RESEARCH PAPER

ASSESSING THE VULNERABILITY INDEX OF COVID-19 PANDEMIC IN INDIA

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ABSTRACT. The coronavirus (COVID-19) outbreak has created havoc all across the States and Union Territories (UTs) of India since its beginning on 30th January 2020. As of 1st January 2021, India has recorded 10,305,788 cases and 149,218 deaths from this deadly pandemic. It has been observed through the data; across states and UTs, the trend and pattern of this disease are not similar at all. There are many reasons for these dissimilarities which are categorized into indicators to assess the vulnerability in this study. We have examined vulnerabilities in 28 states and 8 UTs of India. Livelihood Vulnerability Index (LVI) has been applied with certain modifications to calculate the Vulnerability Index (VI). The figure resulting from the vulnerability assessment corresponds that the factors involved in the three-section exposure, sensitivity, and adaptive capacity had a significant impact on deciding the vulnerability of the population. The result identified the states and UTs which are more vulnerable and need more attention from the government and policymakers. The proposed method of study is unique in its sense as vulnerability index calculation is purely based on a secondary source of data and therefore has an expectation of a higher degree of practical application.

KEYWORDS: India, COVID-19, Exposure, Sensitivity, Adaptive Capacity, Population Density, Vulnerability Assessment

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INTRODUCTION

Pathogens like viruses, bacteria, fungi, and parasites that are responsible for communicable diseases (CDS) have a long history of their inception (Freedman 1966). There has been reporting of different virus-related deadly CDS earlier like that of the Spanish Influenza, Human Immunodeficiency Virus (HIV), Ebola, and others that had affected several globally. Novel Coronavirus (SARS-CoV-2) is responsible for COVID-19, the infectious communicable disease that has been expanding across the length and breadth of the globe (Acharya and Porwal 2020; Avtar et al. 2020; Chaurasiya et al. 2020; Coronavirus Disease (COVID-19); Giovanetti et al. s2020; Lai et al. 2020; Phan et al. 2020; Tosepu et al. 2020). This rapidly spreading disease primarily travels from one infected person to the other through respiratory or saliva droplets via symptomatic, pre-symptomatic, and asymptomatic carriers (Jernigan 2020; Wiersinga et al. 2020). COVID-19 infected patients mostly experience mild to moderate respiratory illness with the serious illness being developed by those having severe underlying medical issues. The first case to be reported in the world was from the Wuhan city of China in early December 2019 (Martínez-Piédrola et al. 2021; Mazinani & Rude 2021). Since then, it has been incresing at an alarming rate with COVID-19 spreading its wings around over 86 million cases globally (Coronavirus Disease (COVID-19). The rate of its gradual expansion and accompanying consequences had resulted in the World Health Organization (WHO) declaring it as a global pandemic on 11th of March 2020. All the COVID-19 hit nations and most importantly nations with friable health infrastructure were affected accordingly (Coronavirus Disease (COVID-19); Lupia et al. 2020; Sohrabi et al. 2020).

Communicable diseases are a major public cause of concern in developing countries where available health infrastructure is not sufficient with the bulging population. These countries are more susceptible because of their high population densities, inadequate health care infrastructure, meager income, and poverty (Gupte and Mitlin 2020). India, a developing country with a population of over 1.3 billion and being home to the world's second-highest population, stands in a high-risk situation owing to its large number of reported cases of infection and death. As of September 2020, COVID-19 had spread its wings around over 32.7 million globally and over 5 million in India (Coronavirus Disease (COVID-19). The first COVID-19 case in India was reported from the state of Kerala on January 30, 2020, whose origin was Wuhan, China (Chaurasiya et al. 2020; Ogen 2020). COVID-19 has not only restricted itself to an increase in infection numbers and deaths but also has wider corresponding implications in terms of social consequences, economic repercussions, environmental changes as well political adverse (Shah and Farrow 2020).

In this article, we empirically try to show the inter-relation between COVID-19 and related vulnerabilities in the States and UTs of India. The article tries looking deeply and demarcating regions depending on the rate of exposure, sensitivity traits, and its nature to adapt. Thus, this piece of original research contributes in three ways firstly, by understanding the scenario of COVID-19 in the country and its corresponding health infrastructure, second looking at the health vulnerabilities of India, state-wise through a range of indicators thereby clearing the cloud on the country's probability to adapt to the pandemic situation and finally, developing the VI to decipher the zonation of health vulnerabilities for quick identification of problem-centric states and UTs for enacting guidelines accordingly.

MATERIAL AND METHODOLOGY

Study area

India, the study area comprises 28 states and 8 union territories located between latitudes 8°4′N and 37°6′N and longitudes 68°7′E and 97°25′E. Physiographically, India is divided into Plains, Himalayas, Plateaus, Coastal areas, Desert regions, and Islands. There is an extensive difference among the Indian states in terms of population density, age structure, social condition, and cultural diversity. The UTs of Jammu & Kashmir and Ladakh have been combined as one entity which is divided into two parts in the year 2019 (Fig. 1a). Previously these two UTs were considered as a single state and therefore some socio-economic data is not available separately for these. In this study, some UTs namely (1. Dadra and Nagar Haveli and Daman and Diu, 2. Lakshadweep) are not included due to the non-availability of COVID-19 of data.

Data collection

The basic idea of the study is to calculate the vulnerability index value for all the states and UTs based on multiple indicators that are divided into three broad categories of exposure, sensitivity, and adaptive capacity according to the IPCC concept (Hahn et al. 2009) Table 1. The dataset used in the study is obtained from secondary sources. The major sources include Central Government official publications, Census of India, (2011), and data available from the website (https://www.indiastat.com/) (Coronavirus Data India - COVID-19 Pandemic Data India with State Wise Growth Statistics Details Figures | Indiastat)

Vulnerability Analysis

Coronavirus vulnerability analysis has been done to calculate the state and UTs level vulnerability related to COVID-19 cases and deaths. Some modifications have been made in the Livelihood Vulnerability Index (LVI) method to adapt the methodology fit for our specific study. The

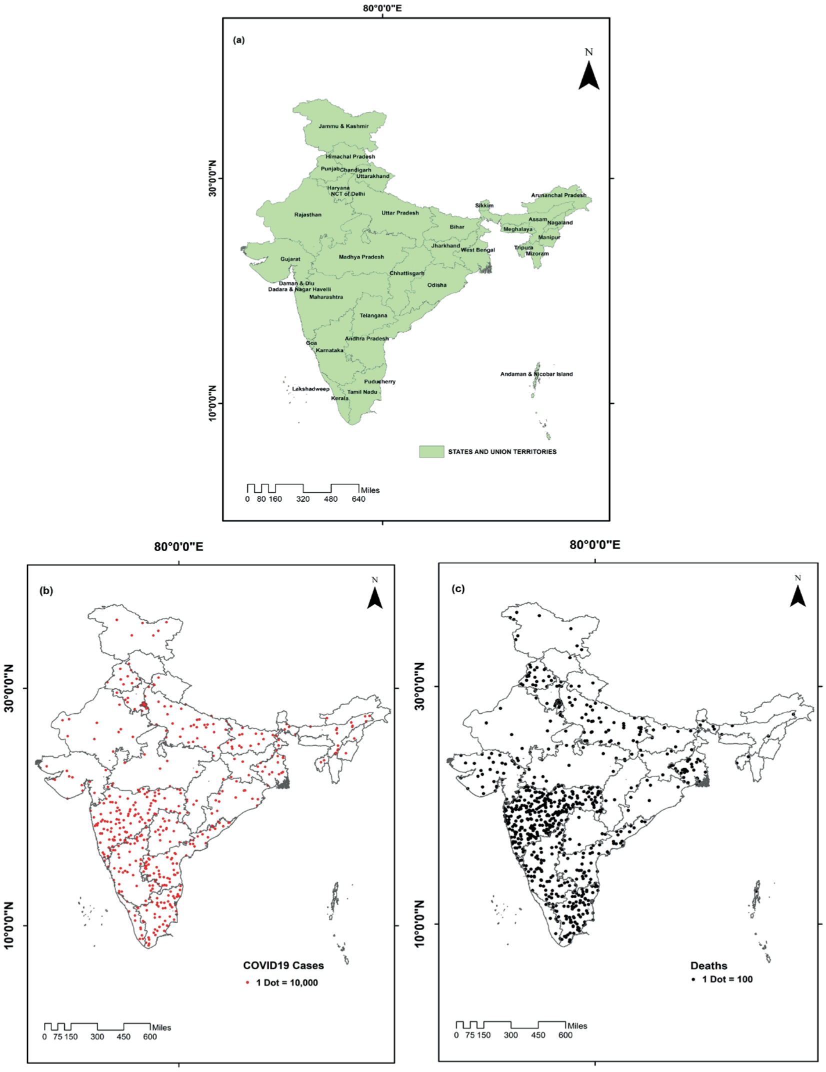

Fig. 1(a). Locational map showing Indian states and Union Territories (UTs). The name of each States and UTs are on the map is inside the administrative boundary (b) total number of COVID19 cases (c) total deaths in Indian states and UTs

stepwise calculation of the VI has been summarized below.

Steps to calculate the Vulnerability Index (VI)

Step 1: Indicators
Values for all the indicators are to be standardized for all the states.
Step 1
The steps can be broadly summarized as:

$$(Ix) = \frac{Ib - I(\min)}{I(\max) - I(\min)}$$

Where, **Ix** = Standardized value for the indicator
Ib= Value for the Indicator I for a particular state or UT, b.
I (min) = Minimum Value for the indicator across all the states and UTs
I (max) = Maximum Value for the indicator across all the states and UTs

Step 2: Profiles
Indicator index Values are combined to get the values for

$$(P) = \sum_{i=1}^{n} \frac{Indicator\ \ Index}{n} i$$

the profiles
Where, **n** – no. of indicators in the profile
Indicator Index i – Index of the i th indicator.

Step 3: Vulnerability Index: The three contributing factors are combined to calculate the VI
Vulnerability Index = (Exposure – Adaptive Capacity) x Sensitivity. The obtained data for the profile section and VI have been classify according to the natural breaks (Jenks) classification. The VI has been scaled from -1 (least vulnerable) to +1 (most vulnerable) and categorized value into four categories very low, medium, high, and very highly vulnerable blocks.

RESULT AND DISCUSSION

India has recorded the second-highest number of COVID-19 cases after the USA since the inception of the disease. Country continues to face a serious threat of outbreak not only due to its large population size, but other factors related to demographics, social negligence, and poor health infrastructure (Acharya and Porwal 2020). COVID-19 pandemic has become a serious challenge to the health and economic status of people. This disease has impacted the economy, social life, health, and other areas and added more vulnerability to human life (Fong et al. 2020). Many factors are responsible for its transmission at many levels of interaction (Deziel et al. 2020). In a recently published pioneer work, it has been observed that COVID-19 has not been evenly distributed on a geographical space due to factors related to uneven demographic distribution and differential available health care infrastructure(Amram et al. 2020). COVID-19 vulnerability index is an effective tool to demarcate the areas of high vulnerability by adding composite scores of factors associated with exposure, sensitivity, and adaptability (Mishra et al. 2020). In the present study, the indicators are based on several studies on disease vulnerability analysis (Bae et al. 2019; Acharya & Porwal 2020; Sarkar and Chauhan 2021; Mishra et al. 2021; Paul 2021).

We have calculated the percentage of COVID-19 cases and related deaths to the total population for each state and UTs separately to understand the level of exposure (Table 2). In the exposure section, the percentage of the population having COVID19 and related deaths both specify the level of exposure to the COVID19 pandemic. The death of people in a region moreover accentuates the insecurity of life. It exposes the populace and the region to much ardent needs of identifying the vulnerable and controlling the deteriorating covid situation. The striking variation could be noted among states and UTs through the calculation which in turn impacts the health of people. We have found huge variation among the states and UTs through the calculation which is certainly affecting the health of the people. The final composite score values of exposure show that Puducherry (0.97) has the highest component value, followed by Delhi (0.86), Goa (0.86), and Maharashtra (0.70). The high population density in these states has accentuated the infection rates causing a high number of cases and deaths (Fig. 2). The least exposure component scores are recorded in Mizoram (0.0), Meghalaya (0.01), and Himachal Pradesh (0.02). A sparse population and physical inaccessibility mainly due to hilly terrain are the major reasons for relatively lower exposure in terms of the number of cases and deaths per capita due to COVID-19 (Fig. 2). Bihar has a less composite score of exposure (0.02) due to fewer deaths and recorded cases attributed to under-reporting and poor diagnosis of cases in the state, otherwise composite score would have

Table 1. The broad categorization of Exposure, Sensitivity, and Adaptive Capacity and their related indicators to calculate Vulnerability Index

COMPONENT	PROFILE	INDICATORS
Exposure	COVID- 19	• % Cases of COVID-19 to the total population • % COVID-19 related deaths to the total population
Sensitivity	Vulnerable factors	• % (age group 0-6 Years) • % (age group above 60 Years) • Density of population
Adaptive Capacity	Healthcare Capacity	• % Total isolation beds (excluding intensive care unit (ICU) Beds) to the total population • % Isolation beds of confirmed cases to the total population • % Isolation beds for suspected cases to the total population • % Oxygen (O2) supported beds to the total population • % ventilators to the total population • % Total ICU beds to the total population

*Data on the indicators of exposure and adaptive capacity section have been compiled from https://www.indiastat.com/, and for the vulnerable population from https://www.indiastat.com/data/demographics/

Table 2. Represents the calculated value for COVID- 19 total confirmed cases and related deaths to the total population in Indian states and UTs

States/ UTs	% Cases of COVID-19 to the total population	% COVID-19 related deaths to the total population
Andaman and Nicobar Islands (UT)	0.92	0.013
Andhra Pradesh	1.11	0.010
Arunachal Pradesh	0.42	0.001
Assam	0.44	0.001
Bihar	0.15	0.001
Chandigarh (UT)	0.69	0.008
Chhattisgarh	0.23	0.002
Delhi (UT)	1.25	0.028
Goa	1.61	0.019
Gujarat	0.18	0.005
Haryana	0.35	0.004
Himachal Pradesh	0.13	0.001
Jammu and Kashmir	0.43	0.007
Jharkhand	0.18	0.002
Karnataka	0.72	0.012
Kerala	0.31	0.001
Madhya Pradesh	0.12	0.002
Maharashtra	0.90	0.026
Manipur	0.27	0.002
Meghalaya	0.12	0.001
Mizoram	0.13	0.000
Nagaland	0.25	0.001
Odisha	0.34	0.001
Puducherry (UT)	1.52	0.029
Punjab	0.27	0.008
Rajasthan	0.14	0.002
Sikkim	0.33	0.001
Tamil Nadu	0.68	0.011
Telangana	0.44	0.003
Tripura	0.50	0.005
Uttarakhand	0.29	0.004
Uttar Pradesh	0.15	0.002
West Bengal	0.22	0.004

been higher like other similar states of Andhra Pradesh (0.50), Karnataka (0.40) and Tamil Nadu (0.38), and Uttar Pradesh (0.12). A relatively lesser number of foreign travelers can also be attributed to fewer cases in Bihar and Madhya Pradesh (0.04). Interestingly, major developed states like Delhi (0.86), Maharashtra (0.70), Andhra Pradesh (0.50), Karnataka (0.40), and Tamil Nadu (0.38) have high composite scores of exposures in comparison to relatively poor states (Fig. 2). Through the map, it is easy to say that the Southern region of the country is highly exposed to this disease in terms of exposure and related deaths. There is need to adopt several strategies like

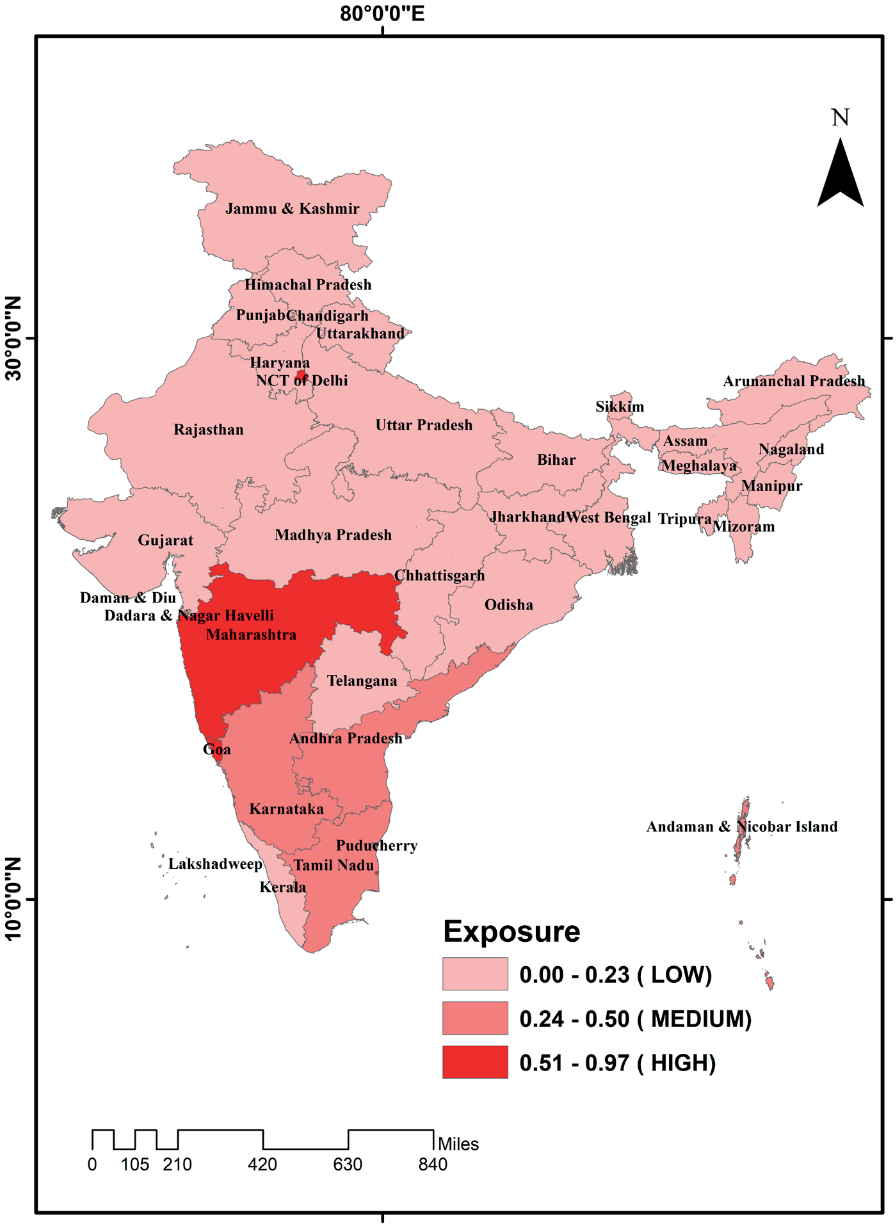

Fig. 2. Exposure value distribution in different States and UTs of India. Value ranges for the exposure are between (0-1)

social distancing, wearing masks, and hygienic practices to reduce exposure in the states and UTs. The availability of better healthcare infrastructure and high literacy rates in the southern states have contributed to high reporting of cases from these states.

The term sensitivity addresses the degree of the impact caused by the exposure factors. Sensitivity is a crucial factor in assessing the vulnerability of the population against the COVID-19 (Mishra et al. 2020). Higher density areas provide fertile ground for the virus to exacerbate its spread (Bhadra et al. 2020). As COVID-19 has its higher ramification on the aged population and spread rapidly in a densely populated region data have been taken for both as an indicator of sensitivity. In addition to this, data of the age group of population between (0-6) years is also included in this study. Both these groups of the population are the most vulnerable group (Acharya and Porwal 2020; Haleemunnissa et al. 2021). The aged population suffers from many comorbidities which makes them sensitive. In a developing country like India, the infant population is facing several challenges like hunger, malnutrition, and diseases. Because of these three major contributing factors, population (0-6) years has been taken as an indicator for our study. It has been observed in the final value for the sensitivity section that states and UTs with relatively high population density and a high share of vulnerable populations have higher scores (Fig. 3). According to health experts, population density plays an important role in the rapid spread of infectious diseases like COVID-19 (Benz et al. 2011; Bray et al. 2020; Coşkun et al. 2021; Zhang and Schwartz 2020). Delhi (0.50) has the highest composite sensitivity score mainly due to very high population density and a greater number of people age sixty and above. It is followed by Bihar (0.45) and Chandigarh (0.40), mainly attributed to high population density and a greater number of people in the age group 0-6 years (Fig. 3). Among the states and UTs, north Indian states have recorded the highest fertility rate. Highly vulnerable states like Bihar, Delhi, Chandigarh, Uttarakhand, Jharkhand, and Jammu & Kashmir fall in the northern region of the country. All the insular states with the least population densities have lesser composite scores e.g., Sikkim (0.11), Andaman and Nicobar (0.12), Arunachal Pradesh (0.20), Nagaland (0.20), Manipur (0.22), Tripura (0.24). As mentioned earlier these states are physically inaccessible and have a sparse population due to hilly terrain. It is, therefore, necessary to ensure better COVID-19 specific medical infrastructure in densely populated states with a high proportion of sensitive age groups. States with high population density

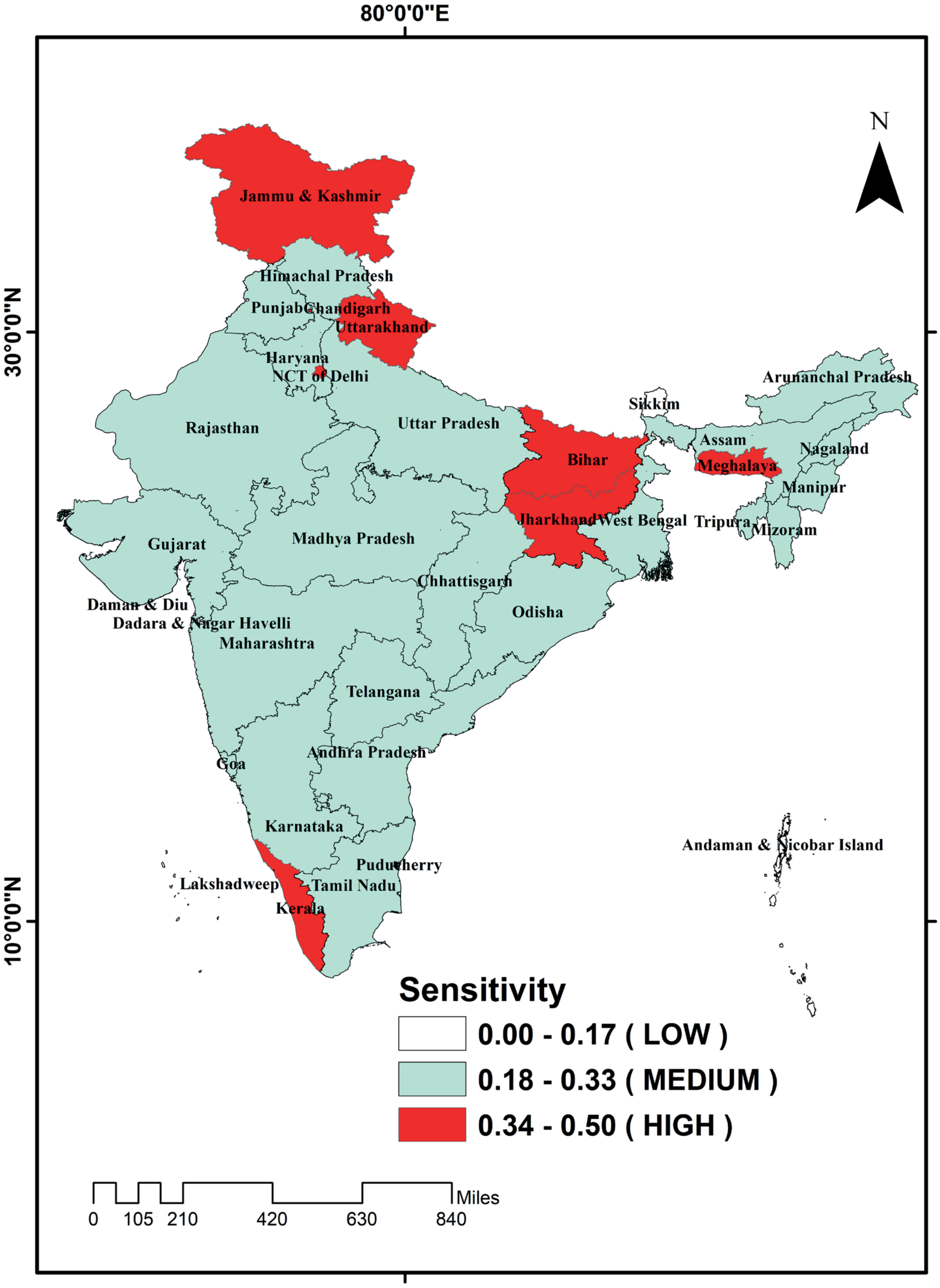

Fig. 3. The map is showing the final Sensitivity value distribution in different States and UTs of India. The final composite value ranges for the exposure is between (0-0.5)

should also make sure that the age-sensitive population with weak immune system should be the priority in dealing with COVID-19.

Adaptive capacity is the ability to effectively tackle the risks associated with COVID-19 exposure (Sarkar and Chouhan 2020). It includes the necessary medical infrastructures to deal with cases and related fatalities. This is particularly good in the states and union territories with relatively viable economic conditions and dynamic social structures with the smooth flow of information and medical practices. The adaptive capacity pattern shows that small states with relatively better medical infrastructure and COVID-19 specific health care facilities can effectively erode the vulnerability. The composite profile values for adaptive capacity underscore the overall status of medical infrastructure linked to COVID-19 control and treatment. Chandigarh (0.74) has the highest composite profile score particularly due to the very effective medical infrastructure preceding the actual COVID-19 outbreaks. This is followed by Maharashtra (0.71), Andaman and Nicobar (0.62), Tamil Nadu (0.59), Uttarakhand (0.57), and Delhi (0.56) (Fig. 4). The Maximum number of COVID-19 cases and related death is recorded in two major cities of the country, Delhi and Mumbai. New Delhi as the capital city of the country situated in Delhi and Mumbai as the economic capital of the country have well-developed and equipped medical facilities. The Government of India has provided full attention to these two cities which places them in a very high adaptive capacity zone. The least composite profile scores were recorded Bihar (0.02), Jharkhand (0.06), Nagaland (0.06), Tripura (0.06), and Himachal Pradesh (0.07) (Fig. 4). It has been observed that the states which are less populous and have viable socio-economic conditions have performed well on the selected indicators, unlike in the underdeveloped states (Fig. 4).

COVID-19 VI has been obtained using the formula (Exposure – Adaptive Capacity) x Sensitivity (Hahn

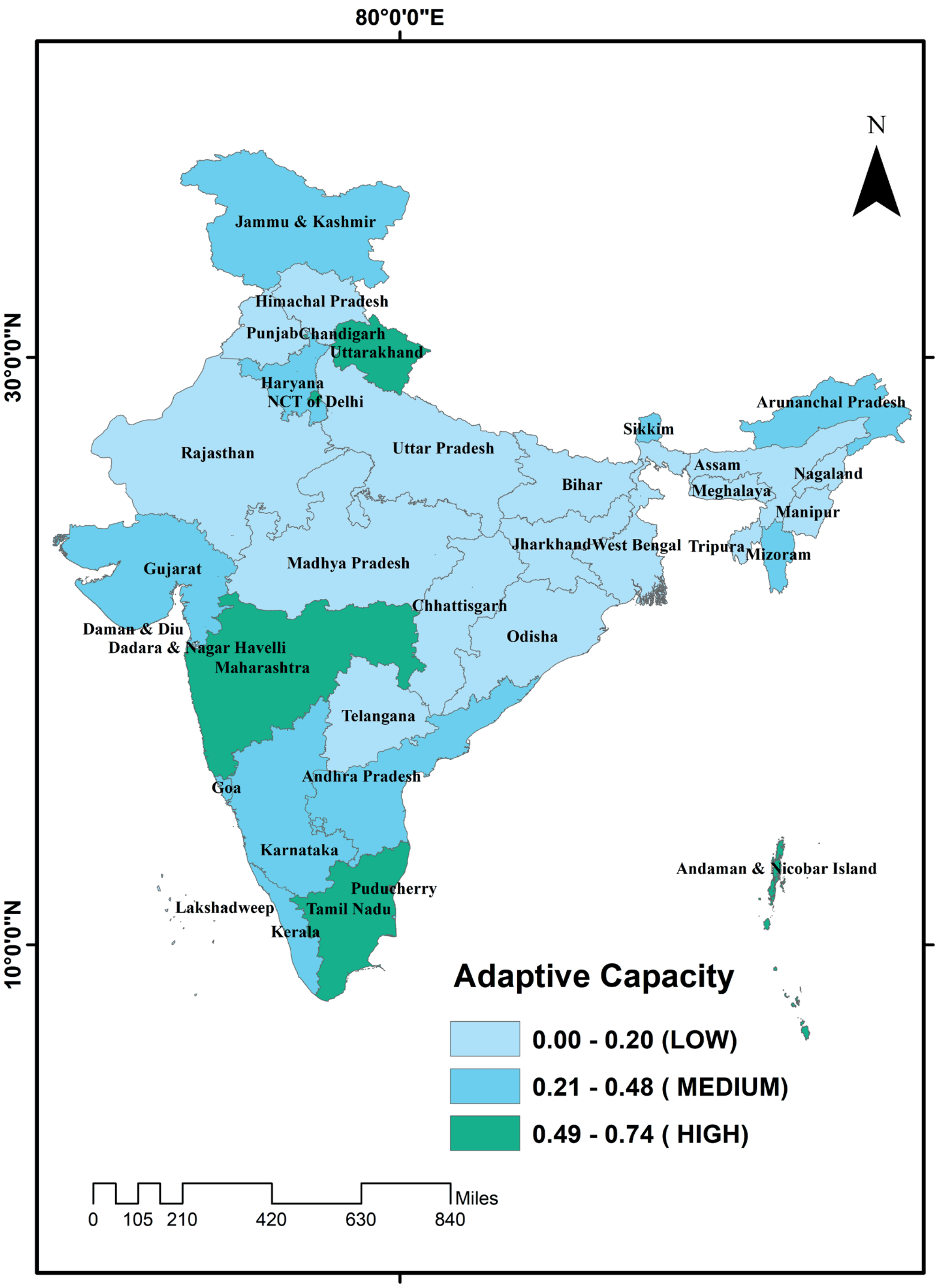

Fig. 4. The map is representing the composite value of Adaptive Capacity in different States and UTs of the country. The final composite value ranges for the adaptive capacity is between (0- 0.74)

et al. 2009). Adaptive capacity erodes the COVID-19 vulnerability whereas exposure and sensitivity accentuate the risks. The scores of the VI range as high as +0.25 to -0.15. The positive values indicate high vulnerability while the negative scores indicate lower vulnerability. The final VI values show that people in Puducherry, Delhi, Goa, Tripura, and Andhra Pradesh, among other states, are relatively more vulnerable to COVID-19 (Fig. 5), on account of high exposure and sensitivity. Though the states like Delhi (0.57), Goa (0.43) and, Puducherry (0.35) scores well on adaptive capacity parameters, the exposure and sensitivity offset the gains when final vulnerability scores are calculated (Fig. 5). People in the states of Uttarakhand, Chandigarh, Mizoram, Haryana, Kerala, and Tamil Nadu have lower vulnerability against COVID-19. Uttarakhand performs well on the adaptive capacity (0.57) parameter against its peers and has relatively less exposure (0.05) (Fig. 5). Chandigarh Performs well due to very good adaptive capacity (0.74) measures, effectively offsetting the high exposure and sensitivity. It is important to note that only relatively smaller states have either very high or very less vulnerability, unlike the big states which have either medium or high vulnerability scores.

CONCLUSION

VI helps understand the priority states, and there is a need for intervention in the high and right direction. Nowadays, globally it has been observed that COVID-19 has developed new strains that spread faster than the original. It can further be added that along with the responsibility of the Government and associated health and related authorities, equal conscious citizens of a nation can play their important role in combating Coronavirus by adopting preventive measures and following guidelines issued by authorities (Shah and Farrow 2020; Zu et al. 2020). Restoring the confidence of the general public in public health measures is crucial,

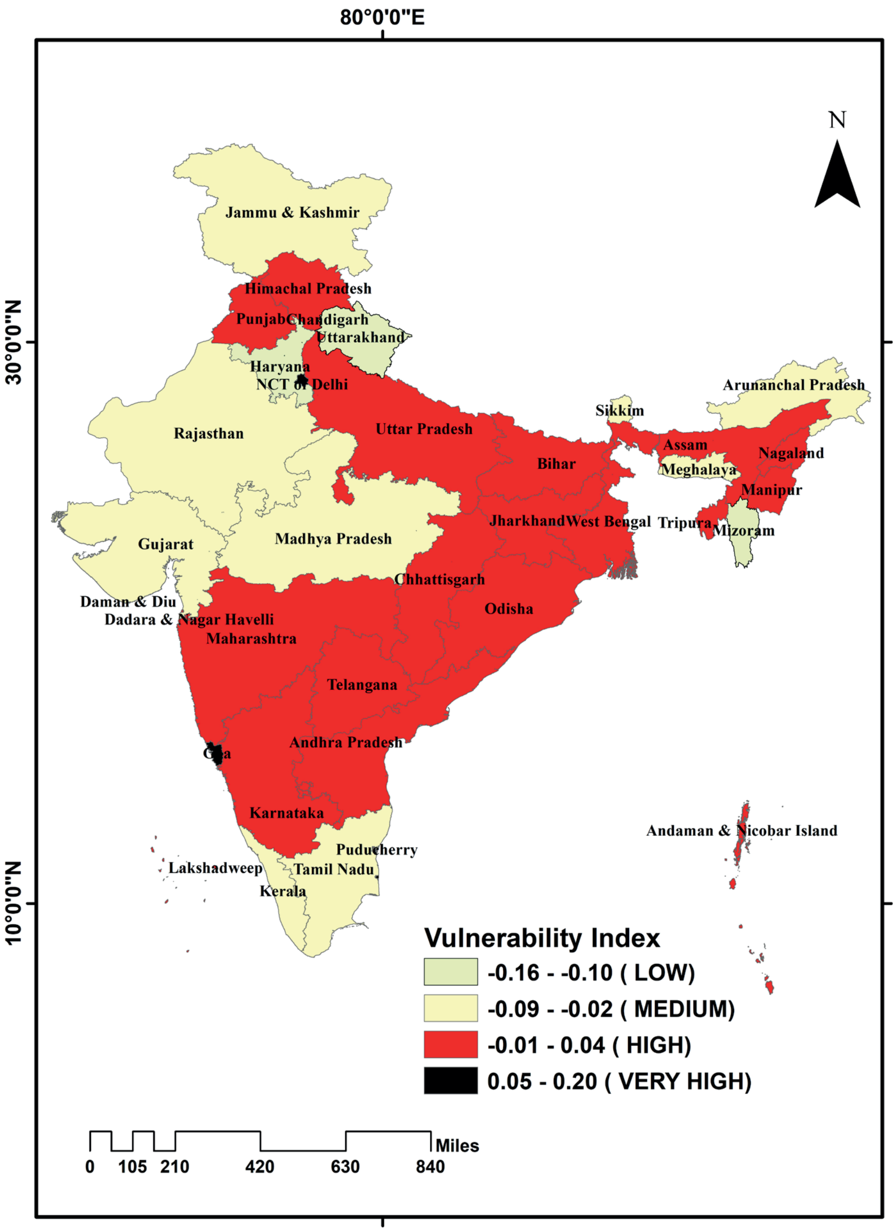

Fig. 5. The Choropleth map is showing the VI value distribution in different States and UTs of the country. The values of the final VI calculation lie between -1 to +1 and have been divided into four classes according to Jenks Natural Breaks classification. The States and UTs having high negative values are categorized as low vulnerable category whereas the States and UTs near positive values and above are categorized into three classes as a medium, high, and very high vulnerable zones

otherwise fear and apprehension might limit the local, national, regional, and international efforts and measures aimed at tackling the COVID-19 outbreak. This is only possible through the joint and coordinated efforts and cooperation between diverse stakeholders at local, national, and global levels (Shah and Farrow 2020). In this situation of wave kind movement of COVID-19 pandemic in the country, this study will be of significant importance for policymakers and will be very helpful to them in identifying the vulnerable states and UTs of the country. ■

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