DOI:https://doi.org/10.18485/ijdrm.2023.5.2.6

Research article

HAZARD RISK EVALUATION OF COVID-19: A CASE STUDY

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Received: 15 October 2023; Accepted: 15 December 2023; Published: 31 December 2023

Abstract: The present research deals with an in-depth analysis of COVID-19 risk in the state of Kerala using the integrated approach of the hazard and vulnerability in a GIS platform. Considering the probable causative factors of this disease, several geo-environmental indicators are analyzed through various statistical and geospatial techniques. Lorenz curve indicates an uneven distribution of COVID-19 instances in Kerala. Hazard analysis is formulated based on the proximity to hotspots and LULC followed by vulnerability analysis using an integrated analytical hierarchy process (AHP). Risk analysis reveals that COVID-19 infection poses a very serious threat to around 2.39% of Kerala's total land area, with high, medium and low risks of 38, 44 and 14% respectively. The outcomes of this research will be a first-hand tool for policymakers to safeguard the population in high-risk potential zones from the future spread of infectious disease.

Keywords: COVID-19, Kerala, geo-environmental factor, C19RA model, AHP, C19HZ, C19VZ, rainfall, forest.

Introduction

World Health Organization (WHO) has released details of an outbreak with an unidentified aetiology that originated in Wuhan, Hubei Province, China on December 31, 2019 (Zhu et al. 2020). This epidemic was officially designated as COVID-19 on February 11, 2020. The isolation and quarantine of those who are afflicted through the imposition of national-level lockdowns by the government have been the only proven method of controlling this pandemic (WHO, 2020). If the pandemic is to be eradicated from every area, whether in developed or developing countries, COVID-19 risk mitigation demands extensive planning (Koonin, 2020). Due to high population densities, inadequate healthcare systems, and poverty, Asia's densely populated nations like India, Pakistan and Bangladesh are substantially more susceptible to this disease (Chongsuvivatwong et al., 2011). Using the rules already established to manage COVID-19 contagiousness, state governments in India have prepared for lockdowns by identifying the locations at varied levels of danger (NSD, 2020). In light of this, COVID-19 risk analysis, planning, and management become significant and fundamental phenomena. The COVID-19 risk assessment methodology utilizes all of the information that is currently readily available to delineate the high-risk regions (Kanga et al. 2021).

Kerala reported the first COVID-19 case in the Thrissur district on January 30, 2020, when students returned from Wuhan, China (India Today 2020). The infection has since spread throughout the state. Many people also work throughout India and other countries, including migrant workers from Kerala. Since then, as of January 26, 2022, a total of 57,25,086 confirmed cases of infection have been reported across Kerala. Ernakulam district recorded the maximum number of cases identified with 732876. As opposed to that, Wayanad district recorded the lowest number of confirmed cases with 144563 (until 26.01.22). COVID-19 cases and deaths are heavily biased towards the spatial distribution of Kerala, India.

This research attempts to (i) investigate the causative geo-environmental factors responsible for COVID-19 infection and (ii) formulate hazard risk assessment by multicriteria decision analysis. The novelty of this research lies in the holistic approach combining statistical and geospatial techniques to establish a comprehensive view of the relationship between geo-environment and Covid-19 propagation. Modelling outcomes of this research will significantly contribute toward COVID-19 risk-informed planning and management in the Kerala state.

Literature review

The higher population density is believed to raise the risk of transmission. It is also true that the degree of urbanization is directly correlated with population density (Biswas et al. 2022; Bhadra et al. 2021; Alam et al. 2021; Iderus et al. 2022). Therefore, the number of COVID-19 cases and deaths are directly correlated with population density and urbanization levels. Climate variables like temperature, air quality, PM_{10}, $PM_{2.5}$, rainfall, etc., might have a significant impact on COVID-19 spread, which makes it essential to comprehend the factors behind the spread of the disease because they will help to determine how to impose restrictive measures (Rosario et al. 2020; Bukhari et al. 2020; Khaniabadi et al. 2022; Sahoo et al. 2021). It has been seen that PM_{10} and $PM_{2.5}$ concentrations have decreased by more than 50% from their pre-lockdown levels (Mahato et al. 2020). According to several studies, the temperature has a positive impact on epidemics (Xie and Zhu, 2020; Iqbal et al. 2020; Tobías et al., 2020; Pani et al. 2020; Islam et al., 2021) and some studies reveal no relationship (Briz-Redón et al., 2020; Jahangiri et al., 2020). According to Mehta et al. (2023), the average number of COVID cases dropped by 18 to 26% following three days of rainfall. It is well known, that having a forest nearby always results in the availability of clean air and a decrease in air pollution. Addition-ally, the stress of COVID-19 instances may be lessened by fresh air. Another theory is that the amount of forest cover affects the incidence of COVID-19 (Biswas et al. 2022). However, Biswas et al. (2022) addressed the fact that there is a negative correlation between COVID-19 deaths and the proportion of forest cover. In addition, the epidemic brought on the worst economic downturn, which made it harder for people to pay for medical care. According to a World Bank report released, the COVID-19 pandemic may have caused over 70 million in-dividuals to experience extreme poverty worldwide in 2020, with 56 million of those people living in India. It is well known that the lockdown related to COVID-19 threatens the lives of millions of people. Poor people are more vulnerable to coronavirus infections because they do not receive adequate food and items needed for precautions (disinfectants, masks, soaps, etc.). So, populations below the poverty level are at much higher risk of being infected with the coronavirus. Literacy rate would be a factor in the propagation of the COVID-19 virus. Awareness and discipline are crucial since the spread of the disease may be slowed by social distance. Also in literate populace is likely to be more disciplined and have a better understanding of the disease (Naik et al. 2020).

Natural hazard management has been the subject of numerous studies that have used a variety of techniques. The modelling and mapping of vulnerabilities made possible by geographic information system (GIS) platforms are crucial for the prevention and management of infectious illnesses. According to the review of the literature, some investigations were conducted in various parts of the world in an effort to spatially simulate COVID-19.So far, many researchers have used a variety of methodologies to delineate risk zones of COVID-19 such as, the AHP technique (Sarkar 2020, Mishra et al. 2020, Mahato et al. 2020, Gao et al. 2021); Getis-Ord statistics and AHP-WSM (Rahman et al. 2020); Geographically Weighted Regression (GWR) analysis and Ordinary Least Squares (OLS) (Hassaan et al. 2021); Malakar et al. (2022). After reviewing the existing literature, it is evident that most researchers in the field of vulnerability evaluation have focused on a single MCDM approach, with AHP being the most widely used method. Moreover, previous studies have mainly concentrated on eval-uating vulnerability using country-level datasets, so there is a scope for research on regional vulnerability modelling. Therefore, the goal of this study is developing a regional risk model that considers multiple parameters influencing the spread of infectious diseases and predicts the risk in areas.

Study area

The state of Kerala is situated in southern India between the latitudes of 8°18' and 12°48' N and the longitudes of 74°52' and 77°22' E. (Fig. 1). Kerala covers an area of around 38,863 sq. km. According to the 2011 Indian census, it has a total population of 33,406,061 and the third-highest population density in India, with 860 people per km^2. Kerala's population is growing at a pace of 3.44%. The state's coastline stretches over 590 km, and its width varies from 11 to 121 km. The area has a humid rainforest environment with sporadic cyclones. The three main geographical regions of Kerala are the western lowlands with coastal plains, the centre plateau and tiny hills, and the cold mountainous area of the Western Ghats on the eastern side. Annual temperatures range from 25.0 to 27.5 ° C in the coastal lowlands to 20.0 to 22.5 ° C in the eastern highlands of the Kerala state. The state's annual rainfall is 307 cm, well above the national average rainfall (110 cm). In India, the 2018 literacy rate survey conducted by the National Statistical Office, India shows that the sex ratio of Kerala is the highest, with 1,084 women per 1,000 men and the highest literacy rate of 96.2%. Natural vegetation occupies 24% of the total area of Kerala. Based on the interpretation of the 2019 Indian Forest Survey, Kerala's forest coverage is 21144 km^2, which is 54.42% of the state's geographical area, indicating an increase in Kerala's forest coverage.

Database and methodologies

Entire research is performed based on the secondary data, collected from different sources (Table 1). State-wise and district-wise COVID-19-related data (from January 30, 2020, to January 26, 2022) were procured from the Official web portal, Government of Kerala. The study area's COVID-19 risk analysis map has been created using GIS and statistical techniques. Methodologies adopted for the current study are broadly categorized into (a) in-depth statistical analysis to find out causative geo-environmental factors responsible for Covid-19 active and death cases; (b)preparation of hazard map using hotspot zone of Kerala Covid-19 data. (c) preparation of vulnerability map and using AHP modelling technique; (d) formulation of risk map based on the outcomes of hazard and vulnerability and(e) validation of risk analysis map. A detailed methodological approach is represented in Fig. 2.

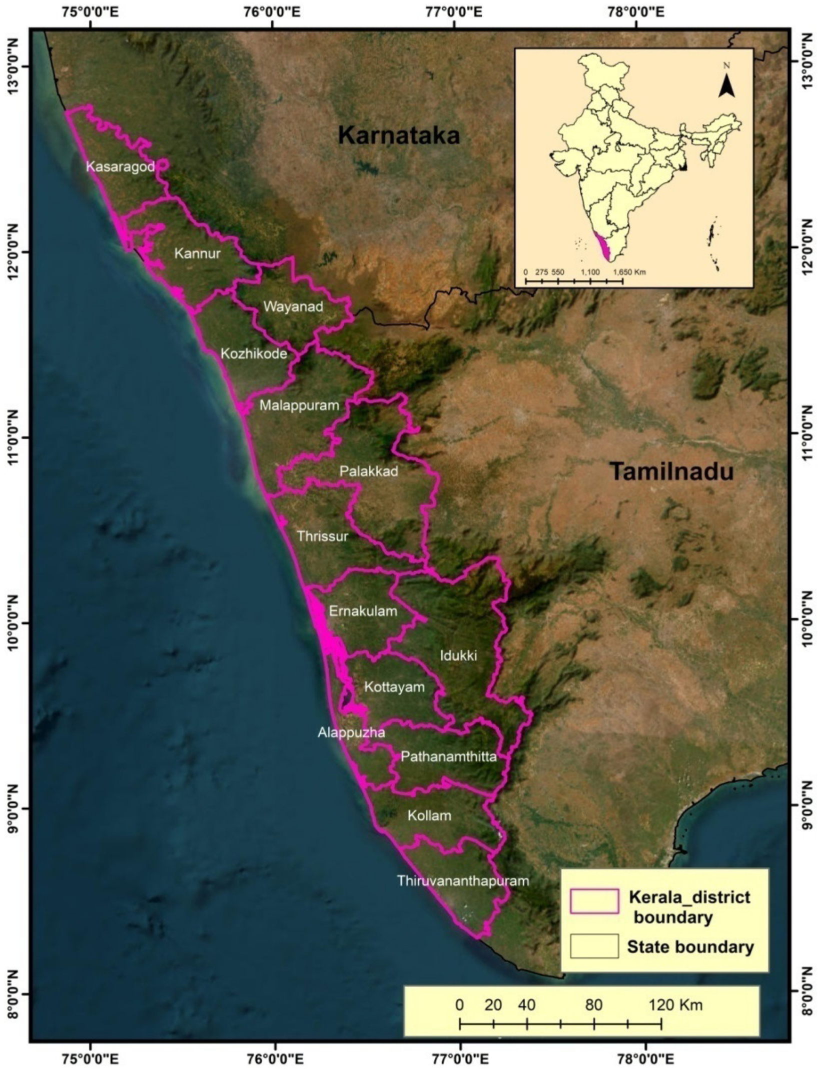


Fig1: Location map of the study area

Table 1: Achieve data source

Data	Source	Web address
Covid-19 data (active and death cases)	Official web portal, Government of Kerala	https://dashboard.kerala.gov.in/covid/
Population Density, Literacy	Census of India 2011	https://censusindia.gov.in/census.website/
Average temperature, Rainfall	Meteorological Department	https://mausam.imd.gov.in/
Population (%) below poverty level	Press Information Bureau, Government of India	https://pib.gov.in/indexd.aspx
API, $PM^{2.5}$,PM^{10}	Central Pollution Control Board	https://cpcb.nic.in/
Forest	District handbook of Kerala	https://forest.kerala.gov.in/
LULC	Landsat8 (2020)	https://earthexplorer.usgs.gov/

Statistical analysis

The Lorenz curve was used to estimate the district-wise spatial distribution of total COVID-19 active cases and their variability. This curve is plotted, keeping the cumulative percentage of the population at the X-axis and the cumulative percentage of COVID-19 active cases at the Y-axis. A line situated at 45 degrees represents perfect equality.

To indicate the spatial disparity in the COVID-19 distribution of Kerala state, the Gini coefficient is estimated here from the Lorenz curve. The Gini coefficient is equal to the area between the line of perfect equality and the Lorenz curve, divided by the total area below the line of perfect equality (Gastwirth 1972).

If the area between the line of equality and the Lorenz curve is considered as A and the area below the Lorenz curve is considered as B–

$$\text{Gini Coefficient} = A/A+B \qquad (1)$$

The Gini coefficient ranges from 0 to 1, where 0 represents perfect equality and 1 represents perfect inequality. In the graph, the perfect equal straight line which forms at 45-degree angle represents the Gini coefficient 0 and the Lorenz curve can represent and regulate the value of the Gini coefficient.

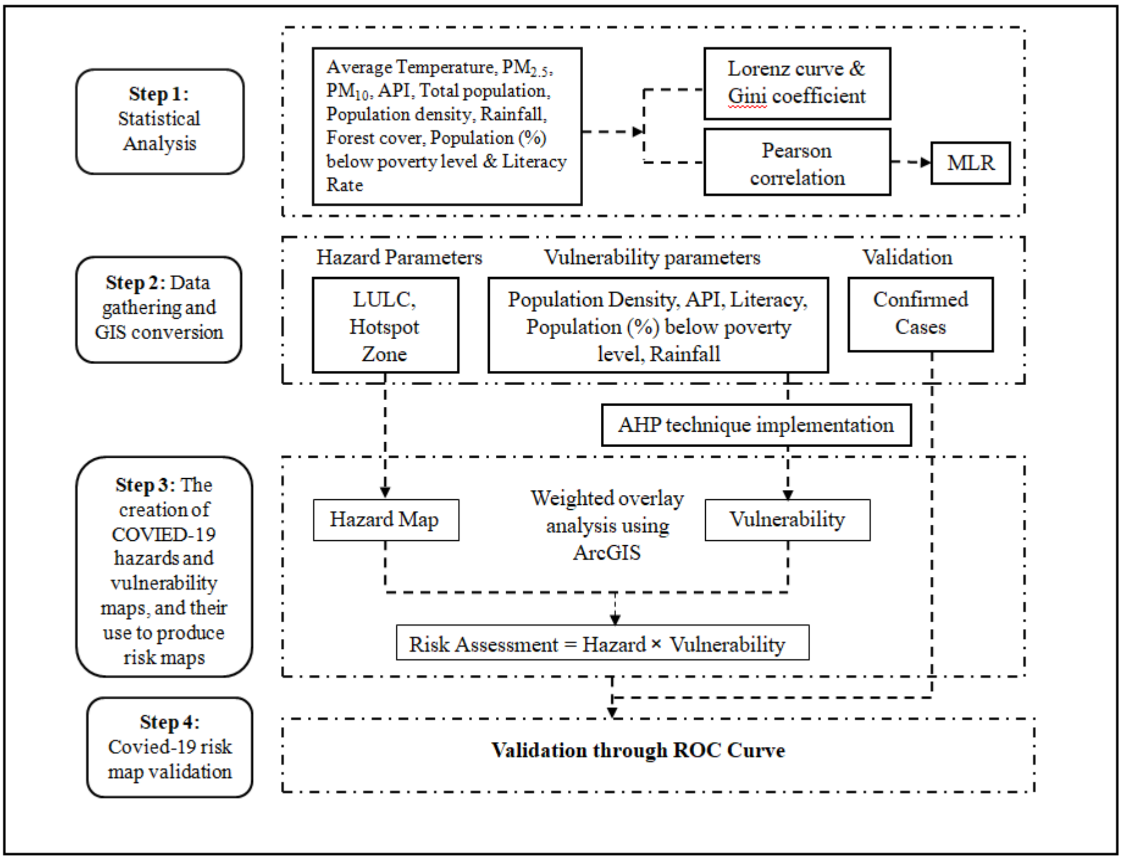


Fig2: Methodological framework of COVID-19 risk assessment mapping

Pearson Correlation Coefficient was estimated between different geo-environmental factors and COVID-19 active and death cases and based on the significant relationships causative variables were filtered out and subsequently multiple regression technique was applied among these variables to derive modelled equations for both confirmed and death cases.

Table 2: Calculation for Lorenz Curve distribution among confirmed cases of COVID-19

District	No COVID-19 confirmed cases (till26/01/22)	Total population (Est. 2020)	% of COVID-19 confirmed cases	% of population	Cumulative % of Population	Cumulative % of COVID-19 cases
					0	0
Wayanad	144563	9,31,859	2.525	2.453	2.453	2.525
Kasaragod	153240	14,90,408	2.676	3.923	6.377	5.201
Idukki	174584	12,64,230	3.049	3.328	9.705	8.251
Pathanamthitta	227259	13,65,050	3.969	3.593	13.299	12.220
Kannur	313922	28,76,223	5.483	7.572	20.871	17.703
Alappuzha	346052	24,25,679	6.044	6.386	27.258	23.748
Kottayam	376811	22,50,988	6.581	5.926	33.184	30.330
Palakkad	408672	31,03,325	7.138	8.170	41.354	37.468
Kollam	442288	30,04,328	7.725	7.909	49.264	45.193
Thrissur	593265	35,58,168	10.362	9.367	58.632	55.556
Malappuram	602385	46,88,729	10.521	12.344	70.976	66.078
Thiruvananthapuram	603020	37,63,627	10.587	9.908	80.885	76.611
Kozhikode	606149	35,18,374	10.587	9.263	90.148	87.198
Ernakulam	732876	37,41,922	12.801	9.851	100	100
TOTAL	5725086	3,79,82,910	100	100	2.453	2.525

Preparation of thematic layers for hazard and vulnerability mapping

The state's Land Use and Land Cover (LULC) and hotspot locations of COVID-19 cases were used in this analysis as hazard parameters. Data on the hotspot locations of COVID-19 infections were gathered from the Kerala Local Self-Government Department and the Directorate of Health Services in Kerala (https://specials.manoramaonline.com). ArcMap10.8 software was used to detect hotspot zones based on proximity analysis. Hotspot zones are ranging from 0-2000 m to 8000-10000 m. ArcMap10.8 software was used to create a Land Use and Land Cover (LULC) map (Landsat8 OLI data) of this state. Various thematic layers such as population density, rainfall, literacy rates, population (%) below the poverty level, and air pollution index were used to generate the vulnerability map. As shown in Fig. 9, these five vulnerability parameters were created in ArcMap 10.8 using an IDW spatial interpolation method.

Ranking and weighting by AHP

The Analytical Hierarchy Process (AHP) technique was developed in the late 1970s and currently, it is the most popular MCDA model for evaluating decision alternatives (Saaty 1987, Saaty 1990). The weights of each parameter were statistically calculated in the current study to create a vulnerability map using the Analytical Hierarchy Process (AHP) technique, and then heuristic approaches/knowledge-driven methods were used to rank each subclass of parameter maps. Based on the author's knowledge and review of the literature, ranks were assigned to the factor's sub-classes (Mishra et al. 2020; Mahato et al. 2020; Kanga et al. 2021).

The following steps are followed to calculate the weight for five themes

Step 1: Values were added to each column using the following pairwise matrix formula,

$$Lj = \sum_{ij=1}^{n} Cij \quad 2$$

Where, C_{ij} is thematic layer used like population density, API etc.

Step 2: Each component of the matrix was divided by the sum of its rows to create a normal pair-based matrix

$$Xij = \frac{Cij}{\sum_{n=1}^{n} Cij} \quad 3$$

Step 3: Divide by the sum of the rows of the matrix Number of criteria used to create criteria (N)

$$Wij = \frac{\sum_{j=1}^{n} Xij}{N} \quad 4$$

Step 4: formula for consistency ratio

$$CI = \frac{\lambda_{max} - n}{n} \quad 5$$

$$CR = \frac{CI}{RCI} \quad 6$$

Where, CI is the Consistency Index, RCI is the Random Consistency Index

The AHP result is acceptable if the CR value is less than 0.1. However, if it is greater than 0.1, the finding is inconsistent with continuing the evaluation, necessitating a revision to the methodology (Table 6).Computed CR for the COVID-19 vulnerability is represented in Table 5.

Table 3: Pair-wise comparison matrix of AHP

	Population Density	**API**	**Literacy**	**Population (%) below poverty level**	**Rainfall**
Population Density	1	2	3	1	3
API	0.5	1	1	1	3
Literacy	0.33	1	1	1	3
Population (%) below poverty level	1	1	1	1	1
Rainfall	0.33	0.33	0.33	1	1
Column Sum	3.16	5.33	6.33	5	11

Table 4: Computation of normalized weights for thematic layers

	Population Density	API	Literacy	Population (%) below poverty level	Rainfall	**Normalized Weighted (W)**
Population Density	0.31	0.37	0.47	0.2	0.27	0.32
API	0.15	0.18	0.15	0.2	0.27	0.19
Literacy	0.10	0.18	0.15	0.2	0.27	0.18
Population (%) below poverty level	0.31	0.18	0.15	0.2	0.09	0.18
Rainfall	0.10	0.06	0.05	0.2	0.09	0.1

Table 5: Calculation table for Consistency Ratio

	Population Density	API	Literacy	**Population (%) below poverty level**	**Rainfall**	**Weightage Sum Value**	**Normalized Weighted (W)**	**Consistency Ratio**
Population Density	0.32	0.38	0.54	0.186	0.3	1.726	0.32	5.39
API	0.16	0.19	0.18	0.186	0.3	1.016	0.19	5.34
Literacy	0.10	0.19	0.18	0.186	0.3	0.956	0.18	5.31
Population (%) below poverty level	0.32	0.19	0.18	0.186	0.1	0.976	0.18	5.24
Rainfall	0.10	0.06	0.05	0.186	0.1	0.496	0.1	4.96

Weighted overlay method

The weighted overlay analysis was carried out in the ArcGIS platform to define the hazard and vulnerability map. In order to define them both the vulnerability and hazard criteria were classified into separate classes and each class was assigned by a weight ranging from 1 to 5, depending on how much of a risk it posed towards the increase in COVID-19 infection (Table 6).The weighted overlay approach was used to integrate all the inputs after factors and their subclasses were given weights and ranks using the following equation:

$$C19VZ = \sum_{i=1}^{n} W_i^V \times S_i^V \qquad (7)$$

where C19VZ is the COVID-19 vulnerability zonation, W_i^V is the weights of vulnerability parametersand S_i^V is the weightage of vulnerability sub-parameters.

Table 6: Model generated weights of the risk indices

COVID-19 Risk Indicators		Classes	Weights	Indexing	Area in (sq km)
Hazard	Hotspot Zones(in m)	2000	5	Very High	16,144.086
		6000	4	High	8187.140
		8000	3	Moderate	12915.641
		10000	2	Low	453.847
	LULC	Settlement	5	Very High	10970.805
		Crop Land	4	High	2290.719
		Vegetation	2	Low	23596.289
		Water body	3	Moderate	837.161
		Barren Land	1	Very Low	13.672

Vulnerability	Population density (in Sq. km)	254.19-574	1	Very Low	2730.041
		574.01-760.96	2	Low	7363.5426
		760.97-947.93	3	Moderate	12661.0452
		947.94-1184.1	4	High	8222.3928
		1184.11-1508.83	5	Very High	6660.9045
	Air Pollution Index	17.7-28.3	1	Very Low	2059.603
		28.31-33.99	2	Low	16150.926
		34-38.42	3	Moderate	10651.383
		38.43-45.54	4	High	6948.481
		45.55-58.04	5	Very High	1885.706
	Literacy (in %)	89.03-91.31	5	Very High	4856.029
		91.32-92.82	4	High	4772.042
		92.83-94	3	Moderate	10037.682
		94.01-95.19	2	Low	10422.084
		95.2-97.21	1	Very Low	7608.263
	Population (%) below poverty level	1.17-5.77	1	Very Low	11351.125
		5.78-9.99	2	Low	14503.759
		10-15.83	3	Moderate	9304.863
		15.84-23.53	4	High	1308.389
		23.54-32.84	5	Very High	1169.788
	Rainfall (in cm)	192-238.22	5	Very High	1416.285
		238.23-273.37	4	High	6937.0101
		273.38-297.46	3	Moderate	10555.2495
		297.47-326.1	2	Low	13841.2431
		326.11-358	1	Very Low	4946.3136

Mapping of COVID-19 risk analysis (C19RA)

Finally, each zone of concern district's risks and vulnerability to this pandemic were integrated into the risk map. The COVID-19 risk (C19R) is defined as (Kanga et al. 2021)

$$C19\ R_i = HAZARD_i \times VULNERABILITY_i, \qquad (8)$$

Equation (8) predicts that the zone of interest's COVID-19 risk will increase as the hazard and vulnerability rise. The final output of the COVID-19 risk zonation map is also divided four zones, i.e., low, medium, high and very high risk zones.

Results and Discussion

Spatial-temporal distribution of COVID-19 cases

The first case of COVID-19 was detected in Kerala on 30.01.2020 and with time the number of COVID-19 active cases became increased over time and crossed 260 on April 6, 2020. Thereafter active cases gradually decreased down to only 16 on 8th May 2020 due to some preventive initiatives taken by the Kerala government. On that day, Kerala accomplished an excellent outcome with a recovery rate of 95% for infected people and an overall mortality rate of 0.78% within India. Later, as infected people became relocated to various parts of the state and also because of migration factors active cases started to rise again (https://dashboard.kerala.gov.in/covid/index.php; 05.08.2020).As on January 26,2022, Kerala recorded a total of 57,25,086 confirmed cases of illness out of which 7,32,876 cases were recorded solely in the state's densely populated Ernakulam district followed by the other districts such as Kozhikode, Thiruvananthapuram, Malappuram, and Thrissur. Minimum numbers of confirmed patients (144563) were reported from Wayanad, district. With respect to the state's infection rate, the central portion of the state recorded the highest cases but on the other hand, it is considerably lower than the national average when compared to the mortality rate. Fig. 3 depicts the rate of COVID-19 death cases and confirmed cases in relation to the population density. Understanding population density can be crucial for finding COVID-19 sufferers and halting the transmission of the virus. This virus is more contagious in densely populated urban areas because population density regulates the rate of urbanization. Therefore, the number of COVID-19 active cases and mortality are directly correlated with population density. The mortality graph of the state is fairly flat, and it is interesting and reassuring to see that it does not follow the curve for the confirmed cases.

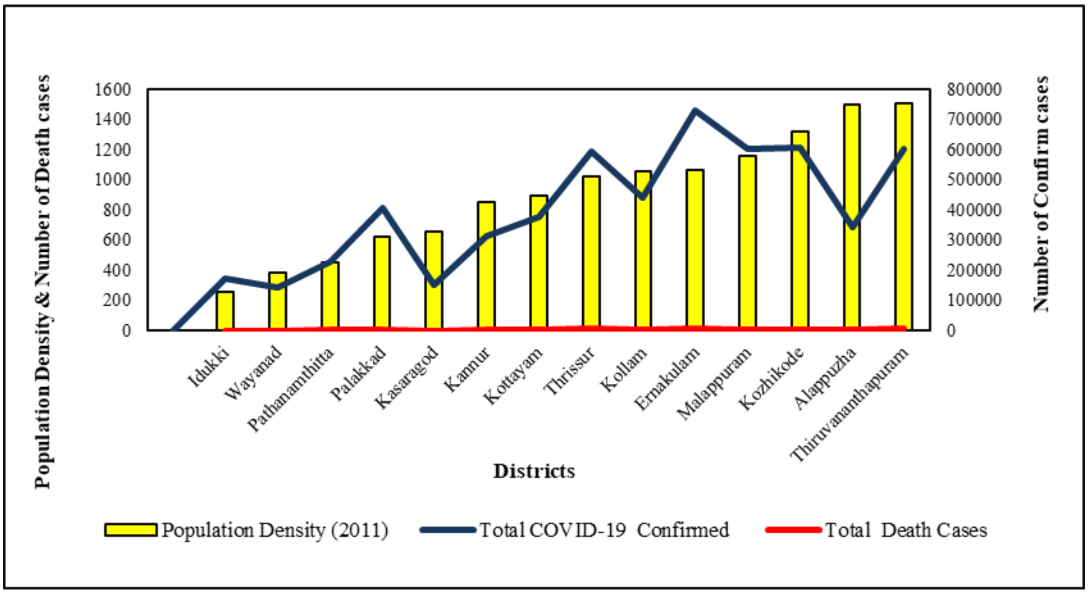


Fig 3. Spatial variation of COVID -19 confirmed and death cases along with population density of the state

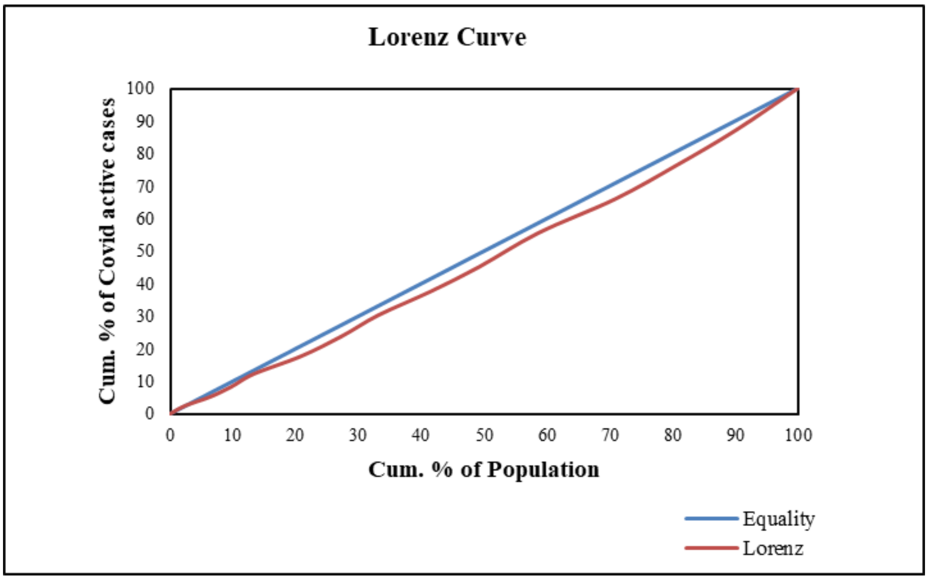


Fig 4. Pictorial representation of Lorenz Curve

Statistical interpretation

In this study, the Lorenz curve has been used to analyze the spatial variance of COVID-19 infection. The district-level total population and COVID-19-confirmed cases are used for Lorenz curve analysis. This curve demonstrates the non-uniformity of the spatial distribution in COVID-19 situations. The Gini coefficient (0.06) of the Lorenz curve also demonstrates a skewed distribution of COVID-19 cases in the studied state. According to data, out of fourteen districts, nine districts contain 49% of the total population and 45% of the COVID-19 active cases. However, 55% of COVID-19 instances are present in the remaining five districts which are Ernakulam, Kozhikode, Thiruvananthapuram, Malappuram, and Thrissur (Table 2 and Fig. 4).

Pearson correlation analysis reveals that the positive correlations persist between the number of confirmed COVID-19 cases population density (r = +0.728), PM_{10} (r = +0.439), API (r = +0.583), and literacy rates (r = +0.409).This means that as these factors increase, so does the prevalence of the disease. While, other variables such as average temperature (r = -0.046), $PM_{2.5}$ (r = -0.004), rainfall (r = -0.335), percentage of forest cover (r = -0.27), and Population (%) below poverty level (r = -0.554) are all adversely correlated with COVID-19 cases (Fig.5). Among these variables, population density, air pollution index (API), and population (%) below poverty level are significant at 0.003%, 0.02%, and 0.03% levels of significance respectively (Fig.5).

Similar kind of positive and negative correlations also exist between death cases and other variables such as average temperature (r = +0.163), $PM_{2.5}$ (r = +0.167), PM_{10} (r = +0.53), API (r = +0.612), Population density (r = +0.783), and Literacy (r = +0.384), forest cover (r = -0.394), rainfall (r = -0.458), and the percentage of the population living in poverty (r = -0.57) (Fig.8). Variables, such as population density, API, PM_{10}, and population (%) below poverty level show significant correlations at levels of 0.0009%, 0.01%, 0.05%, and 0.03%, respectively (Fig.6).

Based on Pearson correlation analysis, the Multiple Linear Regression (MLR) model is also used using the significant ($p<0.01$) variables both for confirmed and death cases and the model-derived equations are as follows:

Confirmed COVID 19 cases = 247.89*Population density + 3584.03* API - 4188.78* Population (%) below poverty level + 91200.86 (9)

Death cases = 2.81*Population density + 35.76* API – 37.07* Population (%) below poverty level + 201.90 (10)

Scatter plots (Fig. 7) based on actual *vs* calculated cases of confirmed and death cases further validate the acceptability of the MLR statistical modeling with an R^2 value of 0.59 and 0.66 respectively.

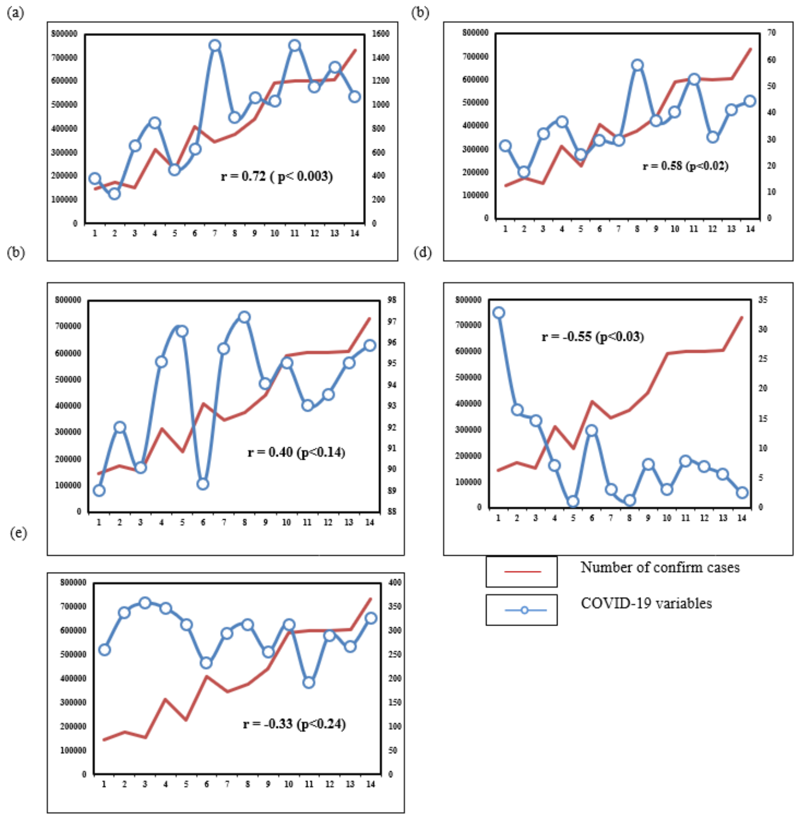


Fig5. Representation of COVID-19 variables (a-Population Density, b-API, c-Literacy Rate, d-Population (%) below poverty level, e-Rainfall) with confirmed cases

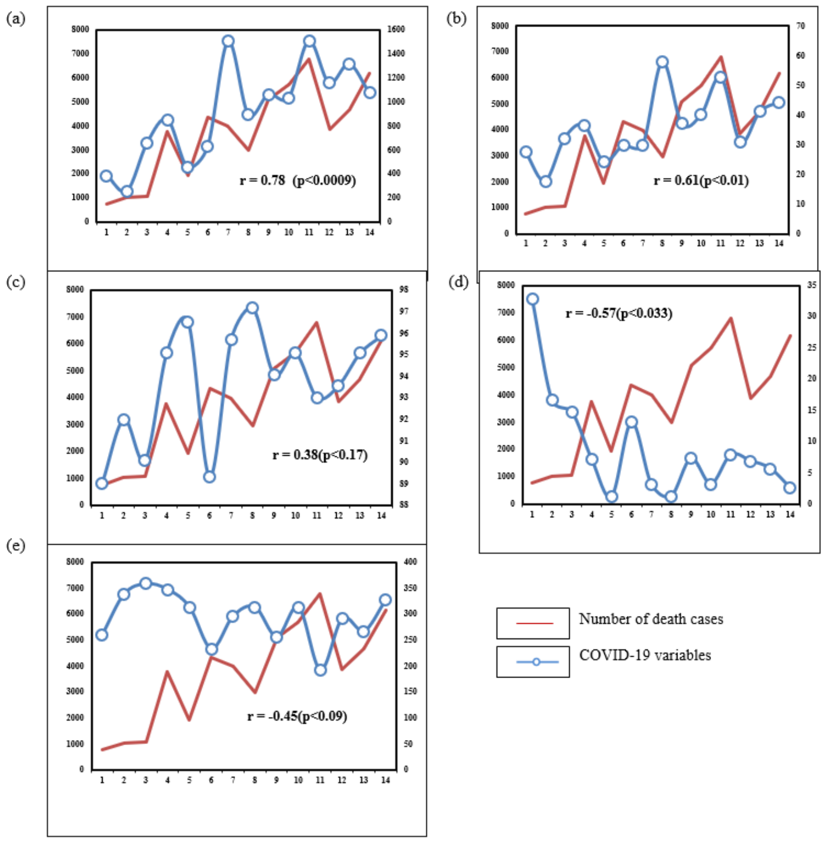
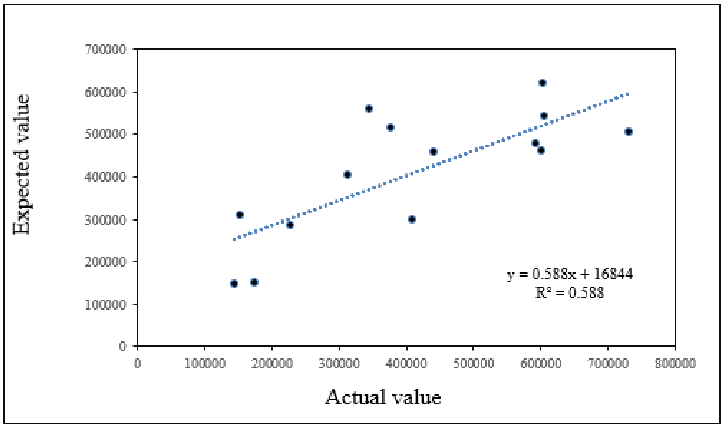


Fig6. Representation of COVID-19 variables (a-Population Density, b-API, c-Literacy Rate, d- Population (%) below poverty level, e-Rainfall) with death cases

(a)



(b)

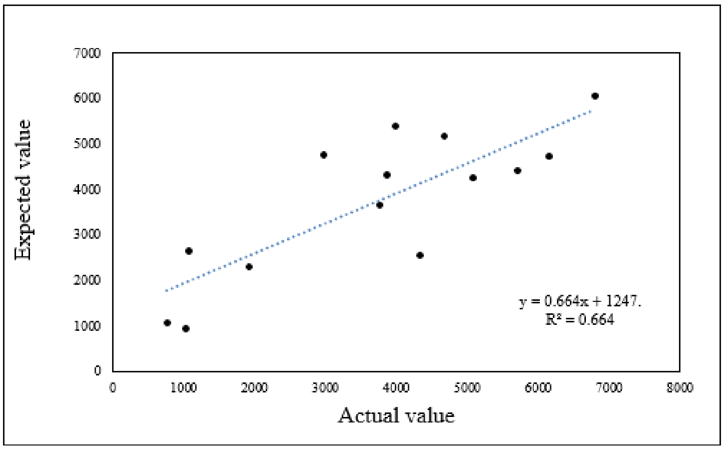


Fig7. Scatter plots representing actual versus expected value of COVID - 19 (a) confirmed cases and (b) death cases

COVID-19 risk analysis

The preparation of the COVID-19 hazards and vulnerability zonation is a key task of the study.The spatial distribution of the hotspot areas in the state of Kerala is shown in Fig. 8.The map reveals that the northern part of the research region has a higher concentration of COVID-19 hotspots. The research area's highly inhabited zone has a very high hotspot density, as can be seen from the map. The region's LULC is displayed in five categories, i.e., settlement, crop land, vegetation, water body, and barren land. From the LULC map, it is clear that Kerala's LULC is dominated by forestland.Reclassified layers of COVID-19 hazard parameters have been integrated into the ArcGIS platform.The "weighted overlay method" was used to create the state's final COVID-19 Hazard Zonation (C19HZ) map. Kerala state has been divided into four COVID-19 hazard groups, namely low, medium, high, and very high, based on pixel values (Fig. 10).With the use of the C19HZ map, it is possible to locate places with greater COVID-19 hazard levels. Overall, the methodology has been used to create a complete and precise C19HZ map of the state of Kerala by combining LULC map with COVID-19 hotspot zones. Subsequently, the statistical analysis identified the highly affected parameter for mapping vulnerability are population density, air pollution index, literacy, population (%) below poverty level, and rainfall. Several studies have shown these five parameters affect COVID-19 infection in this study area (Arif et al. 2021; Archila et al. 2021; Manoj et al. 2020).

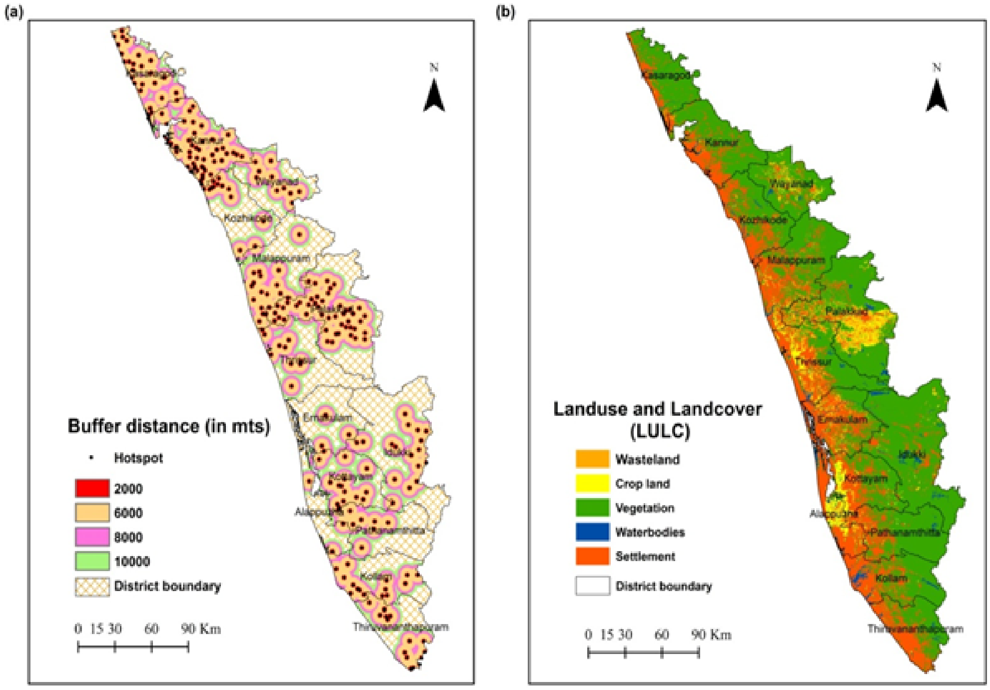
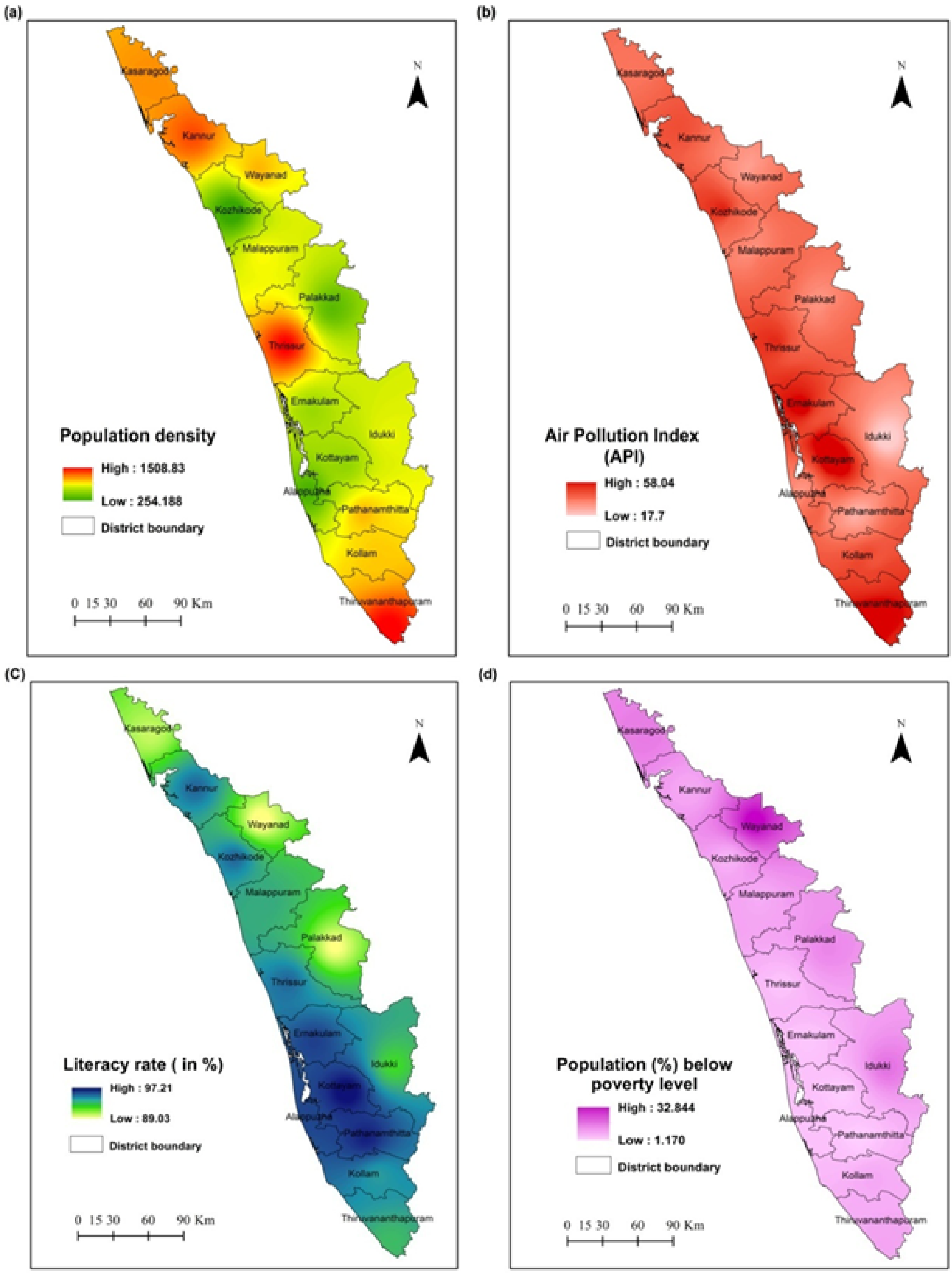


Fig 8. Hazard parameters: (a) Hotspot buffer zones and (b) LULC of Kerala State

The analytical hierarchy process (AHP), a multi-criteria decision-making model has been employed for its effectiveness and reliability to demarcate the C19VZ. It is a pair-based comparison technique that is additive and compensatory and is based on the three concepts of deconstruction, comparative evaluation, and priority setting. By offering a scale to evaluate intangible elements and a tool to set priorities, it is a methodology for detecting, comprehending, and assessing the interactions of a system holistically. Some of the researchers have employed this technique for the development of maps of social vulnerability and risks, and health accessibility (Fang et al. 2020; Sarkar et al.2020; Ghosh et al. 2020) in COVID-19 analysis. On the basis of statistical interpretation, moderate and highly significant variables have been selected for vulnerability analysis. However, tables 4 and 5 display the Pair-wise comparison matrix of various thematic layers and the methods used to derive the normalized weights. Following that, weights are assigned to each factor based on the AHP computation. After that, layers are reclassified, and implementation the Weighted Overlay technique in ArcGIS software (Table 6). The final vulnerability zones are divided into four sub-classes: very high, high, medium, and low (Fig. 10). These subclasses of each denote a distinct degree of vulnerability. Forested areas and places with low population densities are frequently linked to the zones that are categorized as having a low to very low level of vulnerability. This indicates that compared to other areas of the state, these places have a lower risk of COVID-19 infection. Understanding the risks and potential of COVID-19 disease in different parts of the state is aided by the classification of vulnerability sub-classes.


(a)
Kasaragod
Kannur
Wayanad
Kozhikode
Malappuram
Palakkad
Thrissur
Ernakulam
Idukki
Kottayam
Alappuzha
Pathanamthitta
Kollam
Thiruvananthapuram
N
Population density
High : 1508.83
Low : 254.188
District boundary
0 15 30 60 90 Km
(b)
Air Pollution Index (API)
High : 58.04
Low : 17.7
District boundary
(C)
Literacy rate (in %)
High : 97.21
Low : 89.03
District boundary
(d)
Population (%) below poverty level
High : 32.844
Low : 1.170
District boundary

(e)

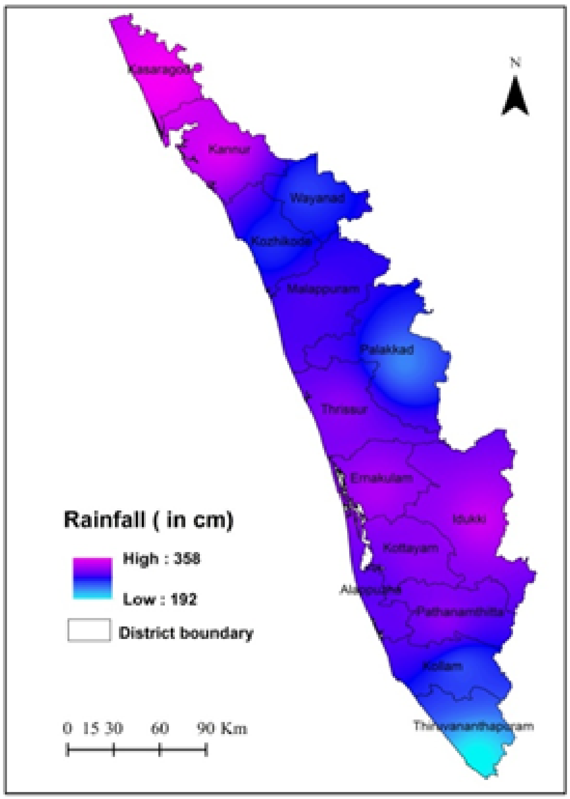
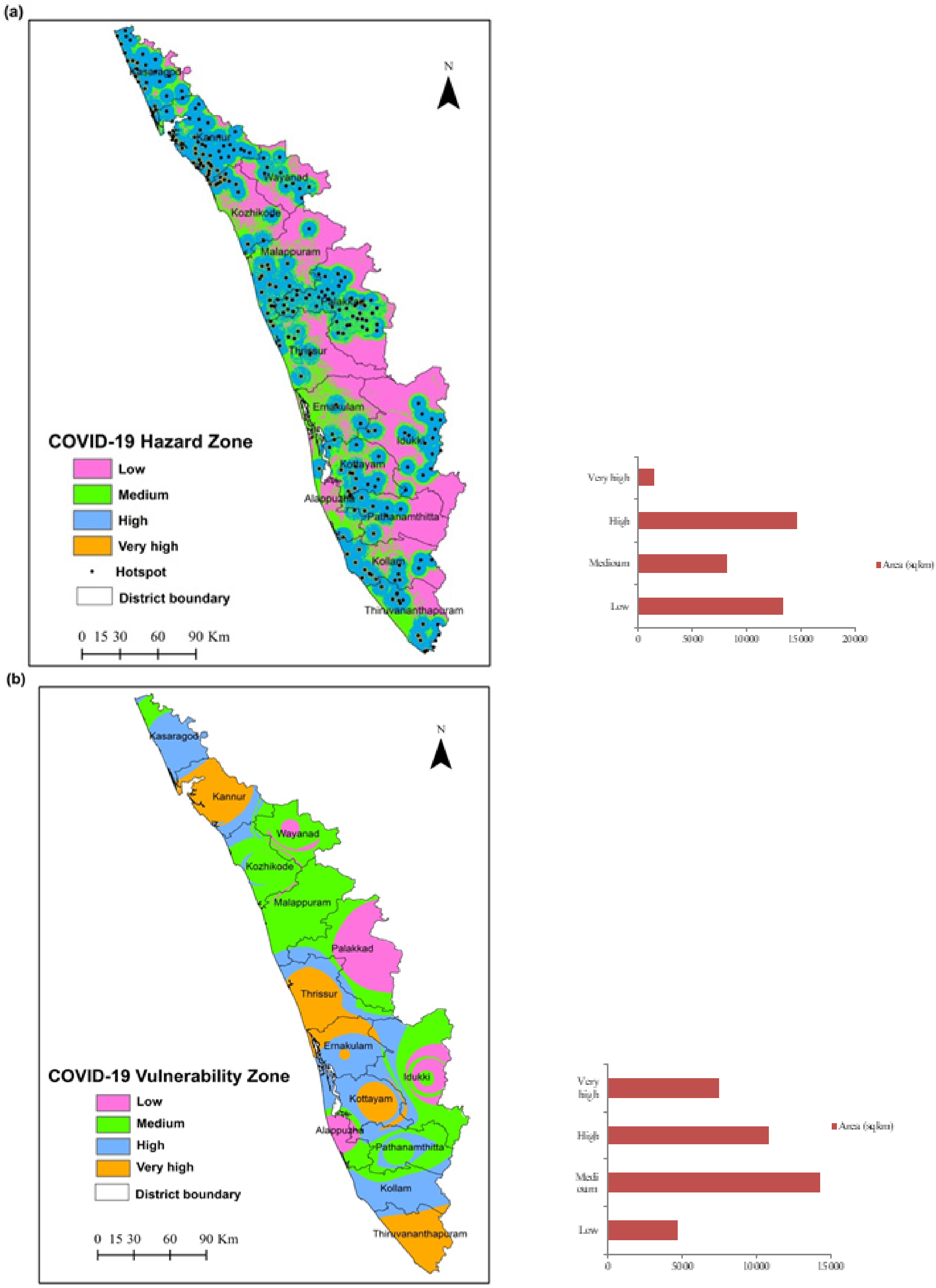


Fig 9: Vulnerability parameters: (a) Population density (b) API (c) Literacy rate (d) Population (%) below poverty level and (e) Rainfall of Kerala State

However, the final COVID-19 risk analysis (C19RA) map has been calculated integrating the hazard and vulnerability to COVID-19 disease in this area. As shown in Fig. 10, the generated C19HZ map has been divided into four classes: low (4745.84 %), medium (14207.98 %), high (10840.57 %), and very high (7500.74 %). The model outcome reveals that, high and very high COVID-19 risk analysis classes are concentrated along the middle and south part of the studied state. However, Thrissur, Thiruvananthapuram, Palakkad, Kollam, and Kannur are the most risk-prone areas. As a result, the population in this district is more seriously threatened by the COVID-19 virus. Some scattered low risk zones fall in Idukki, Pathanamthitta, Alappuzha, and Wayanad districts.

The progression of COVID-19 pandemic disease can only be mitigated by the implementation through risk-informed planning at the panchayat and local mohalla levels in developing nations. This study may act as a standard methodology for similar setups in other parts of the country and the world.

The model-generated output map of the C19RA zone has been compared with the actual COVID-19 confirmed cases in order to establish the C19RA model accuracy in forecasting COVID-19 cases in Kerala state. The 'ArcSDM' tool in the ArcGIS software and the ROC-AUC method has been used to conduct this comparison. A statistical tool called the ROC-AUC method assesses how well a model can distinguish between positive and negative cases. Based on predetermined thresholds, the AUC value classifies the model's overall accuracy into four groups i.e., excellent (>0.9), accepted (0.8–0.9), good (0.7–0.8), and considerable (0.5–0.7).The research found that this model's observed accuracy is 0.735 (73.50%) (Fig.11). Despite having a modest accuracy rate, the study was able to use the C19RA zone map to successfully create a COVID-19 risk map. Based on the satisfaction scale, this result can be deemed a success.


(a)
N
COVID-19 Hazard Zone
Low
Medium
High
Very high
Hotspot
District boundary
0 15 30 60 90 Km
Kasaragod
Kannur
Wayanad
Kozhikode
Malappuram
Palakkad
Thrissur
Ernakulam
Idukki
Kottayam
Alappuzha
Pathanamthitta
Kollam
Thiruvananthapuram
Very high
High
Medium
Low
0
5000
10000
15000
20000
Area (sq km)
(b)
N
COVID-19 Vulnerability Zone
Low
Medium
High
Very high
District boundary
0 15 30 60 90 Km
Kasaragod
Kannur
Wayanad
Kozhikode
Malappuram
Palakkad
Thrissur
Ernakulam
Idukki
Kottayam
Alappuzha
Pathanamthitta
Kollam
Thiruvananthapuram
Very high
High
Medium
Low
0
5000
10000
15000
Area (sq km)

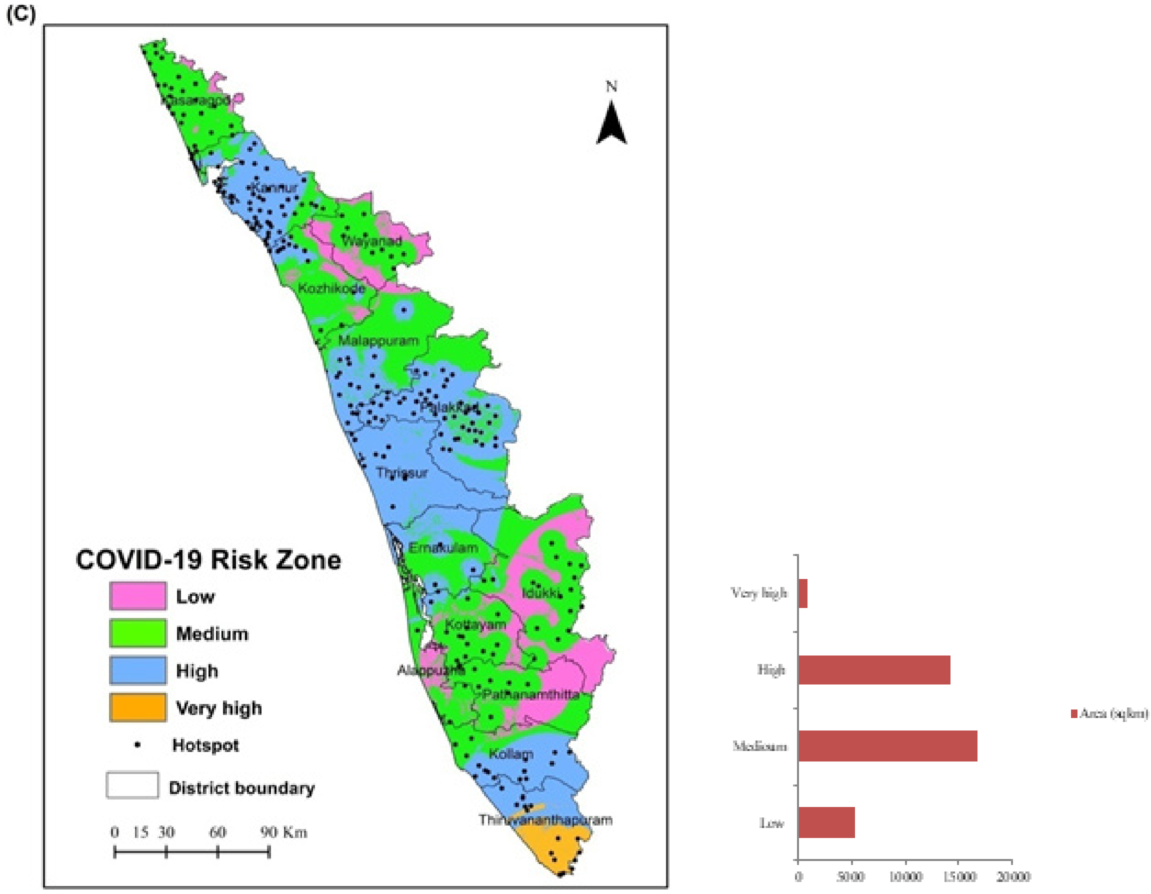


Fig10: (a) Hazard map (b) Vulnerability map and (c) Risk map and their area statistics

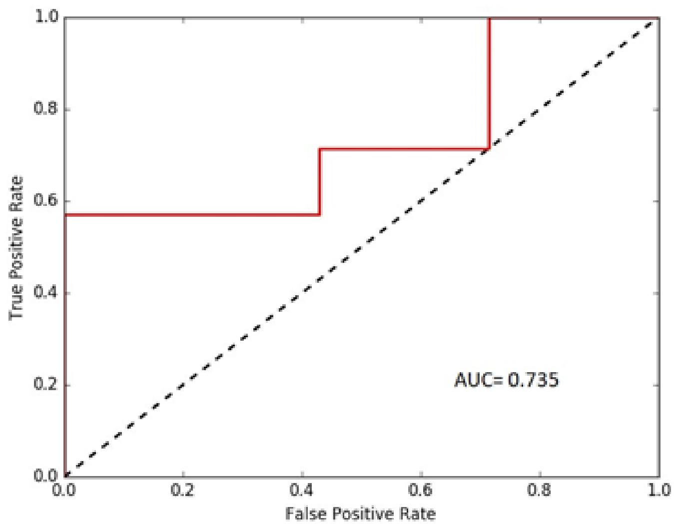


Fig11: ROC-AUC analysis

Conclusion

In this research work, both statistical and geospatial tools seems to be effective for assessing risk of COVID-19 infection in the state of Kerala thereby offering insightful information for the disease's management and control. Statistical analysis reveals that significant correlation persist between population density, population (%) below poverty level and API with confirmed and death cases of Covid-19. Modelled equation build up by MLR analysis also show the significant relationship among the causative geo-environmental factors and confirmed and death cases of Covid-19. Geospatial analysis highlights that Thrissur, Palakkad, Thiruvananthapuram, Kollam, and Kannur districts of Kerala state falls in the high risk zone. Governmental organizations should therefore be more focused and make plans accordingly to protect the population, particularly the area with a high risk future spread of COVID-19 infection.

Author Contribution: Dr Gupta has contributed the analysis and interpretation part of the manuscript and Mr. Ulal has done the statistical analysis on the analyzed data, Ms. Saha has formulated hazard, vulnerability and risk analysis part of the manuscript, lastly Mrs. Karmakar has contributed in terms of overall representation and formatting of the manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

Funding: None of the authors has received any funding for this particular research work.

Acknowledgement

The authors express their gratitude to the Department of Environmental Science, The University of Burdwan for giving access to computer laboratory. Thanks to anonymous reviewers for their valuable suggestions in making the manuscript more scientific.

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