



Geospatial modelling of COVID-19 vulnerability using an integrated fuzzy MCDM approach: a case study of West Bengal, India

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Abstract

COVID-19 is a worldwide transmitted pandemic that has brought a threatening challenge to Indian society and the economy. The disease has become a public health disaster, which has no effective medication. However, proper management and planning, which includes understanding the transmitting pattern, number of containment zones, vulnerable factors, and level of risk, may break the chain of transmission and reduce the number of cases. Hence, this study has attempted to model the COVID-19 vulnerability using an integrated fuzzy multi-criteria decision-making (MCDM) approach, namely fuzzy-analytical hierarchy process (AHP) and fuzzy-technique for order preference by similarity to ideal solution (TOPSIS) for West Bengal, India, through geographic information system (GIS). A total of 15 parameters were utilised to model the COVID-19 vulnerability, which was further categorised into three criteria: social vulnerability, epidemiological vulnerability, and physical vulnerability. The final vulnerability mapping has been done using these three criteria through the GIS platform. This study reveals that COVID-19 infection highly threatens about 20% of the total area of West Bengal, 23.42% moderately vulnerable, and 57.03% of the area comes under low vulnerability. The highly vulnerable region includes the Kolkata, South 24 Paraganas, and North 24 Paraganas, which are considered highly populated districts of West Bengal. Therefore government agencies should be more focused and plan accordingly to safeguard the community, especially the region with very high COVID-19 vulnerability, from further spreading the infection.

Keywords COVID-19 vulnerability · MCDM · Fuzzy-AHP · Fuzzy-TOPSIS · GIS · West Bengal

Introduction

The first coronavirus disease 2019 (COVID-19) case was detected in Wuhan, China, on 12 December 2019 (Columbus et al. 2020). With the emergence of the first case, the infection starts its rapid dispersal across the globe (Bonilla-Aldana et al. 2020). On 11 March 2020, World Health Organization (WHO 2020a) declared the COVID-19 disease “a pandemic” after reviewing the number of cases spread over the globe and issued some preliminary regulatory determinations for healthcare services against this emerging disease. The WHO (2020a) also suggested that all nations take precautionary measures to control the spreading of this contagious disease. As the virus ambit grew beyond

the geographic boundaries, countries started quarantining the patient in hospitals or at their home, depending on the patient's condition (Harapan et al. 2020). The partial and complete lockdown in many countries was quickly adopted. The programs like physical distancing, social isolation, wearing masks, and the use of sanitiser are initiated as the primary strategies to control the spreading of COVID-19 (WHO 2020b).

Like other countries, India is not an exception. On 27 January 2020, the first case of COVID-19 was reported in Kerala, India (Andrews et al. 2020), and as of 29 August 2021, the country's rank was 2nd on the list, with a total of 3.25 crore confirmed cases of COVID-19 worst-hit countries (WHO 2020c). The government of India and the state governments started taking precautionary measures from the initial stage to restrict the spreading of the virus. On 22 March 2020, the Government of India imposed a 1-day lockdown called Janta Curfew, and subsequently, a phase-wise lockdown was imposed starting from 25 March 2020. The lockdown controlled the early stage community spreading,

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but consequently, the lockdown is directly affecting the economy of India (Zou et al. 2020). The shutdown of the economy is not a permanent solution to this pandemic, and the government soon realise the same after having 37 days of lockdown. The government of India began a phase-wise unlocking from 1 June 2020, giving some relaxation in the movement of the economy. Despite lockdown and implementation of restrictions, the number of confirmed cases keeps rising exponentially, directly putting pressure on India's health system and socioeconomic setup (McAlear 2020). The shortage of oxygen, lack of beds, doctors, and nurses, ill-conditioned hospital infrastructure, shortage of medicines, and need for available vaccination increase the risk of exposure to vulnerability (Banik et al. 2020). In addition, the extended duration closure of factories and offices has already cast a lasting effect on the global economic landscape (Ajami 2020). The most vulnerable groups are the migrant workers who are primarily dependent on the daily wages have preferred to go back to their hometown. Most of them started moving to their designated places by walking or cycling thousands of miles, and many of them died on the verge of returning to their hometown due to poor health from hunger and malnutrition (Singh 2020). People started crowding the railway stations and bus terminals in the hope of reaching home; thus, it leads to the spectra of community transmission and the spreading of the virus into vulnerable groups and poses a considerable threat to humanity.

Vulnerability modelling and mapping through geographic information system (GIS) platforms play a significant role in preventing and controlling infectious diseases. GIS, along with geospatial data, is widespread technology where the user can capture, prepare, manage, aggregate, analyse, and visualise the multi-source, non-geospatial, and geospatial data (Rahman and Saha 2008; Rahman et al. 2014, 2015). Reviewing the literature suggests that certain studies were carried out over different parts of the world where researchers attempted to model COVID-19 spatially (Zhou et al. 2020; Murugesan et al. 2020; Roy et al. 2020). Sarkar (2020) investigated COVID-19 susceptibility in districts of Bangladesh using AHP. Mishra et al. (2020) used the AHP method to model the COVID-19 vulnerability index spatially for India. Mahato et al. 2020 attempted to delineate risk zones of COVID-19 in North East India using the AHP and overlay analysis in the GIS platform. Rahman et al. (2021) used integrated AHP and weighted sum method (WSM) to model and map the COVID-19 vulnerability for Bangladesh. Gao et al. (2021) tried to build a regional vulnerability index model using the AHP method for Wuhan, Beijing, Urumqi, and Dalian, China. Shadeed and Alawna (2021) estimated the COVID-19 vulnerability index using AHP and mapped the COVID-19 vulnerability for the West Bank, Palestine. Thus, the literature reviews indicate that the researchers primarily focused on a single MCDM approach

except for Rahman et al. (2021). They mostly used AHP and attempted to evaluate the vulnerability using the country level dataset. In the case of regional vulnerability modelling, the developed model allows the assessment of various parameters that influence the spread of infectious diseases and the risk prediction analysis of unaffected areas (Gao et al. 2021), leading to the objective of this study. The aim of the work is (a) to use conventional regional attributes to model the COVID-19 vulnerability for West Bengal, India, using integrated MCDM models, (b) to map the COVID-19 vulnerability through the GIS platform, and (c) to identify the potentially vulnerable zone of COVID-19 infection that can help the government agencies to control and prevent the spread of the disease.

Data used and methods

Study area

This study geospatially models the COVID-19 vulnerability for the state of West Bengal, India (Fig. 1). The reasons behind the selection of this state will become apparent in the following discussion. In further discussion, two significant aspects will be covered: regional and epidemic information data.

The regional data reveal that West Bengal is situated in the eastern region of India and with 91,347,736 inhabitants and a population density of 1029/km² (CENSUS 2011). The state is stretched from the foot of Darjeeling Himalayas in the North to the Bay of Bengal in the South and from the edge of Chhotanagpur high lands in the west to the border of Bangladesh and Assam in the east (Biswas et al. 2021a). The natural vegetation occupies about 14% of the total area of the state. A significant segment of the population depends on agriculture. A complex combination of cultures, religions, caste, and languages can be found in West Bengal. In this study, the districts were mentioned according to CENSUS 2011. Hence, the newly formed district Jhargram is included under West Medinipur, Alipurduar under Jalpaiguri, Kalimpong under Darjeeling, East, and West Bardhaman were merged into Bardhaman.

Now coming to the epidemic data, on 17 March 2020, West Bengal has reported its first COVID-19-positive case. Later on, the Government of West Bengal started publishing daily bulletin related to COVID-19, and the public can monitor the data available in its official portal for management and researches "<https://www.wbhealth.gov.in/pages/corona/bulletin/>". About 15.4 lakhs of COVID-19 positive cases were reported, 15 lakhs of patients were cured and discharged, and about 18 thousand patients have died in West Bengal till 29 August 2021. A significant number of the positive cases and deceased were found in the district

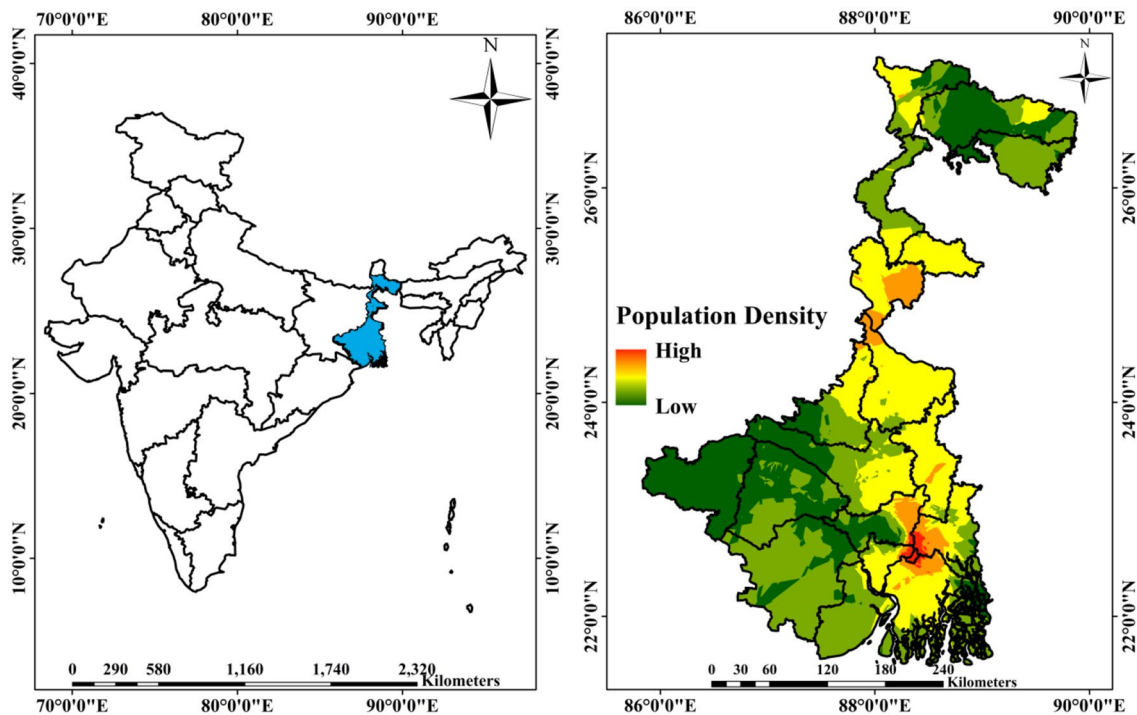


Fig. 1 Location of the study area with population density

of North 24 Paraganas and Kolkata, and these two districts were considered highly populated regions of West Bengal. Almost 400 government and private hospitals were involved in treating COVID-19 cases. Thus, the selection of West Bengal makes this case study an important one. The epidemic data were collected and compiled from the portal of the state government and the central government of India. The subsequent section will highlight the study method and the data used in this study with their authorised sources.

Study method

The study method followed in the modelling of COVID-19 vulnerability involved four components:

- All variables involved in modelling the COVID-19 vulnerability were defined thoroughly and categorised into the social, epidemiological, and physical domains.
- The fuzzy-AHP method was applied to construct the importance matrix and calculate the priority weights of the associated variables.
- The mapping of social, epidemiological, and physical vulnerability has been done using the estimated weights of the variables through the GIS platform.
- The fuzzy-TOPSIS method was applied to estimate the rank of the criteria and mapped the COVID-19 vulnerability for West Bengal, India.

Data used and sources

The datasets used in this study to model the COVID-19 vulnerability are freely available in the public domain (Fig. 2). The social dataset, including the population, number of educated people, employment, urban population, and popular and religious places, were collected from the Office of the Registrar General & Census Commissioner, India “<https://censusindia.gov.in/>”. The parameters involved in the epidemiological domain are compiled from the health bulletin of the Government of West Bengal “<https://www.wbhealth.gov.in/pages/corona/bulletin/>” and the Ministry of Health and Family Welfare, Government of India “<https://www.mohfw.gov.in/>”. The dataset of COVID-19 hospitals was extracted from the West Bengal Integrated COVID Management System “https://excise.wb.gov.in/chms/Portal_Default.aspx/”, and remaining parameters were obtained from OpenStreetMap “<https://www.openstreetmap.org/>”. All the used datasets were last accessed on 29 May 2021.

Model construction and analysis

Multiple criteria decision-making (MCDM) is a general term used for all the models that help make decisions based on decision-makers’ preferences (Zavadskas and Turskis 2011). The MCDM models allow the user to fragment complex problems into minor ones. After considering the proper

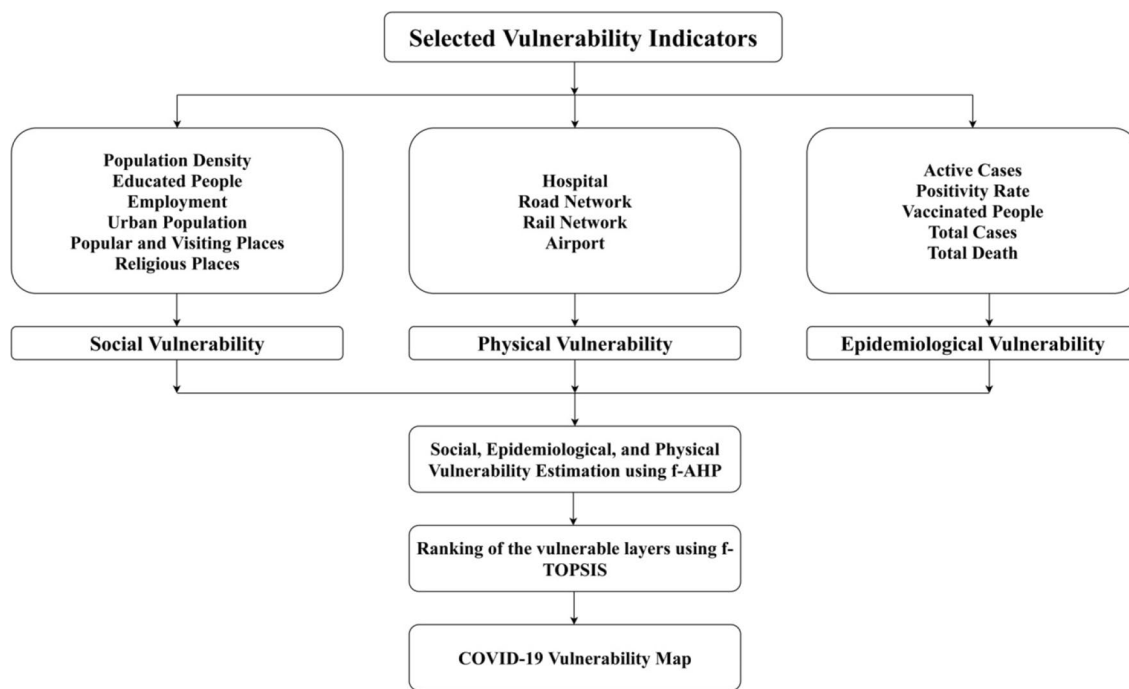


Fig. 2 Flowchart of adopted methodology to model the COVID-19 vulnerability for West Bengal

weights of the variables through experiments, experts' knowledge, and previously available literature, an appropriate judgment can be made for these minor problems. Subsequently, these minor problems can be again resembled to have a clear picture, and the decision-maker will be able to make the appropriate decisions according to their analysis. In this study, two MCDM models were integrated to model the COVID-19 vulnerability: fuzzy-analytical hierarchy process (AHP) and fuzzy-technique for order preference by similarity to ideal solution (TOPSIS). The steps involved in these methods were discussed in detail in the subsequent sub-section.

Fuzzy-analytic hierarchy process

The Analytic Hierarchy Process (AHP) (Saaty 1980) is a widely used MCDM model that can be progressively integrated with many other models. With the advancement, the researchers focused on developing fuzzy techniques that deal with uncertainties. The fuzzy-AHP is an extended version of AHP that supports systematic alternative selection and justification (Zadeh 1965). In fuzzy-AHP, the fixed value was replaced by interval judgment, which gives the user more confidence. Many researchers developed their own fuzzy-AHP methods, but most ones were formulated by Van Laarhoven and Pedrycz (1983), Buckley (1985), and Chang (1996). In the present work,

the fuzzy-AHP method developed by Buckley (1985) was used. The steps of fuzzy-AHP are as follows:

Step 1: Pairwise comparison matrix was generated using the fuzzy triangular scale (Table 1).

Step 2: Compute the fuzzy geometric mean value \tilde{r}_i using Eq. (1) for each criterion.

$$\tilde{r}_i = (\tilde{a}_{i1} * \tilde{a}_{i2} * \dots * \tilde{a}_{in})^{1/n} \tag{1}$$

Step 3: For each criterion, compute the fuzzy weight \tilde{w}_i using Eq. (2)

Table 1 Linguistic variables for pairwise comparison of each criterion (Source: Kannan et al. 2013)

Linguistic variables	Triangular fuzzy scale	Triangular fuzzy reciprocal scale
Equally strong	(1, 1, 1)	(1, 1, 1)
Moderately strong	(2, 3, 4)	(1/4, 1/3, 1/2)
Strong	(4, 5, 6)	(1/6, 1/5, 1/4)
Very strong	(6, 7, 8)	(1/8, 1/7, 1/6)
Extremely strong	(9, 9, 9)	(1/9, 1/9, 1/9)
Intermediate values	(1, 2, 3)	(1/3, 1/2, 1)
	(3, 4, 5)	(1/5, 1/4, 1/3)
	(5, 6, 7)	(1/7, 1/6, 1/5)
	(7, 8, 9)	(1/9, 1/8, 1/7)

$$\tilde{w}_i = \tilde{r}_i * (\tilde{r}_1 + \tilde{r}_2 + \dots + \tilde{r}_n)^{-1}, \tag{2}$$

where $\tilde{r}_k = (l_k, m_k, u_k)$ and $(\tilde{r}_k)^{-1} = (1/u_k, 1/m_k, 1/l_k)$.

Step 4: Defuzzification of the fuzzy weight using the centre of area method

$$\tilde{w}_i = \frac{l_i + m_i + u_i}{3}. \tag{3}$$

Fuzzy-TOPSIS

Hwang and Yoon (1981) formulated the technique for order preference by similarity to ideal solution (TOPSIS). This method considers that the selected alternative should have the shortest distance to Positive Ideal Solution and the farthest distance to the Negative Ideal Solution. Later on, Chen (2000) extended the model and named as fuzzy-TOPSIS. The steps involved in the fuzzy-TOPSIS are as follows:

Step 1: Using the fuzzy triangular scale (Table 1), construct the fuzzy decision matrix of the alternatives.

Step 2: Normalisation of the decision matrix,

$$\tilde{R} = [\tilde{r}_{ij}], \tag{4}$$

For non - beneficial criteria,

$$c_j^- = \min_i \{a_{ij}\} \text{ and } \tilde{r}_{ij} = \left(\frac{c_j^-}{c_{ij}}, \frac{c_j^-}{b_{ij}}, \frac{c_j^-}{a_{ij}} \right), \tag{5}$$

For beneficial criteria, $c_j^* = \max_i \{c_{ij}\}$ and $\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*} \right)$. (6)

Step 3: Compute weighted normalised decision matrix $\tilde{V} = [\tilde{v}_{ij}]$ using Eq. (6)

$$\tilde{v}_{ij} = \tilde{r}_{ij} * \tilde{w}_j. \tag{7}$$

Here, \tilde{w}_j is computed using the fuzzy-AHP method (Table 5).

Step 4: Compute Fuzzy Negative Ideal Solution (FNIS) and Fuzzy Positive Ideal Solution (FPIS)

$$A^- = (\tilde{v}_1^-, \tilde{v}_2^-, \dots, \tilde{v}_n^-) \text{ where } \tilde{v}_j^- = \min_i \{v_{ij1}\}, \tag{8}$$

$$A^* = (\tilde{v}_1^*, \tilde{v}_2^*, \dots, \tilde{v}_n^*) \text{ where } \tilde{v}_j^* = \max_i \{v_{ij3}\}. \tag{9}$$

Step 5: Calculate the distance from each alternative to the FNIS and the FPIS

$$d_i^- = \sum_{j=1}^n d(\tilde{v}_{ij}, \tilde{v}_j^-); \quad d_i^* = \sum_{j=1}^n d(\tilde{v}_{ij}, \tilde{v}_j^*). \tag{10}$$

Step 6: Compute the closeness coefficient for each alternative

$$\text{Closeness coefficient } (CC_i) = \frac{d_i^-}{d_i^- + d_i^*}. \tag{11}$$

Based on the closeness coefficient, the ranking of alternatives has been done. The best alternative has the highest closeness coefficient (Table 6).

Implementation of integrated MCDM models

The parameters were initially standardised based on their influence into five classes (very high, high, medium, low, and very low) using natural breaks on the GIS platform and categorised into social, epidemiological, and physical domains. After standardisation, the next step was to establish weights for the factors based on their relative significance to vulnerability to each of the other parameters. The weights for each parameter were evaluated by fuzzy-AHP and are presented in Tables 2, 3 and 4. Expert knowledge and the previously available literature were thoroughly reviewed for evaluating the weights using the fuzzy-AHP technique. Finally, the social, epidemiological, and physical vulnerability was estimated by a weighted sum method (WSM) and mapped using the GIS platform for West Bengal. Then, fuzzy-TOPSIS is applied as described above to generate the COVID-19 vulnerability map for West Bengal by ranking the three vulnerability layers (Tables 5, 6). The COVID-19 vulnerability map was also classified into five classes using natural breaks as a way of standardisation. Thus, it can be said that the developed model was an integration of fuzzy-AHP and fuzzy-TOPSIS, where the results of fuzzy-AHP were applied to model the COVID-19 vulnerability using fuzzy-TOPSIS through GIS. The following section presents a comprehensive discussion on the used parameters, their influence on the results, and some preventive measures to break the chain of COVID-19 has been given.

Results and discussion

Social domain

The social domain includes the parameters such as population density, educated people, and employability, and urban population, popular and religious places (Fig. 2). Coming to the population density, West Bengal is one of the populated states of India, with a population density of about 1029 km² (CENSUS 2011), having several popular and religious places visited by the locals and the tourists throughout the year. In general, the cities in India are highly crowded and unplanned with rapid urbanisation as more people, especially migrant

Table 2 Assessment of decision matrix, priority, and rank for social vulnerability criteria

	1	2	3	4	5	6
1	(1, 1, 1)	(1, 2, 3)	(1, 2, 3)	(2, 3, 4)	(2, 3, 4)	(4, 5, 6)
2	(1/3, 1/2, 1)	(1, 1, 1)	(1, 2, 3)	(2, 3, 4)	(2, 3, 4)	(3, 4, 5)
3	(1/3, 1/2, 1)	(1/3, 1/2, 1)	(1, 1, 1)	(1, 2, 3)	(1, 2, 3)	(2, 3, 4)
4	(1/4, 1/3, 1/2)	(1/4, 1/3, 1/2)	(1/3, 1/2, 1)	(1, 1, 1)	(1, 2, 3)	(2, 3, 4)
5	(1/4, 1/3, 1/2)	(1/4, 1/3, 1/2)	(1/3, 1/2, 1)	(1/3, 1/2, 1)	(1, 1, 1)	(1, 2, 3)
6	(1/6, 1/5, 1/4)	(1/5, 1/4, 1/3)	(1/4, 1/3, 1/2)	(1/4, 1/3, 1/2)	(1/3, 1/2, 1)	(1, 1, 1)

Sl no	Selected layers	Classes (based on vulnerability)					Priority (%)
		Very low (1)	Low (2)	Moderate (3)	High (4)	Very high (5)	
1	Population density (per km ²)	< 3531	3531–4888	4888–6888	6888–10,602	> 10,602	31.50
2	Educated people density (per km ²)	> 8824	8824–5409	5409–3642	3642–2641	< 2641	25.00
3	Employment (%)	> 41.69	41.69–36.97	36.97–33.62	33.62–30.57	< 30.57	17.30
4	Urban population (%)	< 26.36	26.36–32.47	32.47–36.82	36.82–43.90	> 43.90	11.80
5	Popular and visiting places (per degree ²)	< 558	558–1732	1732–4527	4527–9054	> 9054	09.10
6	Religious places (per degree ²)	< 43	43–174	174–410	410–734	> 734	05.30

Table 3 Assessment of decision matrix, priority, and rank for epidemiological vulnerability criteria

	1	2	3	4	5
1	(1, 1, 1)	(1, 2, 3)	(1, 2, 3)	(2, 3, 4)	(3, 4, 5)
2	(1/3, 1/2, 1)	(1, 1, 1)	(1, 2, 3)	(1, 2, 3)	(2, 3, 4)
3	(1/3, 1/2, 1)	(1/3, 1/2, 1)	(1, 1, 1)	(1, 2, 3)	(1, 2, 3)
4	(1/4, 1/3, 1/2)	(1/3, 1/2, 1)	(1/3, 1/2, 1)	(1, 1, 1)	(1, 2, 3)
5	(1/5, 1/4, 1/3)	(1/4, 1/3, 1/2)	(1/3, 1/2, 1)	(1/3, 1/2, 1)	(1, 1, 1)

Sl no	Selected layers	Classes (based on vulnerability)					Priority (%)
		Very low (1)	Low (2)	Moderate (3)	High (4)	Very high (5)	
1	Active cases (number)	< 2685	2685–4967	4967–8323	8323–12,551	> 12,551	35.70
2	Positivity rate (%)	< 13.95	13.95–18.16	18.16–22.93	22.93–27.70	> 27.70	24.80
3	Vaccination doses (number)	> 746,850	746,850–679,805	679,805–432,798	552,773–432,798	< 432,798	18.20
4	Total confirmed cases (number)	< 37,629	37,629–60,964	60,964–83,850	83,850–109,429	> 109,429	12.80
5	Total death (number)	< 323	323–675	675–1071	1071–1566	> 1566	08.50

Table 4 Assessment of decision matrix, priority, and rank for physical vulnerability criteria

	1	2	3	4
1	(1, 1, 1)	(1, 2, 3)	(2, 3, 4)	(3, 4, 5)
2	(1/3, 1/2, 1)	(1, 1, 1)	(1, 2, 3)	(2, 3, 4)
3	(1/4, 1/3, 1/2)	(1/3, 1/2, 1)	(1, 1, 1)	(1, 2, 3)
4	(1/5, 1/4, 1/3)	(1/4, 1/3, 1/2)	(1/3, 1/2, 1)	(1, 1, 1)

Sl no	Selected layers	Classes (based on vulnerability)					Priority
		Very low (1)	Low (2)	Moderate (3)	High (4)	Very high (5)	
1	Distance from COVID-19 Hospital (km)	< 10.06	10.06–19.09	19.09–32.23	32.23–52.78	> 52.78	44.90%
2	Road Network (km)	< 3.83	3.83–13.01	13.01–29.28	29.28–49.98	> 49.98	28.40%
3	Rail Network (km)	< 7.65	7.65–18.45	18.45–32.39	32.39–50.51	> 50.51	16.70%
4	Distance from Airports (km)	< 29.11	29.11–50.64	50.64–74.06	74.06–103.19	> 103.19	10.00%

Table 5 Decision matrix for ranking the alternatives using the fuzzy-TOPSIS techniques

Criteria/alternatives	Social vulnerability	Epidemiological vulnerability	Physical vulnerability
Social characteristics	(1, 1, 1)	(1, 2, 3)	(2, 3, 4)
Epidemiological characteristics	(1/3, 1/2, 1)	(1, 1, 1)	(1, 2, 3)
Physical characteristics	(1/4, 1/3, 1/2)	(1/3, 1/2, 1)	(1,1,1)
Fuzzy weights calculated based on Fuzzy-AHP	(0.279, 0.540, 0.958)	(0.153, 0.297, 0.603)	(0.097, 0.163, 0.332)

Table 6 Weighted normalised decision matrix and ranking of alternatives using the fuzzy-TOPSIS method

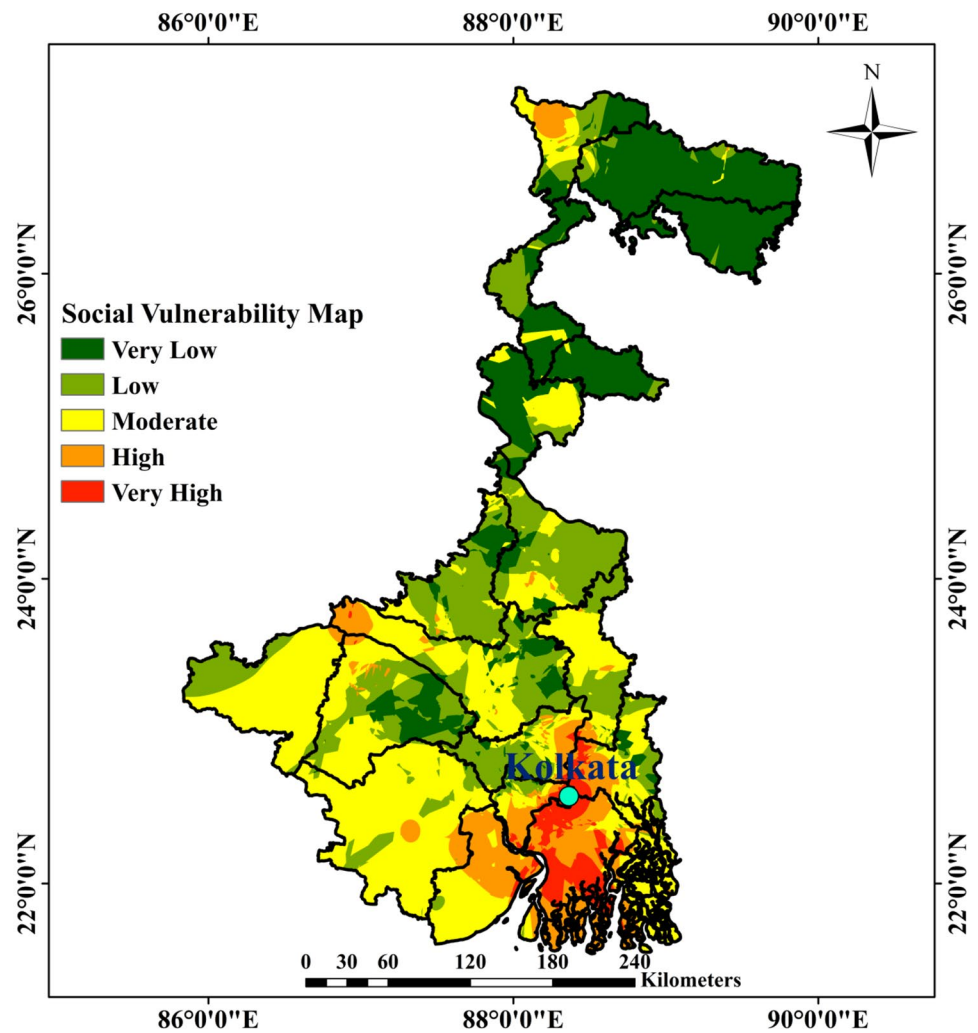
Criteria/alternatives	Social vulnerability	Epidemiological vulnerability	Physical vulnerability	d_i^*	d_i^-	CC	Rank
Social characteristics	(0.279, 0.540, 0.958)	(0.051, 0.198, 0.603)	(0.049, 0.122, 0.332)	0	0.615	1	1
Epidemiological characteristics	(0.093, 0.270, 0.958)	(0.051, 0.099, 0.200)	(0.024, 0.082, 0.249)	0.484	0.414	0.461	2
Physical characteristics	(0.070, 0.180, 0.479)	(0.017, 0.050, 0.200)	(0.024, 0.041, 0.083)	0.767	0	0	3
Fuzzy positive ideal solution formula	(0.279, 0.540, 0.958)	(0.051, 0.198, 0.603)	(0.049, 0.122, 0.332)				
Fuzzy negative ideal solution formula	(0.070, 0.180, 0.479)	(0.017, 0.050, 0.200)	(0.024, 0.041, 0.083)				

workers, start shifting from rural areas to urban areas in the hope of better livelihood. As a result, these migrant workers start creating slums within the cities, increasing the population density region, and creating unnecessary pressure on the available resources. With the creation of the slums, the risk of physical contact will be greater, leading to the spread of highly contagious COVID-19 (Rocklöv and Sjödin 2020; Bhadra et al. 2021). The following parameter used for this study was education, one of the essential resources to overcome the disaster, including COVID-19. Zhong et al. 2020 claimed that education creates awareness, especially among vulnerable groups like children, women, and the physically disabled. With proper education and understanding, one can prevent getting infected and deal with asymptomatic and mild symptomatic persons. Employment is followed by education, another resource of livelihood. As discussed in the introduction section, there is a considerable impact on the economy due to lockdown. Lakhs of people get unemployed, and this disaster mainly hits the migrant workers, making them vulnerable to infection due to malnutrition/hunger (Ahmed et al. 2020). With urbanisation, the demand for convenience becomes more, and because of that, malls, parks, and religious places keep developing in India, and West Bengal is not an exception. The government should timely and adequately update the information about populated sites, sacred places, and visiting places to minimise the risk factor (Wisner et al. 2003).

The weight of the parameters included in the social domain was calculated using the fuzzy-AHP (Table 2). With the help of calculated weights, the geospatial mapping has been done and termed as 'social vulnerability.' The social

vulnerability shows non-uniformity with very high vulnerability in Kolkata and some portions of North and South Paraganas (Fig. 3). These areas were mostly dominated by higher population density, one of the leading parameters of social vulnerability. In the northern part of West Bengal, the social vulnerability is very low, including Cooch Behar and Jalpaiguri, as the population density is much lower in the districts at the foot of the Himalayan range. The very low social vulnerability has also occupied the South and North Dinajpur and Malda districts. A significant portion of the area includes under moderate vulnerability, i.e., about 36.65% (Table 7), including West Medinipur, Purulia, and some significant segments of Bankura, Bardhaman, West Medinipur, and Nadia district. The numerical values also reveal that 23.59% of the total area included under the low vulnerability; in contrast, only 4.17% of the region was considered a very high vulnerability region. Interestingly, a substantial number of people reside in this 4.17% area, which makes the area more socially vulnerable, and the chances of spreading the COVID-19 virus are also higher. 24.78% of the area comes under low vulnerability and residual under high social vulnerability (Table 7). The West and East Medinipur, Bankura, Purulia, and the region of Sunderban include a significant section of the rural population of West Bengal with less literacy rate and employment (as most of them depending on agriculture). Still, due to less population density, these regions were included in moderate-to-high social vulnerability. As discussed earlier, education is crucial in handling COVID-19 patients and is succeeded by employment. Therefore, it is suggested that government can break the chain of infection by giving proper education

Fig. 3 Social vulnerability map



and training, especially to the rural section of the state. It is also recommended that the government focuses on the regions with very high social vulnerability and restrictions with adequate measures that can be implemented in highly crowded regions.

Epidemiological domain

The total active cases, positivity rate, vaccinated people, confirmed cases, and deceased, all these parameters were included in the epidemiological domain (Fig. 2). It was discussed earlier that currently, India ranks just after the United States of America in terms of total COVID-19 cases (WHO 2020c). Within India, West Bengal ranks 7th with about 15.4 lakhs positive cases (Ministry of Health and Family Welfare 2021). In the epidemiological domain, the forecast factor is the total number of active cases. Several reported cases from a particular region may push it to become a hotspot for further spreading (Imdad et al. 2021). Hence, to reduce the further spreading of the virus, the authority should take

preventive and strict measures, and rapid testing can also be done, which leads to the positivity rate. The positivity rate gives an approximate idea about the percentage of infected people out of the total number of tested persons. A higher positivity rate in an area indicates that the virus keeps dispersion to a significant population, making the region vulnerable. The next one is the number of deceased people. The second wave of COVID-19 in India took many lives, primarily due to obsolete and poor healthcare facilities. It creates tremendous pressure on the health care system, and West Bengal is not an exception. Biswas et al. 2021b concluded that according to gender, the increased risk of mortality is more in male COVID-19 patients compared to females. In terms of age group, patients with age ≥ 50 years were at a significantly high risk of mortality compared with those aged < 50 years. The mortality rate is also higher in patients with a medical history of kidney disease, cardiovascular disease, cerebrovascular disease, respiratory disease, hypertension, diabetes, and cancer. The immediate solution to eliminating the COVID-19 is the complete vaccination.

Table 7 Area under different vulnerabilities in West Bengal

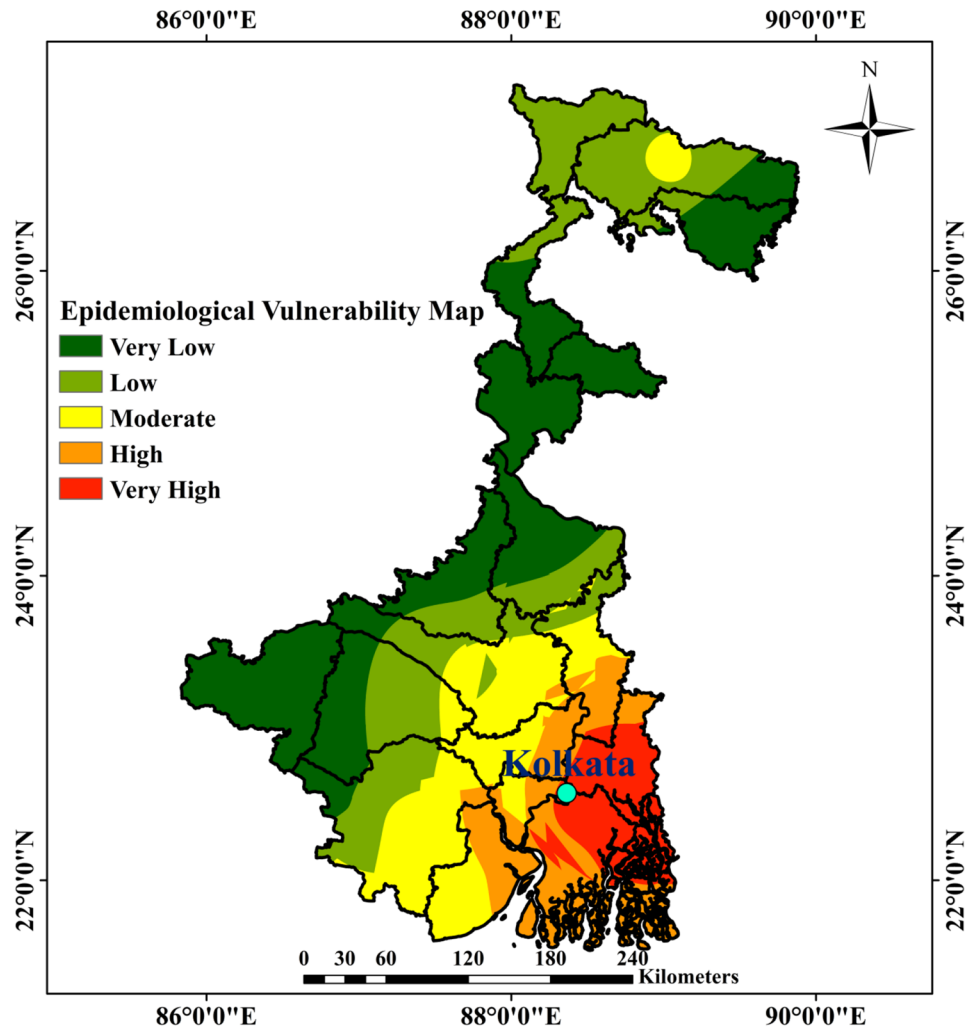
Vulnerability	Level of vulnerability	Area (km ²)	Area (%)
Social vulnerability	Very low	20,937	23.59
	Low	21,997	24.78
	Moderate	32,524	36.65
	High	9596	10.81
	Very high	3698	4.17
			88,752
Epidemiological vulnerability	Very low	30,281	34.12
	Low	22,517	25.37
	Moderate	16,990	19.14
	High	11,498	12.96
	Very high	7466	8.41
			88,752
Physical vulnerability	Very low	31,711	35.73
	Low	29,716	33.48
	Moderate	16,273	18.34
	High	8191	9.23
	Very high	2861	3.22
			88,752
COVID-19 vulnerability	Very low	26,585	29.95
	Low	24,038	27.08
	Moderate	20,787	23.42
	High	11,741	13.23
	Very high	5601	6.31
			88,752

Many countries attempted to develop the vaccinations, and some of the authorised vaccines are Moderna (United States of America), Sputnik V (Russia), CoronaVac (China), AstraZeneca, also known as Covishield (United Kingdom), Covaxin (India). In India, the most used vaccines are Covishield and Covaxin, which are freely available in government health care units and paid one at private hospitals. About 61 crores of total vaccination doses were provided in India till 29 August 2021; out of that, 3.5 doses were given in West Bengal (National Co-Win Statistics 2021).

In the developed model, the weights of the parameters included in the epidemiological domain are estimated using the fuzzy-AHP technique (Table 3). The highest importance was given to the total active cases, as the active cases are the carrier of the virus, and they might infect others directly or indirectly. The map developed using the evaluated weights is termed 'epidemiological vulnerability' and shows non-uniformity in the included areas (Fig. 4). Nearly 60% of the total area is included under the very low–low epidemiological vulnerability; in contrast, only 21.37% of the area comes under very high–high vulnerability. The remaining area is moderately vulnerable (Table 7). The developed map reveals that Kolkata and North and South 24 Paraganas have a very high epidemiological vulnerability. In West Bengal, the highest number of confirmed cases was registered by

North 24 Paraganas which includes almost 21% of the total number of cases in West Bengal, followed by Kolkata, including 20.3% cases; cumulatively, about 41.3% of cases came from these two majorly populated districts (National Co-Win Statistics 2021). As discussed earlier, these two districts are highly populated and urbanised, so the chances of spreading the virus are much higher in these regions. In terms of death related to COVID-19, Kolkata ranked one, followed by North 24 Paraganas, and cumulatively included 52% of the total deceased in West Bengal (National Co-Win Statistics 2021). Regarding positivity, the North 24 Paraganas have the highest positivity rate, almost 36%, followed by Nadia and Kolkata having a positivity rate of more than 30% (Ministry of Health and Family Welfare 2021). Thus, the government is more focused on applying adequate restrictions and preventive measures, especially in these districts, and attempting to vaccinate the majority of the population. Kolkata received the maximum number of doses out of the total vaccination doses applied in the people of West Bengal, followed by North 24 Paraganas and Bardhaman. A significant segment of Nadia, Hooghly, Howrah, and East Medinipur districts were included under high epidemiological vulnerability. South Dinajpur, Purulia, Malda, and the considerable portion of Cooch Behar, North Dinajpur, Murshidabad, Birbhum, and Bankura are very low

Fig. 4 Epidemiological vulnerability map



epidemiologically vulnerable. Purulia has the least number of active cases, followed by South Dinajpur and Birbhum and concerning positivity rate Cooch Behar, Murshidabad, Malda, and Purulia are the only districts having a positivity rate of less than 10% (National Co-Win Statistics 2021). Therefore, it is suggested that the government should focus more on vaccinating the people, especially in areas with very high epidemiologically vulnerable.

Physical domain

The physical domain is an essential criterion for modelling and mapping the COVID-19 vulnerability, including parameters like COVID-19 hospitals, road and rail networks, and airport distance. As discussed in the study area, almost 400 government and private hospitals treated the COVID-19 patients. Imdad et al. (2021) commented that in India, the facilities available in the primary health care systems were obsolete and ill-maintained, which cannot handle COVID-19 patients efficiently. Hence, the hospitals involved in

COVID-19 are mostly multi-super-speciality hospitals with a good number of beds, staff, and the facility of ICU and ventilation for critical patients. The government of West Bengal tried its best to accommodate at least one COVID-19 super-speciality hospital in a district. Still, some hospitals are far from the reach of the rural section of the population. In that scenario, the patient has to depend on the road or rail network. In some critical instances, the patient must be transferred to another location via aircraft for better facility and treatment; otherwise, we might lose the patient, while Albrecht et al. (2020) discussed the challenges faced by air ambulance services when transporting highly infectious COVID-19 patients. With the increment in the number of cases and implementation of lockdown with restrictions in the movement of the trains in several worst-affected states, the patients are mainly dependent on the road networks. The Indian railway works effectively to fulfil oxygen requirements, which was the primary necessity of patients during the second wave of COVID-19 through the freight train called 'Oxygen Express.' Around 480 Oxygen Expresses

were operationalised throughout India. The Indian railway also transported 200 metric tons of liquid medical oxygen to Bangladesh (Ministry of Railways 2021).

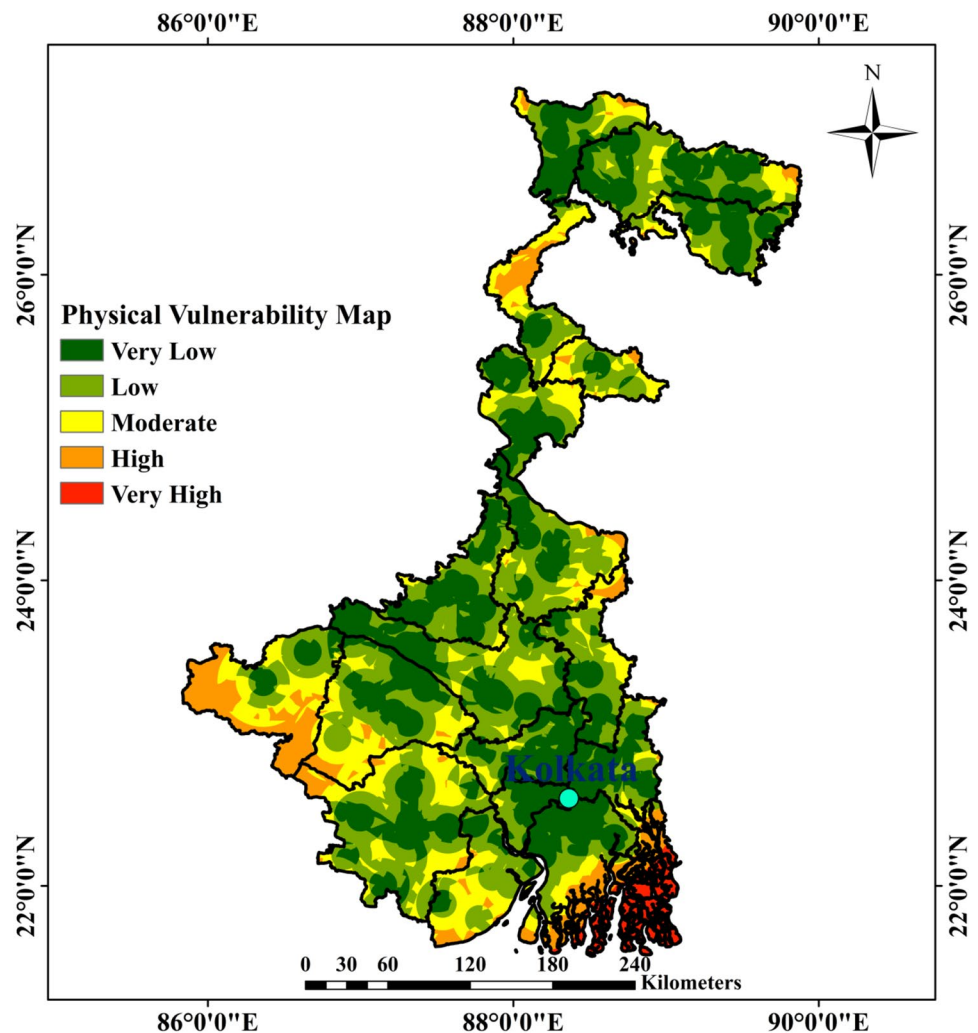
The physical vulnerability map has been developed using the weights calculated by the fuzzy-AHP method (Table 4). The numerical value indicates that about 70% of the total area comes under low-to-very low physical vulnerability. In contrast, high-to-very high vulnerability includes about 13% of the total landmass, which shows that the government of West Bengal and the central government work hand in hand to develop infrastructure and communication networks, and the residual area is moderately vulnerable (Table 7). The geospatial mapping of physical vulnerability reveals that most major cities, including Kolkata, are well connected and have many COVID-19 hospitals (Fig. 5). Most of the COVID-19 hospitals, primarily private hospitals, are available in metropolitan cities. The Sunderban region in North and South 24 Paraganas, where most of the portion is covered by mangrove forest, is highly vulnerable. A significant percentage of the rural population in this region depends on

the forest for their livelihood. The construction of road or rail networks may harm the natural ecosystem and the livelihood of the locals. The state government provides primary health care facilities in this region which can deal with mild COVID-19 cases. However, in severe cases, the patients are referred to the nearest town or super-speciality hospital, where the patient has to travel far through an undeveloped road network. A large fraction of the area of Purulia, North Dinajpur, comes under high vulnerability and also includes a minor segment of Bankura, Hooghly, East Medinipur, and Nadia. Hence, the government of West Bengal is trying its best to allocate hospitals and beds specialised for handling COVID-19 cases. For critical cases, the central government allows defence airports and emergency railway services to carry the patients to other locations as per the requirements.

COVID-19 vulnerability mapping

The fuzzy-TOPSIS methodology was applied to rank the available criteria and mapped the COVID-19 vulnerability

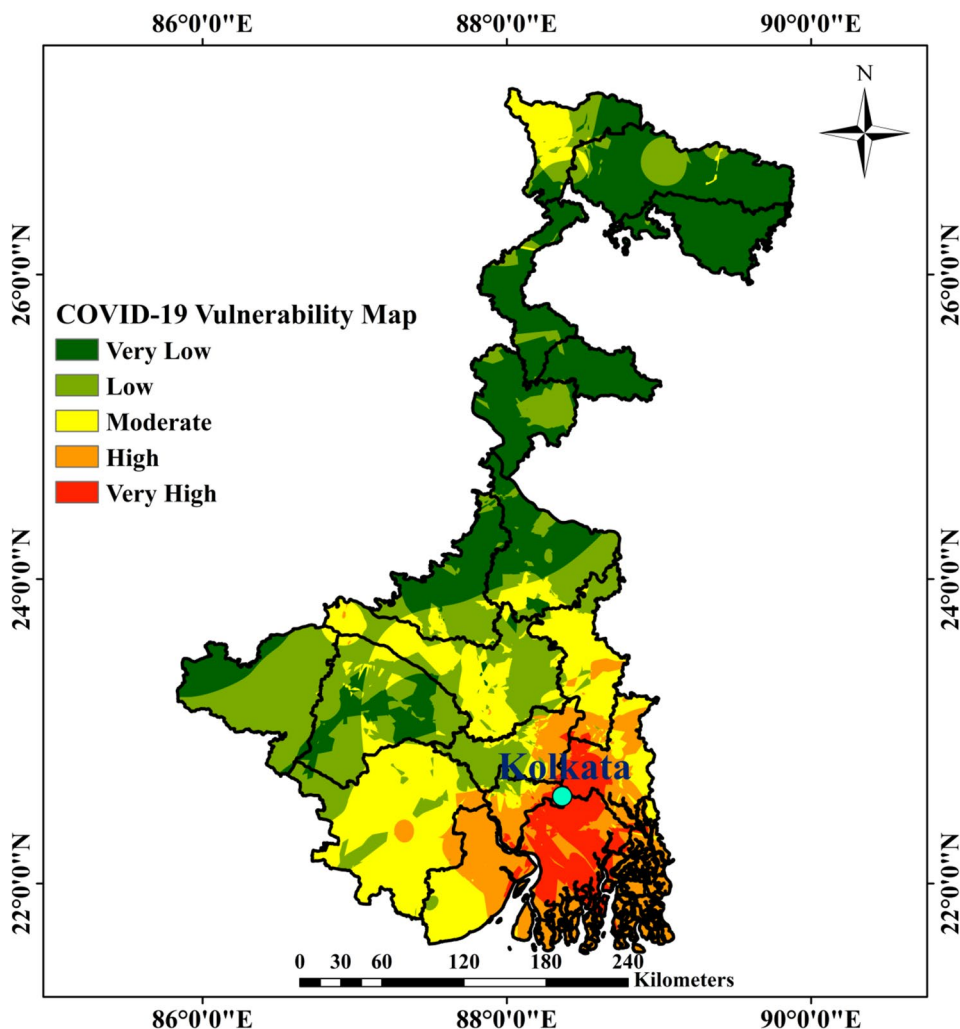
Fig. 5 Physical vulnerability map



through the GIS platform. The entire calculation of the adopted method is presented in Tables 5 and 6. The result shows that 29.95% of the total area is under very low COVID-19 vulnerability, 27.08% low vulnerability, 23.42% moderately vulnerable, 13.23% highly vulnerable, and only 6.31% of the total area is under a very high threat of COVID-19 (Table 7). Interestingly, this 6.31% of the area covers almost 24% of the total population of West Bengal, which includes Kolkata, North and South 24 Paraganas, and a minor segment of East Medinipur and Howrah. It was discussed earlier that the highest number of confirmed cases was registered by North 24 Paraganas and followed by Kolkata, making these districts more vulnerable to spreading the virus. The region under high vulnerability includes the significant portion of East Medinipur, Hooghly, Howrah, North 24 Paraganas, and a small section of Nadia. The northern part of West Bengal is primarily covered under very low vulnerability with moderate vulnerability in Darjeeling (Fig. 6). Darjeeling is considered one of the crowded districts in the northern part of West Bengal, where tourists

visit throughout the year and enjoy the scenic beauty of the Himalayan region, making the area moderately vulnerable. The moderate vulnerability also includes almost 90% of the area of West Medinipur, a significant portion of Bardhaman, East Medinipur, and Nadia, and a small region of the district Bankura, Murshidabad, North 24 Paraganas, and Birbhum. The East and West Medinipur regions are primarily rural residents with casual and seasonal employment with fewer educated people. The district North and South Dinajpur, Malda, Birbhum, and Murshidabad is mainly covered with low-to-very low COVID-19 vulnerability. Therefore, it is suggested that the government of West Bengal and the government of India should work hand in hand with more focus on the districts having highly vulnerable to the spreading of COVID-19. The foremost thing which can minimise the number of cases is the complete vaccination of the population. The government can also give proper training, education, and spread awareness among the vulnerable group of the society, which is already discussed earlier in the social domain section. The governments should also

Fig. 6 COVID-19 vulnerability map



provide employment, especially migrant workers who left their workplaces during the lockdown. Last but not least, governments should appoint more health workers, increased the number of beds and hospitals as per the requirements.

Conclusions

The present study combined the information obtained from the different data sources to identify social, epidemiological, and physical vulnerability for West Bengal. The fuzzy-AHP model can be applied quantitatively to evaluate the importance of various vulnerability parameters involved in this study. Furthermore, the fuzzy-TOPSIS model can be used to rank the three criteria. A complete regional COVID-19 vulnerability model was developed, and the geospatial mapping was done through the GIS platform. Hence, it can be established that the developed model was an integration of fuzzy-AHP and fuzzy-TOPSIS, where the results of fuzzy-AHP were applied to model the COVID-19 vulnerability using fuzzy-TOPSIS.

The spatial distribution of COVID-19 vulnerability is strongly uneven in West Bengal, where the Kolkata and North 24 Paraganas registered the highest number of cases included under very high COVID-19 vulnerability. The northern part of West Bengal is primarily covered under very low vulnerability with moderate vulnerability in Darjeeling. The numerical figures indicate that 29.95% of the total area is under very low COVID-19 vulnerability, 27.08% low vulnerability, 23.42% moderately vulnerable, 13.23% highly vulnerable, and 6.31% of the total area is under a very high threat of COVID-19, which includes 24% of the total population of West Bengal. We can say that highly populated and rapidly urbanised areas, especially Kolkata and North 24 Paraganas, are highly vulnerable to spreading the virus. The government agencies should take proper preventive measures, especially in the highly vulnerable region, to reduce the number of cases, and this can be done by complete vaccination. The agencies should train, educate, and spread awareness to the vulnerable group of the community, so that they can deal with asymptomatic and mild symptomatic cases and vaccinated themselves.

Nevertheless, there is always a scope for improvement. Future researchers can apply other MCDM approaches or machine learning techniques to model the COVID-19 vulnerability with updated datasets. More parameters can be added, such as climatic factors, ethnic factors, age distribution, and other additional indicators, directly or indirectly influencing the spread of infectious disease (Paez et al. 2020; Wadhwa et al. 2020), may give more strength to this study. The researchers can also include the spatio-temporal components that make the results more detailed.

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Declarations

Conflict of interest There is no conflict of interest to declare.

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