45
46	Goa	North Goa	0.053	46
47	Kerala	Alappuzha	0.049	47
48	Andhra Pradesh	West Godavari	0.045	48
49	Kerala	Kasaragod	0.042	49

50	Tamil Nadu	Thanjavur	0.041	50
51	Kerala	Kozhikode	0.041	51
52	Karnataka	Dakshina Kannada	0.037	52
53	Kerala	Kannur	0.032	53
54	Tamil Nadu	Thiruvarur	0.032	54
55	Goa	South Goa	0.030	55
56	Tamil Nadu	Cuddalore	0.026	56
57	Kerala	Thrissur	0.020	57
58	Tamil Nadu	Kanyakumari	0.016	58
59	Gujarat	Amreli	0.011	59
60	Kerala	Thiruvananthapuram	0.011	60
61	Tamil Nadu	Viluppuram	0.009	61
62	Kerala	Ernakulam	0.005	62
63	Kerala	Kollam	0.004	63
64	Daman & Diu	Diu	0.002	64
65	Andhra Pradesh	Vizianagaram	0.000	65

State	District	Hazard Index_2001	Rank	State
Odisha	Balasore	1.000	1	Odisha
West Beng	Medinipur	0.929	2	Gujarat
West Beng	South 24 Parganas	0.788	3	Odisha
Odisha	Bhadrak	0.701	4	Odisha
Gujarat	Anand	0.576	5	Odisha
Gujarat	Rajkot	0.575	6	Gujarat
Odisha	Puri	0.550	7	Odisha
Andhra Pra	Nellore	0.519	8	West Beng
Odisha	Jagatsinghpur	0.512	9	Odisha
Odisha	Kendrapara	0.506	10	West Beng
West Beng	North 24 Parganas	0.502	11	Gujarat
Andhra Pra	East Godavari	0.458	12	Andhra Pra
Gujarat	Bharuch	0.424	13	Andhra Pra
Tamil Nadu	Ramanathapuram	0.411	14	Tamil Nadu
Andhra Pra	West Godavari	0.396	15	Tamil Nadu
Tamil Nadu	Nagapattinam	0.385	16	Tamil Nadu
Odisha	Ganjam	0.385	17	Tamil Nadu
Andhra Pra	Krishna	0.384	18	Andhra Pra
Maharasht	Raigad	0.367	19	Tamil Nadu
Andhra Pra	Prakasam	0.364	20	Maharasht
Maharasht	Thane	0.362	21	Gujarat
Maharasht	Greater Mumbai	0.341	22	Andhra Pra
Tamil Nadu	Kanchipuram	0.316	23	Maharasht
Tamil Nadu	Pudukkottai	0.316	24	Tamil Nadu
Maharasht	Ratnagiri	0.314	25	Tamil Nadu
Tamil Nadu	Thanjavur	0.313	26	Andhra Pra
Tamil Nadu	Thiruvarur	0.302	27	West Beng
Goa	North Goa	0.274	28	Andhra Pra
Andhra Pra	Guntur	0.254	29	Tamil Nadu
Gujarat	Jamnagar	0.242	30	Andhra Pra
Gujarat	Valsad	0.235	31	Gujarat
Daman & D	Daman	0.235	32	Andhra Pra
Andhra Pra	Vizianagaram	0.235	33	Tamil Nadu
Tamil Nadu	Tirunelveli	0.234	34	Tamil Nadu
Gujarat	Kutch	0.230	35	Karnataka
Tamil Nadu	Thoothukkudi	0.230	36	Maharasht
Maharasht	Sindhudurg	0.215	37	Karnataka
Gujarat	Surat	0.210	38	Gujarat
Andhra Pra	Srikakulam	0.209	39	Gujarat
Gujarat	Junagadh	0.200	40	Kerala
Gujarat	Porbandar	0.197	41	Kerala
Gujarat	Navsari	0.195	42	Kerala
Daman & D	Diu	0.195	43	Andhra Pra
Tamil Nadu	Thiruvallur	0.178	44	Kerala
Puducherry	Puducherry	0.159	45	Gujarat
Tamil Nadu	Viluppuram	0.153	46	Kerala
Kerala	Thrissur	0.149	47	Tamil Nadu
Kerala	Alappuzha	0.145	48	Gujarat
Andhra Pra	Visakhapatnam	0.145	49	Gujarat

Karnataka	Udupi	0.144	50	Tamil Nadu
Karnataka	Uttara Kannada	0.139	51	Kerala
Tamil Nadu	Cuddalore	0.134	52	Gujarat
Kerala	Kozhikode	0.124	53	Kerala
Kerala	Kollam	0.120	54	Karnataka
Tamil Nadu	Chennai	0.119	55	Kerala
Goa	South Goa	0.119	56	Gujarat
Karnataka	Dakshina Kannada	0.114	57	Maharashtı
Gujarat	Amreli	0.114	58	Kerala
Gujarat	Bhavnagar	0.106	59	Puducherry
Kerala	Kasaragod	0.100	60	Tamil Nadu
Kerala	Kannur	0.095	61	Maharashtı
Kerala	Malappuram	0.094	62	Goa
Kerala	Ernakulam	0.065	63	Goa
Tamil Nadu	Kanyakumari	0.013	64	Daman & [
Kerala	Thiruvananthapuram	0.000	65	Daman & [

District	Vulnerability Index_2001	Rank	State
Balasore	1.000	1	Tamil Nadu
Valsad	0.973	2	Maharashtra
Jagatsinghp	0.941	3	Daman & Diu
Kendrapara	0.924	4	Puducherry
Bhadrak	0.918	5	Gujarat
Navsari	0.903	6	Gujarat
Puri	0.885	7	Maharashtra
Medinipur	0.871	8	Gujarat
Ganjam	0.863	9	West Bengal
South 24 Pa	0.824	10	Maharashtra
Bharuch	0.785	11	Tamil Nadu
Vizianagara	0.751	12	West Bengal
Srikakulam	0.745	13	West Bengal
Viluppuram	0.740	14	Tamil Nadu
Thiruvarur	0.720	15	Andhra Pradesh
Pudukkotta	0.706	16	Gujarat
Nagapattin	0.706	17	Gujarat
Nellore	0.695	18	Odisha
Ramanatha	0.690	19	Gujarat
Ratnagiri	0.677	20	Odisha
Surat	0.671	21	Andhra Pradesh
Prakasam	0.670	22	Karnataka
Sindhudurg	0.670	23	Maharashtra
Cuddalore	0.667	24	Tamil Nadu
Thanjavur	0.647	25	Gujarat
Visakhapat	0.646	26	Andhra Pradesh
North 24 Pa	0.643	27	Odisha
East Godav	0.634	28	Gujarat
Tirunelveli	0.630	29	Andhra Pradesh
Guntur	0.627	30	Tamil Nadu
Kutch	0.623	31	Tamil Nadu
West Goda	0.609	32	Gujarat
Thoothukk	0.599	33	Odisha
Kanyakuma	0.598	34	Maharashtra
Uttara Kani	0.596	35	Kerala
Raigad	0.592	36	Andhra Pradesh
Udupi	0.583	37	Andhra Pradesh
Amreli	0.582	38	Goa
Anand	0.571	39	Andhra Pradesh
Kollam	0.571	40	Odisha
Thiruvanan	0.568	41	Kerala
Kasaragod	0.567	42	Tamil Nadu
Krishna	0.562	43	Kerala
Malappura	0.558	44	Karnataka
Bhavnagar	0.549	45	Karnataka
Alappuzha	0.544	46	Kerala
Kanchipura	0.542	47	Kerala
Junagadh	0.538	48	Kerala
Porbandar	0.532	49	Goa

Thiruvallur	0.526	50	Odisha
Kozhikode	0.520	51	Gujarat
Jamnagar	0.518	52	Gujarat
Kannur	0.501	53	Kerala
Dakshina K	0.479	54	Tamil Nadu
Thrissur	0.475	55	Daman & Diu
Rajkot	0.460	56	Kerala
Thane	0.435	57	Tamil Nadu
Ernakulam	0.352	58	Gujarat
Puducherry	0.344	59	Tamil Nadu
Chennai	0.307	60	Tamil Nadu
Greater Mu	0.287	61	Kerala
North Goa	0.243	62	Andhra Pradesh
South Goa	0.229	63	Tamil Nadu
Daman	0.014	64	Tamil Nadu
Diu	0.000	65	Andhra Pradesh

District	**Exposure Index_2001**
Chennai	1.000
Greater Mumbai	0.925
Daman	0.571
Puducherry	0.556
Kutch	0.436
Jamnagar	0.388
Thane	0.384
Surat	0.322
Medinipur	0.272
Ratnagiri	0.259
Ramanathapuram	0.252
South 24 Parganas	0.241
North 24 Parganas	0.222
Nagapattinam	0.218
Srikakulam	0.208
Bhavnagar	0.192
Valsad	0.192
Balasore	0.190
Junagadh	0.179
Puri	0.177
Nellore	0.176
Uttara Kannada	0.176
Raigad	0.173
Thoothukkudi	0.172
Bharuch	0.169
Visakhapatnam	0.159
Bhadrak	0.154
Rajkot	0.149
East Godavari	0.146
Thiruvallur	0.137
Kanchipuram	0.136
Porbandar	0.129
Kendrapara	0.127
Sindhudurg	0.113
Malappuram	0.111
Krishna	0.111
Prakasam	0.109
South Goa	0.097
Guntur	0.094
Ganjam	0.091
Kasaragod	0.086
Kanyakumari	0.086
Thiruvananthapuram	0.086
Udupi	0.085
Dakshina Kannada	0.082
Kannur	0.081
Alappuzha	0.080
Kozhikode	0.080
North Goa	0.077

Jagatsinghpur	0.075
Navsari	0.069
Anand	0.065
Ernakulam	0.060
Tirunelveli	0.055
Diu	0.050
Thrissur	0.047
Cuddalore	0.047
Amreli	0.038
Pudukkottai	0.035
Thanjavur	0.028
Kollam	0.027
West Godavari	0.023
Thiruvarur	0.019
Viluppuram	0.019
Vizianagaram	0.000

State	District	Risk Index_Current	Risk Index_2001	Risk Difference
Tamil Nadu	Kanchipura	0.356	0.166	0.191
Odisha	Jagatsinghp	0.347	0.204	0.142
Gujarat	Anand	0.288	0.150	0.138
Tamil Nadu	Viluppuram	0.144	0.009	0.135
Daman & D	Daman	0.454	0.322	0.132
Tamil Nadu	Thiruvallur	0.238	0.106	0.131
Daman & D	Diu	0.132	0.002	0.130
Tamil Nadu	Thiruvarur	0.157	0.032	0.125
West Beng	South 24 Pa	0.877	0.754	0.123
Tamil Nadu	Cuddalore	0.146	0.026	0.120
Tamil Nadu	Thanjavur	0.161	0.041	0.119
Tamil Nadu	Pudukkotta	0.164	0.055	0.109
West Beng	North 24 Pa	0.506	0.421	0.085
Andhra Pra	Vizianagara	0.082	0.000	0.082
Odisha	Ganjam	0.257	0.178	0.079
Tamil Nadu	Tirunelveli	0.127	0.055	0.072
Gujarat	Rajkot	0.345	0.276	0.069
Andhra Pra	Prakasam	0.237	0.170	0.067
Gujarat	Amreli	0.076	0.011	0.064
Andhra Pra	Guntur	0.167	0.104	0.063
Andhra Pra	West Goda	0.105	0.045	0.061
Andhra Pra	Visakhapat	0.177	0.124	0.053
Gujarat	Bhavnagar	0.168	0.117	0.051
Gujarat	Navsari	0.126	0.080	0.046
Tamil Nadu	Kanyakuma	0.061	0.016	0.045
Kerala	Kozhikode	0.082	0.041	0.041
Kerala	Thrissur	0.057	0.020	0.038
Andhra Pra	Krishna	0.199	0.163	0.037
Kerala	Ernakulam	0.041	0.005	0.035
Maharasht	Raigad	0.276	0.247	0.029
Odisha	Kendrapara	0.341	0.313	0.028
Gujarat	Porbandar	0.135	0.107	0.028
Andhra Pra	East Godav	0.289	0.261	0.028
Gujarat	Junagadh	0.181	0.156	0.025
Tamil Nadu	Nagapattin	0.378	0.353	0.025
Andhra Pra	Srikakulam	0.249	0.225	0.024
Kerala	Malappura	0.076	0.056	0.019
Gujarat	Bharuch	0.332	0.316	0.016
Tamil Nadu	Ramanatha	0.436	0.420	0.016
Andhra Pra	Nellore	0.376	0.362	0.015
Karnataka	Dakshina K	0.050	0.037	0.013
Odisha	Balasore	0.851	0.839	0.012
Tamil Nadu	Thoothukk	0.183	0.174	0.009
Kerala	Kollam	0.010	0.004	0.006
Gujarat	Valsad	0.268	0.265	0.003
West Beng	Purba Med	1.000	1.000	0.000
Kerala	Kannur	0.030	0.032	-0.002
Odisha	Puri	0.434	0.437	-0.003
Kerala	Kasaragod	0.037	0.042	-0.005

Goa	South Goa	0.023	0.030	-0.007
Karnataka	Udupi	0.047	0.056	-0.008
Odisha	Bhadrak	0.476	0.486	-0.009
Kerala	Thiruvanan	0.000	0.011	-0.011
Gujarat	Surat	0.319	0.331	-0.012
Goa	North Goa	0.040	0.053	-0.014
Gujarat	Kutch	0.443	0.459	-0.016
Kerala	Alappuzha	0.032	0.049	-0.017
Gujarat	Jamnagar	0.366	0.386	-0.019
Karnataka	Uttara Kan	0.103	0.128	-0.025
Maharasht	Sindhudurg	0.087	0.115	-0.028
Maharasht	Thane	0.384	0.466	-0.082
Maharasht	Ratnagiri	0.262	0.350	-0.088
Tamil Nadu	Chennai	0.482	0.577	-0.095
Puducherry	Puducherry	0.179	0.372	-0.192
Maharasht	Greater Mu	0.693	0.938	-0.245

State	District	Hazard Index_Current	Hazard Index_2001	Hazard Difference
Andhra Pra	Vishakhapa	0.233	0.145	0.088
Tamil Nadu	Nagapattin	0.467	0.385	0.082
Gujarat	Bhavnagar	0.185	0.106	0.079
Tamil Nadu	Cuddalore	0.208	0.134	0.074
Gujarat	Amreli	0.184	0.114	0.07
Andhra Pra	Krishna	0.445	0.384	0.061
Andhra Pra	Vizianagara	0.296	0.235	0.061
Orissa	Ganjam	0.445	0.385	0.06
Kerala	Kozhikode	0.183	0.124	0.059
Maharasht	Greater Mu	0.398	0.341	0.057
Gujarat	Porbandar	0.254	0.197	0.057
Gujarat	Junagadh	0.256	0.200	0.056
Gujarat	Anand	0.631	0.576	0.055
Andhra Pra	Srikakulam	0.264	0.209	0.055
Daman and	Diu	0.250	0.195	0.055
Gujarat	Navsari	0.248	0.195	0.053
Gujarat	Rajkot	0.627	0.575	0.052
Andhra Pra	East Godav	0.506	0.458	0.048
Andhra Pra	Guntur	0.302	0.254	0.048
Gujarat	Jamnagar	0.289	0.242	0.047
Kerala	Thrissur	0.195	0.149	0.046
West Beng	South 24 Pa	0.832	0.788	0.044
Kerala	Ernakulam	0.107	0.065	0.042
Maharasht	Thane	0.401	0.362	0.039
Tamil Nadu	Pudukkotta	0.355	0.316	0.039
Tamil Nadu	Thanjavur	0.352	0.313	0.039
Tamil Nadu	Ramanatha	0.449	0.411	0.038
Tamil Nadu	Villupuram	0.190	0.153	0.037
West Beng	North 24 Pa	0.537	0.502	0.035
Kerala	Malappura	0.129	0.094	0.035
Gujarat	Surat	0.245	0.210	0.035
West Beng	Purba Med	0.962	0.929	0.033
Andhra Pra	West Goda	0.428	0.396	0.032
Gujarat	Bharuch	0.455	0.424	0.031
Tamil Nadu	Thiruvallur	0.209	0.178	0.031
Daman and	Daman	0.265	0.235	0.03
Andhra Pra	Prakasam	0.394	0.364	0.03
Gujarat	Valsad	0.265	0.235	0.03
Gujarat	Kutch	0.258	0.230	0.028
Maharasht	Raigarh	0.392	0.367	0.025
Tamil Nadu	Chennai	0.144	0.119	0.025
Orissa	Bhadrak	0.725	0.701	0.024
Tamil Nadu	Tirunelveli	0.254	0.234	0.02
Maharasht	Ratnagiri	0.333	0.314	0.019
Puducherry	Puducherry	0.178	0.159	0.019
Goa	South Goa	0.137	0.119	0.018
Tamil Nadu	Thiruvarur	0.320	0.302	0.018
Tamil Nadu	Kanchipura	0.332	0.316	0.016
Orissa	Kendrapara	0.521	0.506	0.015

Tamil Nadu	Thoothukk	0.243	0.230	0.013
Orissa	Jagatsinghp	0.523	0.512	0.011
Tamil Nadu	Kanyakuma	0.024	0.013	0.011
Maharasht	Sindhudurg	0.221	0.215	0.006
Karnataka	Dakshin Ka	0.119	0.114	0.005
Orissa	Balasore	1.000	1.000	0
Kerala	Thiruvanan	0.000	0.000	0
Karnataka	Uttar Kann	0.138	0.139	-0.001
Orissa	Puri	0.545	0.550	-0.005
Kerala	Kasaragod	0.090	0.100	-0.01
Andhra Pra	Nellore	0.509	0.519	-0.01
Kerala	Alappuzha	0.132	0.145	-0.013
Kerala	Kannur	0.077	0.095	-0.018
Karnataka	Udupi	0.117	0.144	-0.027
Kerala	Kollam	0.093	0.120	-0.027
Goa	North Goa	0.241	0.274	-0.033

State	District	Vulnerability Index_Current	Vulnerability Index_2001	Vulnerability Difference
Daman & [	Daman	0.365	0.014	0.352
Daman & [	Diu	0.324	0.000	0.324
Andhra Pra	Srikakulam	0.843	0.745	0.098
Andhra Pra	West Goda	0.672	0.609	0.063
Andhra Pra	Prakasam	0.733	0.670	0.063
Andhra Pra	Krishna	0.623	0.562	0.061
Andhra Pra	East Godav	0.695	0.634	0.061
Andhra Pra	Vizianagara	0.808	0.751	0.057
Gujarat	Porbandar	0.582	0.532	0.050
Andhra Pra	Nellore	0.745	0.695	0.049
Gujarat	Junagadh	0.587	0.538	0.049
Andhra Pra	Visakhapat	0.692	0.646	0.046
Andhra Pra	Guntur	0.670	0.627	0.044
Gujarat	Bhavnagar	0.591	0.549	0.041
Gujarat	Jamnagar	0.555	0.518	0.037
West Benga	North 24 Pa	0.672	0.643	0.029
Gujarat	Rajkot	0.486	0.460	0.026
Gujarat	Amreli	0.604	0.582	0.021
Gujarat	Anand	0.584	0.571	0.013
Gujarat	Bharuch	0.798	0.785	0.013
Odisha	Ganjam	0.870	0.863	0.007
Maharasht	Sindhudurg	0.671	0.670	0.001
Odisha	Balasore	1.000	1.000	0.000
Tamil Nadu	Thiruvarur	0.718	0.720	-0.002
Karnataka	Uttara Kan	0.593	0.596	-0.003
Gujarat	Navsari	0.899	0.903	-0.004
Tamil Nadu	Cuddalore	0.662	0.667	-0.005
Maharasht	Thane	0.428	0.435	-0.007
Tamil Nadu	Ramanatha	0.678	0.690	-0.012
Tamil Nadu	Viluppuram	0.721	0.740	-0.019
Tamil Nadu	Thoothukk	0.577	0.599	-0.022
Tamil Nadu	Thanjavur	0.621	0.647	-0.027
Gujarat	Valsad	0.943	0.973	-0.030
Tamil Nadu	Nagapattin	0.674	0.706	-0.032
West Benga	Purba Med	0.836	0.871	-0.034
Odisha	Bhadrak	0.879	0.918	-0.039
Tamil Nadu	Kanyakuma	0.557	0.598	-0.041
Tamil Nadu	Pudukkotta	0.664	0.706	-0.042
Odisha	Puri	0.842	0.885	-0.043
Gujarat	Kutch	0.568	0.623	-0.055
Odisha	Kendrapara	0.866	0.924	-0.058
Tamil Nadu	Thiruvallur	0.467	0.526	-0.059
Karnataka	Dakshina K	0.414	0.479	-0.064
Tamil Nadu	Tirunelveli	0.563	0.630	-0.068
Maharasht	Raigad	0.524	0.592	-0.068
Maharasht	Ratnagiri	0.605	0.677	-0.072
West Benga	South 24 Pa	0.740	0.824	-0.084
Karnataka	Udupi	0.497	0.583	-0.086
Tamil Nadu	Chennai	0.220	0.307	-0.087

Maharasht	Greater Mu	0.194	0.287	-0.093
Tamil Nadu	Kanchipura	0.435	0.542	-0.107
Puducherry	Puducherry	0.223	0.344	-0.121
Kerala	Malappura	0.436	0.558	-0.122
Kerala	Ernakulam	0.226	0.352	-0.126
Kerala	Kasaragod	0.440	0.567	-0.127
Kerala	Kannur	0.371	0.501	-0.130
Kerala	Kozhikode	0.378	0.520	-0.142
Kerala	Alappuzha	0.395	0.544	-0.149
Kerala	Kollam	0.419	0.571	-0.151
Gujarat	Surat	0.517	0.671	-0.154
Kerala	Thrissur	0.320	0.475	-0.154
Kerala	Thiruvanan	0.413	0.568	-0.155
Odisha	Jagatsinghp	0.783	0.941	-0.159
Goa	South Goa	0.057	0.229	-0.172
Goa	North Goa	0.000	0.243	-0.243

State	District	Exposure Index_Current	Exposure Index_2001
Tamil Nadu	Kanchipuram	0.323	0.136
Tamil Nadu	Thiruvallur	0.284	0.137
Tamil Nadu	Villupuram	0.119	0.019
Daman and	Diu	0.144	0.050
Tamil Nadu	Kanyakumari	0.165	0.086
Tamil Nadu	Cuddalore	0.12	0.047
Tamil Nadu	Thiruvarur	0.069	0.019
Orissa	Jagatsinghpur	0.123	0.075
Tamil Nadu	Thanjavur	0.073	0.028
Kerala	Ernakulam	0.104	0.060
West Benga	South 24 Parganas	0.284	0.241
Tamil Nadu	Pudukkottai	0.069	0.035
Tamil Nadu	Tirunelveli Kattabc	0.089	0.055
Gujarat	Anand	0.087	0.065
Kerala	Kozhikode	0.099	0.080
West Benga	North 24 Parganas	0.239	0.222
Kerala	Thrissur	0.063	0.047
Gujarat	Amreli	0.053	0.038
Gujarat	Surat	0.335	0.322
Gujarat	Kutch	0.446	0.436
Maharasht	Raigarh	0.177	0.173
Kerala	Malappuram	0.114	0.111
Tamil Nadu	Chennai	1	1.000
Andhra Pra	Vizianagaram	0	0.000
Goa	North Goa	0.076	0.077
Andhra Pra	Guntur	0.092	0.094
Karnataka	Dakshin Kannad	0.077	0.082
Andhra Pra	Prakasam	0.104	0.109
Gujarat	Rajkot	0.142	0.149
Kerala	Kannur	0.073	0.081
Orissa	Ganjam	0.08	0.091
West Benga	Purba Medinipur	0.261	0.272
Kerala	Kollam	0.013	0.027
Gujarat	Bhavnagar	0.178	0.192
Tamil Nadu	Thoothukkudi	0.157	0.172
Tamil Nadu	Ramanathapuram	0.237	0.252
Goa	South Goa	0.08	0.097
Daman and	Daman	0.553	0.571
Kerala	Kasaragod	0.067	0.086
Orissa	Kendrapara	0.108	0.127
Orissa	Puri	0.157	0.177
Gujarat	Navsari	0.047	0.069
Andhra Pra	Nellore	0.153	0.176
Andhra Pra	West Godavari	0	0.023
Orissa	Balasore	0.166	0.190
Karnataka	Udupi	0.061	0.085
Andhra Pra	Vishakhapatnam	0.134	0.159
Tamil Nadu	Nagapattinam	0.187	0.218
Gujarat	Bharuch	0.137	0.169

Gujarat	Valsad	0.16	0.192
Kerala	Thiruvananthapura	0.053	0.086
Gujarat	Junagadh	0.145	0.179
Gujarat	Porbandar	0.094	0.129
Andhra Pra	Krishna	0.073	0.111
Orissa	Bhadrak	0.115	0.154
Andhra Pra	East Godavari	0.106	0.146
Kerala	Alappuzha	0.04	0.080
Andhra Pra	Srikakulam	0.161	0.208
Karnataka	Uttar Kannand	0.122	0.176
Gujarat	Jamnagar	0.33	0.388
Maharasht	Sindhudurg	0.043	0.113
Maharasht	Ratnagiri	0.178	0.259
Maharasht	Thane	0.3	0.384
Maharasht	Greater Mumbai	0.779	0.925
Puducherry	Puducherry	0.321	0.556

Exposure Difference
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