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A district-level vulnerability assessment of next COVID-19 variant (Omicron BA.2) in Uttarakhand using quantitative SWOT analysis

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Abstract
COVID-19 has had an impact on the entire humankind and has been proved to spread in deadly waves. As a result, preparedness and planning are required to better deal with the epidemic's upcoming waves. Effective planning, on the other hand, necessitates detailed vulnerability assessments at all levels, from the national to the state or regional. There are several issues at the regional level, and each region has its own features. As a result, each region needs its own COVID-19 vulnerability assessment. In terms of climate, terrain and demographics, the state of Uttarakhand differs significantly from the rest of India. As a result, a vulnerability assessment of the next COVID-19 variation (Omicron BA.2) is required for district-level planning to meet regional concerns. A total of 17 variables were chosen for this study, including demographic, socio-economic, infrastructure, epidemiological and tourism-related factors. AHP was used to compute their weights. After applying min–max normalisation to the data, a district-level quantitative SWOT is created to compare the performance of 13 Uttarakhand districts. A COVID-19 vulnerability index (normalised R_i) ranging between 0 and 1 was produced, and district-level vulnerabilities were mapped. Quantitative SWOT results depict that Dehradun is a best performing district followed by Haridwar, while Bageshwar, Rudra Prayag, Champawat and Pithoragarh are on the weaker side and the normalised Ri proves Dehradun, Nainital, Champawat, Bageshwar and Chamoli to be least vulnerable to COVID-19 (normalised $R_i \leq 0.25$) and Pithoragarh to be the most vulnerable district (normalised $R_i > 0.90$). Pauri Garwal and Uttarkashi are moderately vulnerable (normalised R_i 0.50 to 0.75).

Keywords COVID-19 · Quantitative SWOT · Vulnerability assessment · Vulnerability index

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1 Introduction

COVID-19 has a tendency to spread in episodic waves and has claimed thousands of lives in two deadly waves (Ali & Parvin, 2022; Iftimie et al., 2021; Kaxiras & Neofotistos, 2020). A third wave has already hit India, as predicted, and the fear of coming waves is anticipated (Sherrif, 2021). The complete vaccination and providing booster doses to everyone are still far-reaching goals for a giant population (Sharma, 2021). Therefore, planning and preparing beforehand for the coming waves to ward off the preventable deaths are highly recommended (Lin et al., 2020; Bag et al., 2020). For better planning, it is crucial to find out areas that need special attention (Nisari et al., 2016). This purpose is served by conducting a vulnerability assessment done on various grounds using statistical methods (Nikolopoulos et al., 2021), vulnerability indices (Tuite et al., 2020; Campos et al., 2021) and geospatial techniques (Ali et al., 2021; Parvin et al., 2021). Researchers have also tried to assess the impact and modelled the vulnerabilities of COVID-19 on different part of the society (Daras at al., 2021) and various economic classes (Bidisha et al., 2021; Rahman et al., 2021). Many of the scholars focussed COVID-19 vulnerability assessments on different geographical regions (Anil & Alagha, 2021) and mountains (Kedia et al., 2021; Seaman, 2021). Selection of principal component analysis (PCA) has been effective in vulnerability assessments in order to assign scores to the factors in the wake of pandemic (Kim & Bostwick, 2020; Wilson, 2021). The PCA has been utilised for modelling socio-economic as well as climatic vulnerability of COVID-19 (Salvacian, 2022). Multi-criteria decision-making (MCDM) was adopted for vulnerability assessments of Brazil (Campos et al., 2021) and Argentina (Özkaya and Özkaya, 2022). GIS and overlay techniques have been highly useful in the assessment of COVID-19. For instance, Ihinegbu et al., 2021 have used weighted overlay to model COVID-19 vulnerability in Nigeria, while Vishwanathan et al., 2022 have applied GIS-assisted weighted overlay on factors like pollution to prepare vulnerability assessment in Malaysia.

In India, no dearth nationwide vulnerability assessments have been undertaken since the beginning of 2020 (Nath et al., 2021; Bherwani et al., 2021). Indices have been developed by scholars like Septanaya et al., 2021; Sahu & Mishra 2021, while Murugesan et al. focussed on GIS-based mapping. Statistical analysis and assessment of COVID-19 vulnerability are also conducted (Baruah, 2020).

In spite of plenty of research available on India and although a variety of methods have been used for vulnerability assessments of COVID-19, region- and state-specific studies are still scanty. Indian states represent strong physio-climatic and demographic variability of the country (Ishaque & Jayapal, 2019), and therefore, it is highly practical to investigate the impact of COVID-19 state-wise at district and sub-district level using state-specific factors, especially if a given state is highly peculiar in its socio-economic, demographic or topographic characteristics. Uttarakhand is one such state that holds fundamental demographic, infrastructure and topographic uniqueness due to its singular climate and rugged terrain. Transportation facilities are finite due to precarious topography, and many areas are not well connected to mainstream world. With these pretexts, transmission of any contagious disease is difficult, but once it catches, catering health facilities is challenging. However, no intensive, state-based COVID-19 vulnerability assessment is conducted in Uttarakhand. However, limited works are available at district level at Dehradun (Sharma, 2021) and Haridwar only (Bhatt et al., 2021). Thus, it is of paramount importance that the state of Uttarakhand is properly investigated for COVID-19 vulnerabilities and factors are selected carefully for making the assessments.

In this study, a district-level vulnerability assessment is presented by applying quantitative SWOT. This method is adopted first time for the performance assessment of districts in dealing with the epidemic. A COVID-19 vulnerability index was prepared by giving special attention to the region-specific distinct factors at district level of Uttarakhand. At district level, it varies tremendously in terms of population density and distribution, area covered by 1 km distance from road, socio-economic conditions, education status, availability of health services, tourist flux, etc. Variations in such feature are presumed to influence the performances of the districts while dealing with COVID-19. In the present study, all of these variables have been incorporated together with other epidemiological variables. The validity of adoption of these variables lies in the fact that they been utilised previously also. For instance, in the development of COVID-19 vulnerability indices, according to scholars like Wong et al., 2020 and Tiwari et al., 2021, who considered poor health and transportation infrastructure as a weak point when coping with COVID-19, and Arif & Sengupta 2021 and Boterman 2020, who considered populations, higher population densities increase the risk of COVID-19 spread. Likewise, Acharya and Porwal, 2021, have also taken into consideration the elderly age-group. Hesami Arani et al., 2021; 2022, efficiently utilised SWOT matrix for factors for modelling COVID-19 risk modelling in hospitals and industries, respectively. In the present study, in total, 17 indicators were selected for the conducting of quantitative SWOT and vulnerability index which can be broadly categorise as demographic indicators: infrastructural and socio-economic.

2 Description of the study area

Uttarakhand is 27th state of India, formed on 9 November 2000, located between 30.0668°N and 79.0193°E (Fig. 1). Being part of the central Himalayas, it enjoys submontane to mountainous climate. There is a vast altitudinal variation giving rise to distinctive microclimates at over short distances (Joshi et al., 2018). The transportation infrastructure is poorly developed under the physiological restrictions and rail network is extremely limited (Siddique & Khan, 2019). Cool climate coupled with picturesque beauty compels tourist inflow increasing potential infections while undermined health infrastructure under the effect of compromised infrastructure makes the situation gloomy; however, there are 141 hospitals in the state as identified on the maps developed by Government of Uttarakhand. Population distributions and per unit area densities area are highly uneven population being highest in Haridwar, i.e. 1,927,029 persons to being lowest in Rudraprayag, i.e., 236,857 persons, while density ranges from 44 persons/sq.km. in Uttarkashi to 679 persons/sq.km. in Haridwar as par NASA's CEDA worldpop raster. The state is the land of serene beauty, attracting lakhs of foreign as well as domestic tourists each year. Tourism is vital for the economic development of Uttarakhand, but the local people have to incur a price in the form of spread of infections and extra burden on the already limited health facilities. In the times of pandemic, tourism affects COVID spread (Hâncean et al., 2020); therefore, people of Uttarakhand are vulnerable to COVID-19 due to the tourism industry. There is great economic disparity across the districts of Uttarakhand with slightly uneven literacy rates.

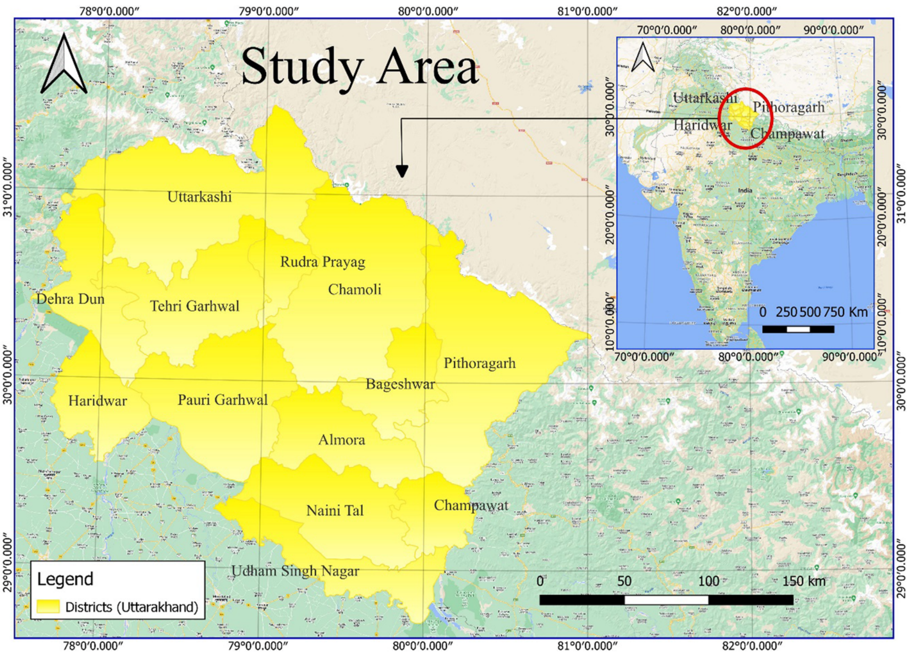

Fig. 1 Geographical location of study area: map showing location of Uttarakhand district in India

3 Materials and methods

For assessing the performance districts in COVID-19, vulnerability, several factors are aggregated. For that purpose, quantitative SWOT and ratioing methods are employed in association with multi-criteria decision-making (MCDM). AHP weights are assigned to the normalised values of the selected variables. The methodological application is showed in Fig. 2.

3.1 Selection of variables and database

Variable selection is a very crucial part in vulnerability assessment and modelling. There is an ocean of information regarding the factors with the potential to worsen the condition of COVID-19. Many scholars have emphasised the socio-economic and demographic variables. Economically backward region, low-income population groups and uneducated people have relatively high susceptibility to the pandemic. Likewise, inaccessible region, poorly served areas in terms of health services areas, like hospitals and oxygen plants, have greater vulnerability. The process of variable selection can be highly differing from region to region and from community to community. Hence, in the present study, 17 variables are selected each with its intrinsic importance for Himalayan state of Uttarakhand. They are related to the peculiar demographic, socio-economic, infrastructural and health-related issue of the state. The selected variables are broadly discussed, and the sources are supplied in Table 1. All of the variable are secondary in

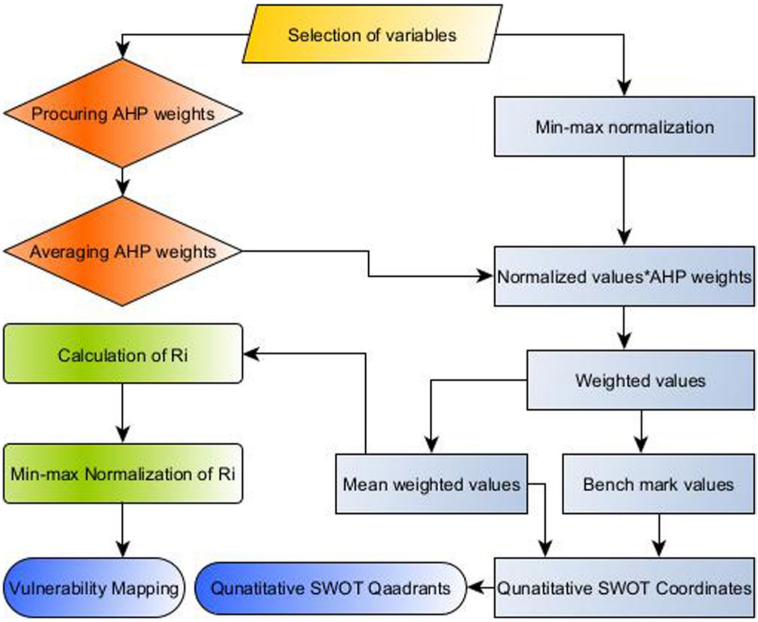

Fig. 2 Graphical presentation of methodological work

nature and are taken from online sources except service area of hospitals and oxygen plants.

3.1.1 Demographic variables

The nature of the COVID-19 is such that the pace of spread and mortality rates due to epidemic is highly dependent on the demographic construct of the population; therefore, demographic factors should be part of a vulnerability assessment. For instance, Boterman 2020; and Fielding-Miller et al., 2020, attributed larger populations to increased COVID-19 risk, while Rocklöv & Sjödin 2020 asserted that higher population densities increase the risk of COVID-19 spread. In this paper, the indicators like population distribution, district-wise population density, district-wise COVID-19 cases and district-wise fraction of population were considered to represent the demographic composition of a population in the context of COVID-19 (Fig. 3).

3.1.2 Socio-economic variables

The social construct and economic conditions play a vital role in a segment of human population in coping with epidemic. COVID-19 has presented itself as extreme blow to the economic resources (Bamweyana et al., 2020). Economic regions with higher gross domestic product (GDP) and district domestic product (DDP) seemed to have performed better in the desperate times of pandemic (Bhattacharya & Banerjee, 2021) and literacy rates seemed to have a negative correlation with the spread of COVID-19 (Tamrakar et al., 2021). The economically weaker section of the society with low per capita income has

Table 1 Domains of vulnerability and variables within

Selected variables	Variable description	Source
Demographic		
District-wise proportion of younger population	Calculated as proportion of individuals in the population 19 years or younger and normalised	District handbooks (2017–2018)
District-wise population density	Calculated as number of persons per unit area (sq. km.) and then normalised	Sum for each district is calculated from the population raster obtained from CEDA, NASA earth data for the year of 2020; district area is calculated using Diva-GIS shapefile. District population sum is divided by area of district shapefile in ArcGIS
District-wise fraction of population	Calculated as ratio of population districts to the total population and then normalised	World pop data from CEDA, NASA for the year of 2020 was obtained and processed in ArcGIS
Socio-economic		
District-wise district domestic product	Used directly in numerical form in rupees and normalised	Data extracted from report (2011-12 and 2017-18) of direct of economics and statistics, Department of Planning, Uttarakhand (https://des.uk.gov.in)
District-wise per capita income	Used directly in numerical form in rupees and normalised	Data extracted from report (2011-12 and 2017-18) of direct of economics and statistics, Department of Planning, Uttarakhand (https://des.uk.gov.in)
District-wise literacy rates	Used directly in numerical form in rupees and normalised	District handbooks (2017–2018)
Infrastructural modelling:		
District-wise area covered by 1 km distance from road	Calculated as area under 1 km distance from road and normalised	Roads: OSM Shapefiles, distance from roads are modelled using buffer analysis in ArcGIS environment.
Service area modelling of healthcare system		
District-wise service area of hospitals (within 10 km range)	Calculated in sq. km. and normalised	Hospital: The maps available on UK government website (health.uk.gov.in) were geo-reference and shapefiles are created for hospital locations; Roads: OSM Shapefiles, Service area is generated using Network Analysis of ArcGIS with 10 km tolerance. Area of service area geometries is calculated.

Table 1 (continued)

Selected variables	Variable description	Source
District-wise service area of hospitals (within 30 km range)	Calculated in sq. km. and normalised	Hospital: The maps available on UK government website (health.uk.gov.in) were geo-reference and shapefiles are created for hospital locations; Roads: OSM Shapefiles, Service area is generated using Network Analysis of ArcGIS with 30 km tolerance. Area of service area geometries is calculated.
District-wise unserved area of hospitals (beyond 60 km)	Calculated in sq. km. and normalised	Hospital: The maps available on UK government website (health.uk.gov.in) were geo-reference and shapefiles are created for hospital locations; Roads: OSM Shapefiles, Service area is generated using Network Analysis of ArcGIS with 60 km tolerance. Area of service area geometries is calculated and subtracted from the district shapefiles.
District-wise service area established oxygen plants (within 40 km range)	Calculated in sq. km. and normalised	Oxygen Plants: Google Earth Pro kml. files for oxygen plants converted into shapefiles, Roads: OSM Shapefiles, Service area is generated using Network Analysis of ArcGIS with 40 km tolerance. Area of service area geometries is calculated.
District-wise unserved area of oxygen plants (beyond 40 km)	Calculated in sq. km. and normalised	Oxygen Plants: Google Earth Pro kml. files for oxygen plants converted into shapefiles, Roads: OSM Shapefiles, Service area is generated using Network Analysis of ArcGIS with 40 km tolerance. Area of service area geometries is calculated and subtracted from the district shapefiles.
District-wise increase in service area of oxygen plants (within 40 km range)	Calculated in sq. km. and normalised	Proposed Oxygen Plants: Google Earth Pro kml. files for oxygen plants converted into shapefiles, Roads: OSM Shapefiles, Service area is generated using Network Analysis of ArcGIS with 40 km tolerance. Area of service area geometries is calculated and subtracted from the current oxygen plant service area shapefile.

Table 1 (continued)

Selected variables	Variable description	Source
Epidemiological		
District-wise COVID cases	Calculated as total number of COVID cases as of 12 June 2021.	Directorate of Medical health & Family Welfare, Uttarakhand (2021)
District-wise death rates	Calculated as proportion of persons died due to COVID-19	Directorate of Medical health & Family Welfare, Uttarakhand (2021)
District--wise recovery rates	Calculated as proportion of persons who discharged from the hospital	Directorate of Medical health & Family Welfare, Uttarakhand (2021)
Tourism		
District-wise tourist Influx	Enumerated as total number of tourists	Uttarakhand Tourism, (2020)

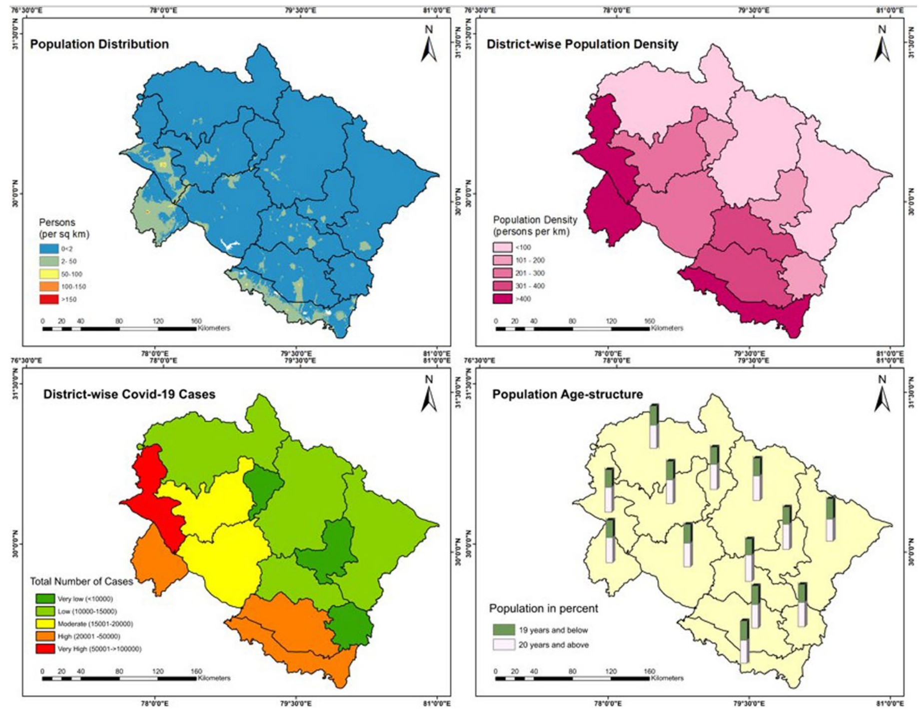

Fig. 3 Selected demographic variables for next COVID-19

been seriously impacted by COVID-19 all around the world (Mukherji, 2020; Karaye & Horney, 2020; Daras et al., 2021). It is, therefore, logical to adopt DDP, per capital income and literacy as socio-economic factors (Fig. 4).

3.1.3 Infrastructural variables

Distance from road plays a key role in determining the spatial coverage of a health system and accessibility to health facilities (Mohammadkhan et al., 2011; Browning & Lee, 2017). A patient is more like to get quicker medical facility when there is short distance from road (Silalahi et al., 2020). Therefore, distance from has also played a key role in the availing the health facilities in the hilly state of Uttarakhand. However, a small distance from road can also be attributed to a greater degree of human movement which is linked to spread of COVID-19 (Mollalo et al., 2020). In this paper, area covered by 1 km distance from road in Uttarakhand was modelled using buffer analysis with 1 km. District-wise proportion of area covered by 1 km distance from road modelled buffer is considered as infrastructural variable for the COVID-19 vulnerability assessment (Fig. 5).

3.1.4 Epidemiological variables

There are several epidemiological factors that might make a population vulnerable to higher mortality by COVID-19. Thus, it is valid to incorporate these factors to vulnerability assessment (Acharya & Porwal, 2020). Till now COVID-19 has shown high fatality

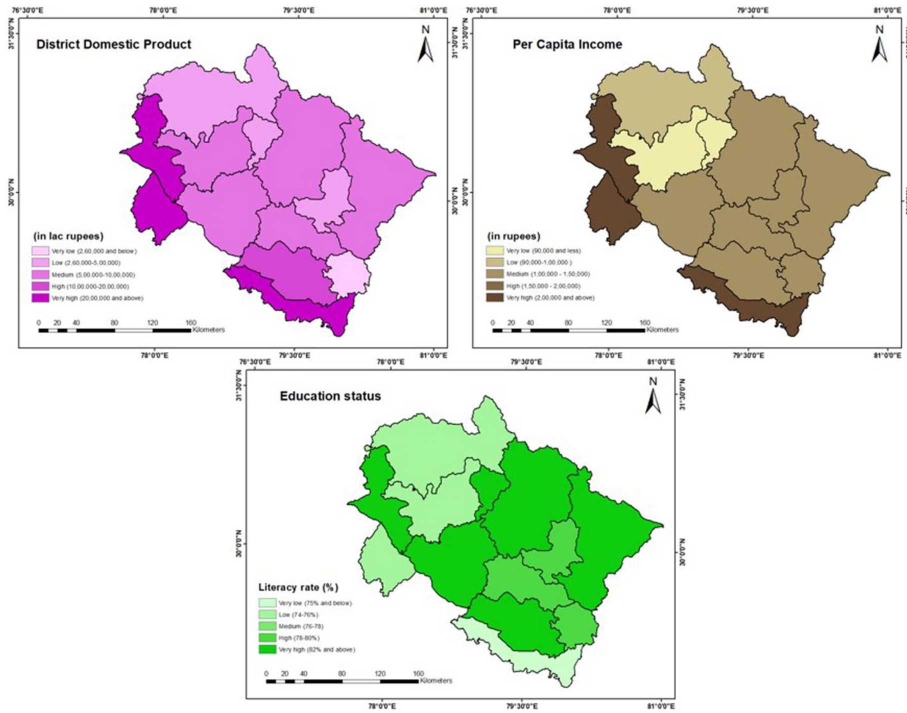

Fig. 4 Selected socio-economic variables in the Uttarakhand district

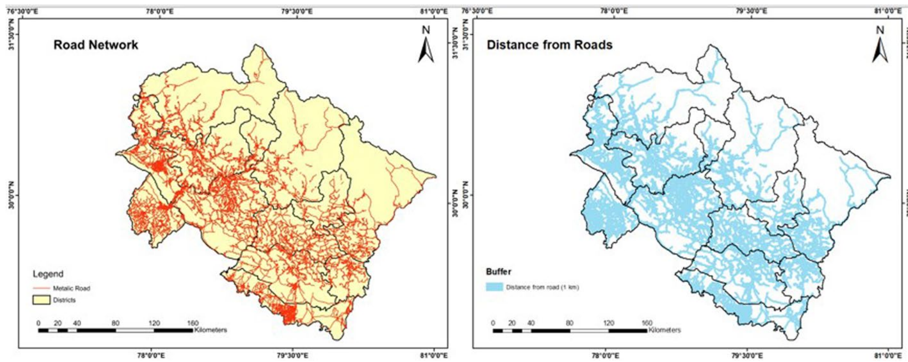

Fig. 5 Infrastructural variables selected for next COVID-19 variant

rates in older population, but the third wave has been to be more deadly for the younger age groups (Chua et al., 2021, Neuberge et al., 2021, Fisayo & Tsukagoshi 2021). Apart from that, there is a direct relationship between number of COVID-19 cases in the region and the rate of infections and deaths (Dowd et al., 2020; Chhabra & Agrawal, 2020). Also, different populations have shown differing recovery rates. Therefore, in the present study, proportion of individuals in the population 19 years, district-wise total number of COVID-19 cases, death rates and recovery rates were included.

3.1.5 Tourism-related variables

Tourism can incur a social cost on the region as more tourists mean more outsiders interaction with the local population and increased risk of infections (Qiu et al., 2020). Uttarakhand has numerous tourist destinations. The state receives thousands of tourists each year. As of Uttarakhand tourism report, instead of pandemic, the state received a total of 7,874,765 tourists in 2020. There is a variation in tourist influx at district level. In the present work, the tourism influx data for the assessment of COVID-19 vulnerability assessment were incorporated.

3.2 Service area modelling of healthcare system using GIS

The treatment-seeking ability of a population and management of epidemic are dependent on the spatial coverage of heath care (Khashoggi & Murad, 2020). Network analysis is one of the techniques that have been in use for spatial modelling of spatial coverage of healthcare system (Walsh et al., 1997; McLafferty, 2003; Gibson et al., 2011) and is being utilised by the scholars during epidemic also (Silalahi et al., 2020; Price et al., 2021; Ghorbanzadeh et al., 2021). In this study, the service area of healthcare system was modelled using GIS-based network analysis technique. A service area represents all the streets that are covered in a specific time or distance. It is delineated by adding buffer around a transit facility based on Euclidian distance. It is a useful method for dealing with problem of estimation in straight lines (Gutiérrez and García, 2008). The second method involves time as threshold. The choice of the method significantly affects the final result (Upchuch et al., 2004). Unlike previous studies that used hospitals, we also incorporated the oxygen plants while modelling the service area due to high significance of oxygen availability during the COVID-19 (Fig. 6). The hospitals include both district hospitals and private hospitals. A district-level classification as served and unserved area was developed. Service area was classified on the basis of distance into the following five variables to represent health security, district-wise service area of hospitals (Within 10 km range), district-wise service area of hospitals (Within 30 km range), district-wise unserved area of hospitals (Beyond 60 km) and district-wise service area established oxygen plants (Within 40 km range). The rational to select distance as impedance is the distance is independent of mode of transportation and has inverse relation with time taken in travelling from point

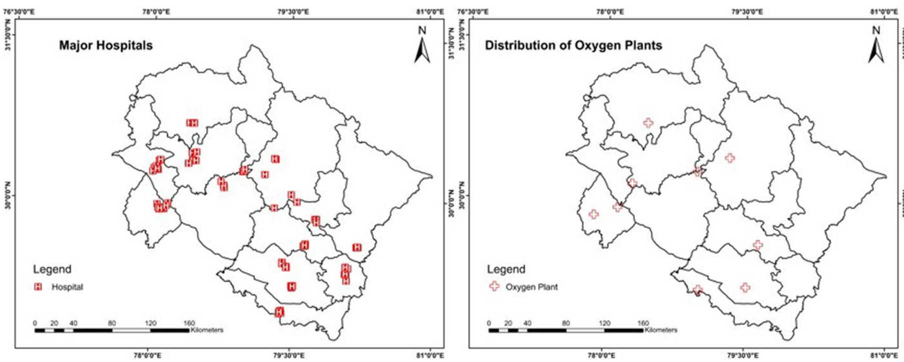

Fig. 6 Distribution of hospitals and oxygen plants in the Uttarakhand district

"A" to point "B". The service area is classified on the basis of different impedances to create servicer areas relatively better served or theoretically "unserved" as distance is a continuous variable and needs to be binned to utilise it relativity.

3.3 Quantitative SWOT analysis

The multi-attribute decision-making (MADM)-based quantitative SWOT analysis was used to make a comparative assessment of performances of multiple objects (Chang & Huang, 2006). When combined with analytical hierarchical process (AHP), it becomes a robust technique to run performance analysis (Görener et al., 2012) which was constructed according to the four elements of decision-making: alternatives, criteria, performance and weight. Alternatives represent objects to be compared with (in the present case, districts of Uttarakhand). Criteria refer to the variables of external assessment and internal assessment. In the present study, the AHP matrix was performed based on expert's judgement. The experts were invited through email, video call, voice call and direct face-to-face interaction to give their judgement using Saaty's scale. Performance refers to the performance of the objects put into comparison under the evaluation of all the variables. Performance structure represents the weights of the variables. Normalisation was performed to convert calculated values of performances to dimensionless units. The indicators were categorised as cost indicators and effective indicators. The calculated weighted values were then multiplied with AHP weights. The following equations represent the cost indicator (Eq. 1) and effective indicator (Eqs. 2 and 3):

$$E_{ij} = P_{if} / \left\{ \max_j \left(P_{ij} \right) \right\},\ i,j = 1, 2, \ldots n \tag{1}$$

$$E_{ij} = \left\{ \min_j \left(P_{ij} \right) \right\} / P_{ij},\ i,j = 1, 2, \ldots n \tag{2}$$

$$0 \leq E_{if} \leq 1 \Sigma_j E_{ij} = 1 \tag{3}$$

where P_{ij} and E_{ij} denote normalised and non-normalised performance values of j candidate objects with i^{th} evaluative indicator.

In the present study, quantitative SWOT was adopted to analyse the performance of districts to deal with COVID-19. To conduct quantitative SWOT, 17 factors as evaluative indicators were selected and grouped into two categories: one that helps coping with COVID-19 or effective indicators, i.e. strengths and opportunities, and the other that exacerbates the situation or cost indicators, i.e. weaknesses and threats. After applying min–max normalisation on variables, weights were assigned to the variables using analytical hierarchical process (AHP). In AHP, factors were presented as matrices A_1, $A_2 \ldots A_n$, while weights are represented as w_1, $w_2 \ldots w_n$ (Eq. 4).

$$A = \begin{bmatrix} 1 & a12 & \ldots an \\ 1/a12 & 1 & \ldots a2n \\ \vdots & \vdots & \ddots \\ 1/a1n & 1/an2 & 1 \end{bmatrix} \tag{4}$$

where matrix element $a_{ij} = 1/\ a_{ij,}$ and $i = j$, $a_{ij} = 1$. The values of *wi* vary from 1 to 9, where 9 represents absolute importance and 1 represents least importance. The relative importance of a.i. and *aj* is depicted as *aij* (Eq. 5).

$$A = \left[aij\right] = \begin{bmatrix} w1/w1 & w1/w2 & \dots w1/wn \\ w2/w1 & 1w2/w2 & \dots w2/wn \\ \vdots & \vdots & \ddots \\ wn/w1 & wn/w2 & wn/wn \end{bmatrix} \tag{5}$$

where w_i was calculated as (Eq. 6):

$$w_i - 1/\lambda_{\max} \sum\nolimits_{j=1}^{n} aijwj \tag{6}$$

For consistency test, consistency index (CI) and consistency ratio (CR) were computed as follows (Eqs. 7 and 8):

$$\mathrm{CR} = \frac{CI}{RI} \tag{7}$$

$$\mathrm{CR} = \frac{(\lambda\mathrm{max} - 1)}{(n - 1)} \tag{8}$$

The weights elicited from AHP were multiplied with the normalised values of the selected variables to obtain weighted values. The weighted values of were give a positive and negative symbol for determining the polarity of these values on the coordinate system. These weighted values were then averaged to get weighted means for all the districts (D_1 to D_{13}). Mean of all weighted means was calculated to obtain the bench mark value. The process is performed separately on both internal and external variables. The coordinate for each district is obtained by subtracting bench mark values from corresponding weighted mean values. The coordinate values are then plotted on the quadrants.

3.4 Construction of vulnerability index

Construction of vulnerability index of the deadly COVID-19 is essential for better predictability of the spread and impact of the disease (DeCaprio et al., 2020; Amram et al., 2020). In our study, COVID-19 vulnerability index was constructed by dividing the weighted sums of weaknesses and threats to the weighted sums of strengths and opportunities that was developed for quantitative SWOT. The vulnerability index was calculated by normalised values of ratios between weighted means of cost indicators, i.e. weaknesses and threats, and effective factors, i.e. strengths and opportunities (Eqs. 9 and 10).

$$R_i = \frac{Weighted\,mean\,c}{weighted\,mean\,d} \tag{9}$$

$$\text{Vulnerabilityindex} = \frac{R_i - R_{\min}}{R_{\max} - R_{\min}} \tag{10}$$

where weighted mean ^{c} denotes cost indicators, weighted mean ^{d} denotes effective indicators and R_i denotes ratio of weighted means.

4 Results

All of the major evaluative factors considered in this study were mapped in order to gauge impact of COVID-19 on districts of Uttarakhand. Population distribution, population density, COVID-19 cases, population below 19 years, area covered by 1 km distance from road, hospitals and oxygen plants at district level were mapped. Both population distribution and population density maps confirmed the concentration of population in the Tarai belt districts, i.e. Udham Sigh Nagar, Haridwar and in the state capital Dehradun. Dehradun has the highest prevalence of COVID-19 cases. Road density is also highest around these aforesaid districts. However, hospital and oxygen plant distribution does not seem to be specifically uneven except for Pauri Garhwal and Bageshwar where no oxygen plant is available. However, the importance of road connectivity was taken into consideration when a district-level service area of hospitals (Fig. 7) and oxygen plants (Fig. 8) were generated using network analysis of ArcGIS 10.5 exploiting the location data of road network, hospitals and oxygen plants. Almora, Champawat, Nainital and Rudra Prayag have 100% of the area cover with a hospital in 60 km range. Almora is the only district with no unserved area, while Pithoragarh is the district with maximum unserved area being 59% where there are no hospitals in the range of 60 km (Fig. 9). In regard to oxygen plants, Bageshwar is completely devoid of oxygen services within the range of 40 km followed by Pithoragarh with only 1% area of oxygen plant within the range of 40 km (Fig. 10).

For the composition of district-level vulnerability index of COVID-19 in Uttarakhand, cost and effective indicators were calculated and normalised (Table 2). The normalised values were then employed to construct vulnerability map for evaluating the districts for COVID-19 vulnerabilities (Fig. 11). The vulnerability index map has five classes ranging from very low vulnerability to very high vulnerability. Pithoragarh falls in the very high vulnerability class. Nainital, Champawat, Bageshwar, Dehradun and Chamoli represent very low vulnerability. On this map, Pauri Garhwal and Uttarkashi fall in moderately vulnerable class, while Haridwar, Udham Singh Nagar, Almora, Tehri Garhwal and Rudra Prayag also fall in low vulnerability class.

For conducting quantitative SWOT, cost and effective indicators were categorised internal and external indicators, respectively. Vulnerability assessment for the district of Uttarakhand using SWOT analysis was conducted (Tables 3, 4 and 5, and Fig. 12). Then using the quantitative SWOT, vulnerability index was developed (Table 6). For brevity, actual and normalised values of the research are presented in supplementary tables (*S-1* and *S-2*). Findings showed patterns of different vulnerabilities across the state of Uttarakhand and different performances of the candidate districts while dealing the pandemic.

5 Discussion

In the context of India, several researches have been conducted on COVID-19 and its vulnerability assessments have been prepared extensively using various dimensions and pre- and post-lockdown impacts have been assessed (Sahoo et al., 2021). For instance, Banerjee and Bhattacharya, (2020), studied COVID-19 vulnerability in the context of homelessness across India. Acharya and Porwar 2020 prepared a nationwide vulnerability index using socio-economic, demographic and healthcare availability.

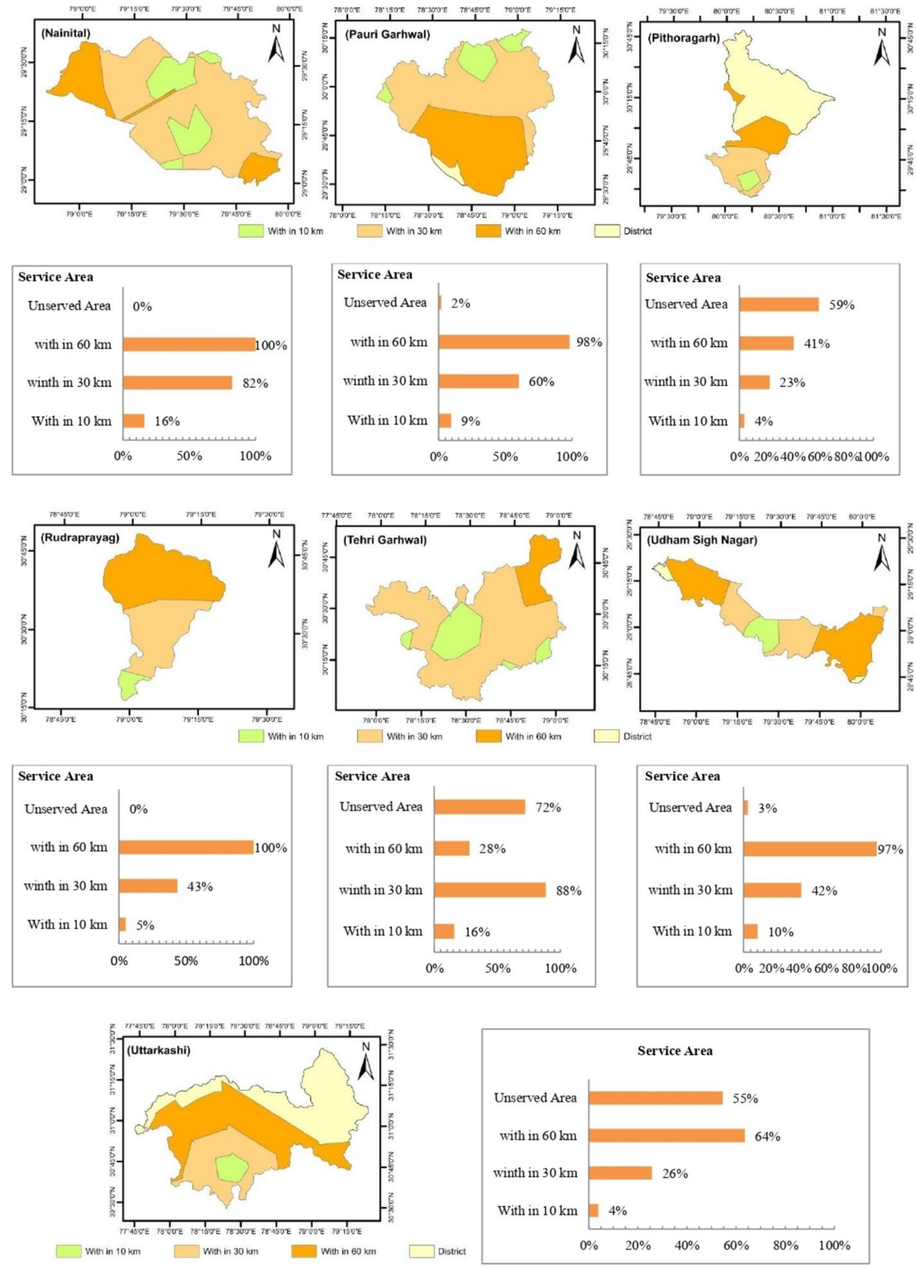

Fig. 7 District-wise service area of hospitals based on road connectivity

Each of these selected factors was assessed separately. However, in these studies, there is a lack application of any aggregating method to assess the cumulative vulnerability of all the factors; rather, vulnerability assessment was done on an ordinal scale using ranking method. Lal et al., (2021), prepared a pan-India across all the states focussing

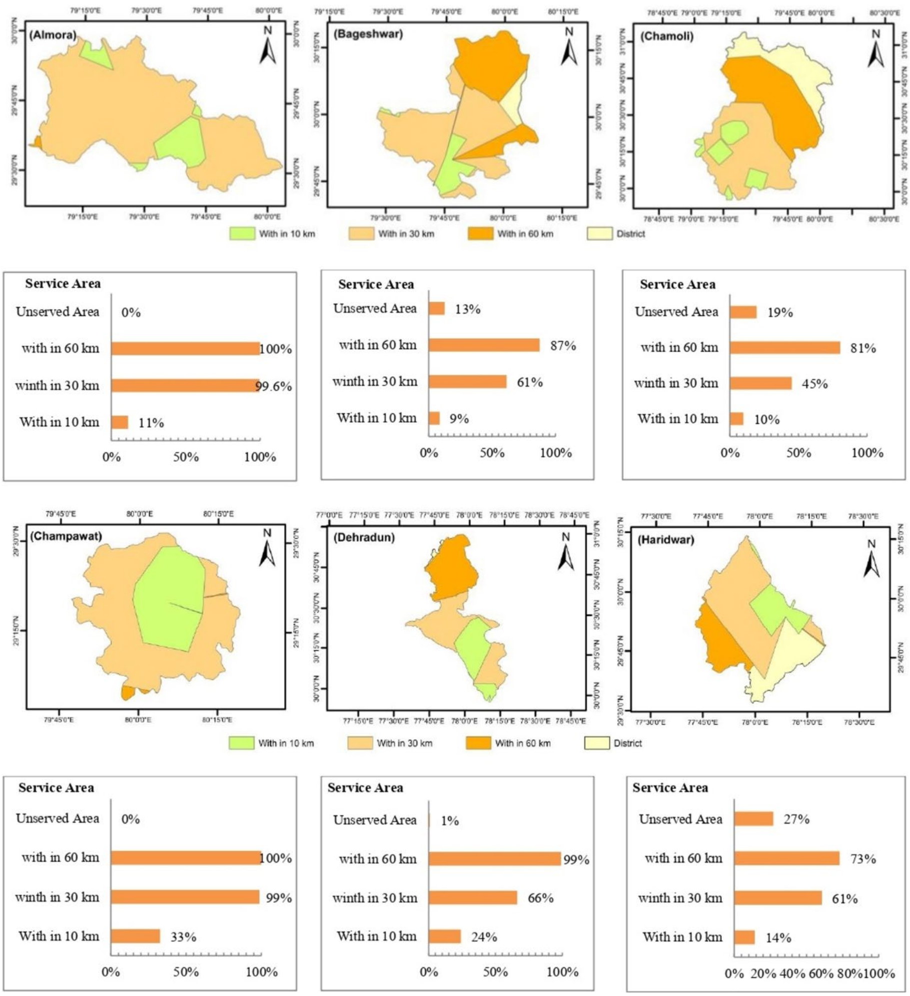

Fig. 7 (continued)

socio-economic factors. They used AHP method for vulnerability modelling simply applying criteria weights to the factors. Hesami Arani et al., (2021), in their research have utilised SWOT for the assessment of COVID-19 in the industries of Iran. SWOT matrix was also adopted to assess the COVID-19 vulnerability of central hospitals of Keshan in Iran (Hesami Arani et al., 2022). However, the application of this method is scarce in case of India. Sarkar and Chouhan 2021 used principal component analysis for preparing COVID-19 vulnerability index.

A vast county-level, interstate comparison and assessment were prepared in great deal (Mishra Gayen, 2020; Imdad et al., 2021; Sarkar and Chouhan, 2021; Jha et al., 2021). Acharya and Porwar, 2020, with the help of vulnerability index can give a broader picture of the disease, but the articulation of the vulnerability assessment is based on 15 indicators that remain constant across the country, while Imdad et al., 2021, internalise other factors like education, ambient environment and climatic conditions which we come to terms with.

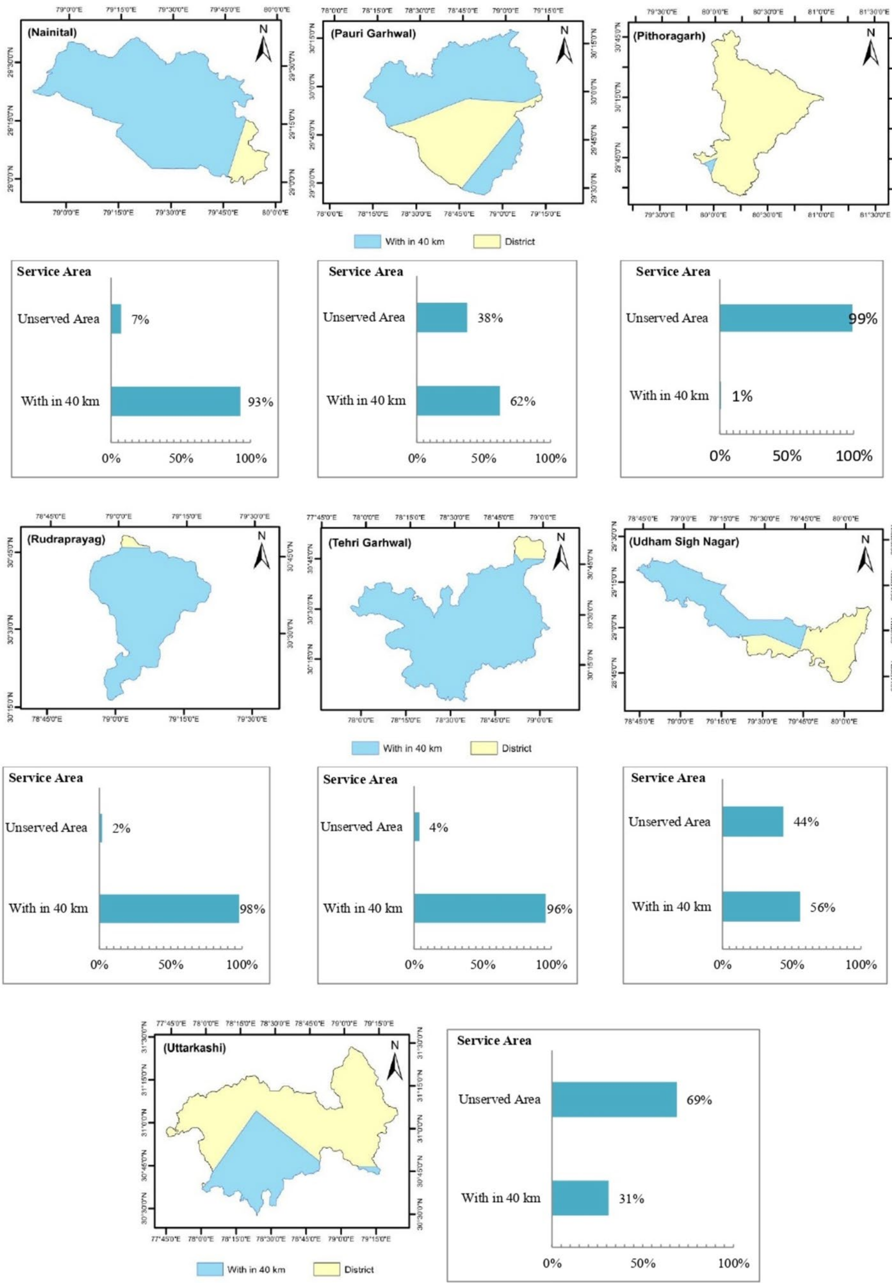

Fig. 8 District-wise service area of oxygen plants based on road connectivity

All of these aforesaid research works have its own significance, yet they either lack region-specific analysis or have not adopted for the case of India. For instance, in India SWOT or quantitative SWOT has not been used for micro-level studies conducted by

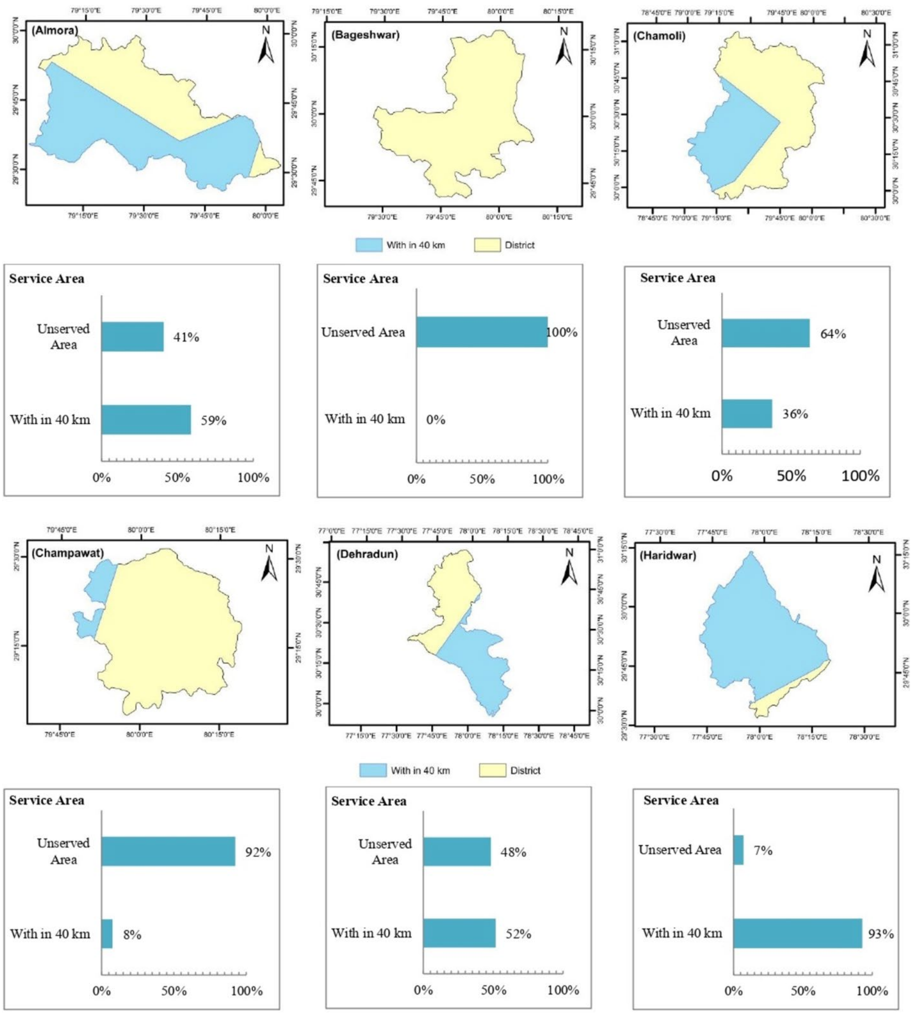

Fig. 8 (continued)

Hesami Arani et al., (2021); (2022). These studies, however, have limited efficiency to draw detailed picture of varying vulnerability of individual states.

The AHP method adopted by Acharya and Porwar, 2020, and PCA method used to extract principal components, adopted by Sarkar and Chouhan, 2021, do not classify the conditioning variables as "cost" variable and "effective" variable unlike present study where selected variables are categorised into "cost" and "effective" and the values of "cost" variables are countered by the values of "effective" variables in mathematical division. This mathematical ratioing methods is easy and simple.

The selection of variables cannot be kept uniform across 28. Therein, we also argue that each region and state have their own fragilities and strengths and thus. Therefore, the state of Uttarakhand has its own special status in terms of accessibility, socio-economic variability and population distribution, and has remained infamous for its response in desperate times (Sharma et al., 2014). The variable selection is highly crucial. The study

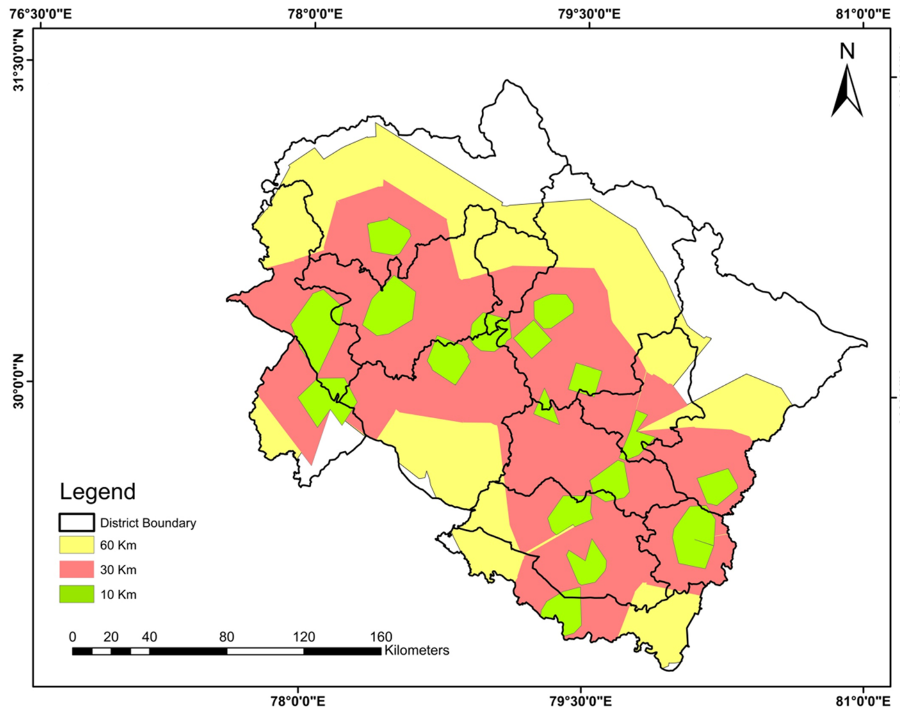

Fig. 9 Service area of hospitals in the Uttarakhand district

also requires a robust technique to aggregate all the variables that are most crucial for vulnerability assessment of Uttarakhand. Hence, 17 indicators are carefully selected for Uttarakhand and added service areas of health facilities. Uttarakhand has difficult terrain and limited transportation facility; in such cases, modelling service area of hospitals and oxygen plants as indicators is of key importance, other than demographic epidemiological factors along socio-economic disparity, while composing quantitative SWOT and vulnerability index. No previously conducted nationwide study has used network analysis and service area modelling as variable for COVID-19.

Most of the previous studies conducted nationwide have propounded very different results for Uttarakhand than that of the present research. Key differences are seen in the vulnerability evaluation of districts. Northernmost district of Pithoragarh concluded to be least affected with COVID-19 with lowest vulnerability index (Imdad et al., 2021; Sarkar and Chouhan, 2021; Jha et al., 2021) contrasting to present study where Pithoragarh is most vulnerable on vulnerability index, followed by Uttarkashi, Haridwar and Udham Singh Nagar. In-accessibility of health services, i.e., hospitals and oxygen plants under compromised road network, is the deciding cause for the district like Pithoragarh to be more vulnerable to COVID-19. Nainital and Chamoli are the safest as of the present study.

Furthermore, no study has used quantitative SWOT analysis to measure COVID-19 vulnerability in India or for any state previously. Dampson et al., (2020) utilised SWOT to evaluate COVID-19 in Ghana, whereas Dorcheh et al., (2021) used a hybrid-SWOT to evaluate COVID-19's influence on economic conditions. This method, on the other

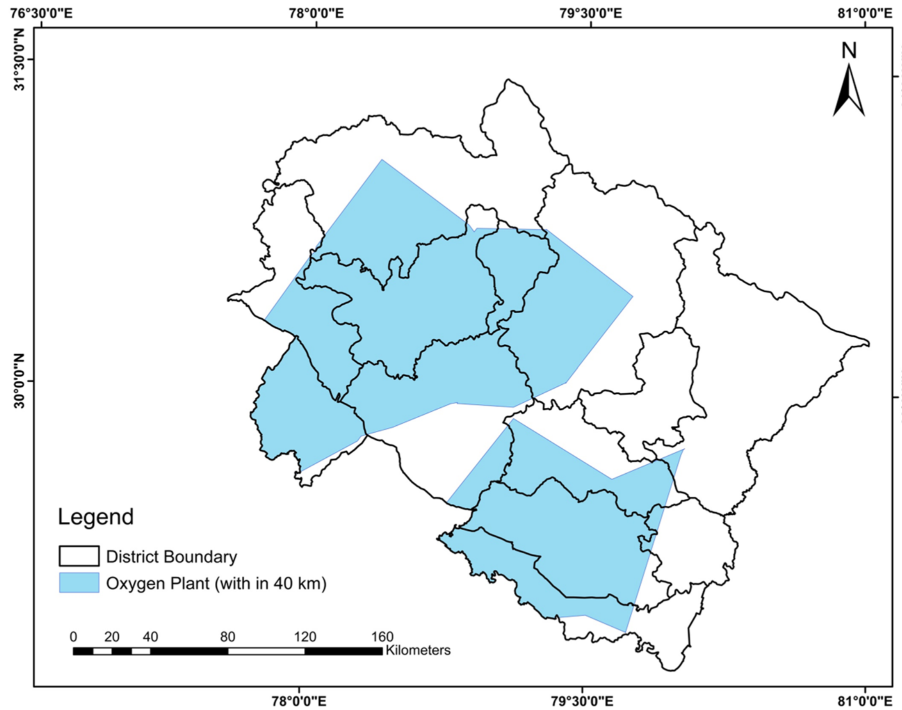

Fig. 10 Service area of oxygen plants in the Uttarakhand district

hand, has never been applied in a major study to compare the performance of regions or nations in dealing with COVID-19. As a result, quantitative SWOT was used in the present study to perform a comparison assessment of the districts in Uttarakhand, making it one of a kind for states and also in the pan-India context, opening up new possibilities for diving into potential management techniques for the current epidemic.

6 Conclusion and suggestions

The present study deals with the district-level vulnerability across Uttarakhand. Construction vulnerability index and quantitative SWOT are used to assess the vulnerabilities of the districts and their comparative performances in coping with COVID-19. As far as the quantitative SWOT analysis is concerned, only two districts, Dehradun and Haridwar, are in the first quadrant, i.e. in opportunities and strengths, and the Chamoli district in the second quadrant being weak yet better in opportunities. Rest of the districts are almost parallel to the strength–weakness axis. Bageshwar, Champawat, Rudra Prayag, Uttarkashi and Pithoragarh fall in the third quadrant and are far-flung to the left showing worst performance of dealing with COVID-19. Almora, Tehri Garhwal and Udham Sigh Nagar are in the fourth quadrant, but are parallel to the strength–weakness axis.

It is noteworthy that the quantitative SWOT results and the created vulnerability map represent a strange coherence. Pithoragarh, for example, is in the worst possible shape in terms of both performance and vulnerability. Dehradun and Haridwar, on the other hand,

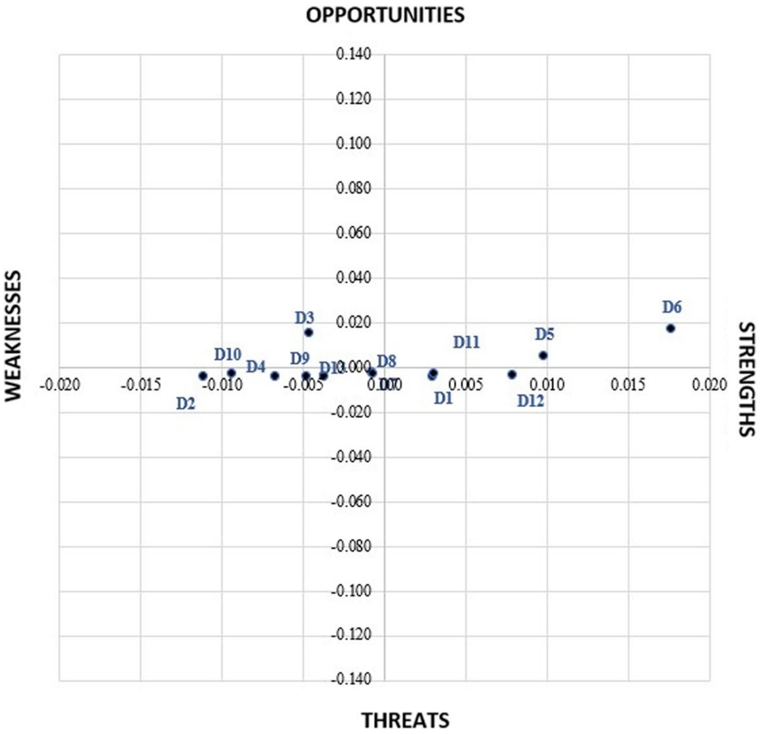

Fig. 11 Quantitative SWOT plot of next COVID-19 variant

are high-performing districts on quantitative SWOT with very low vulnerability. All districts in the quadrant parallel strength–weakness axis show average performance. Pauri Garhwal reflects medium performance and moderate vulnerability.

Mitigation efforts to cope up with the COVID-19 epidemic and manage its far-reaching consequences need effective planning and require the right kind of data. In this study, we assess and report a district-level comparison and a vulnerability index that is designed to help government in planning effectively respond to the coming COVID-19 epidemic waves in Uttarakhand. These data are meant to be used by government officials and planners to pin point the vulnerable districts and support them to prepare for, and to mitigate and reduce, health and socio-economic consequences of the epidemic. Despite the usefulness of these two methods, there are some limitations. There is not an ideal consistency between the results of quantitative SWOT and the vulnerability index. It is ideal to construct quantitative SWOT and vulnerability index at sub-district level, but due to the lack of fundamental database it was not practically possible. Hence, this analysis is restricted to the district level. Therefore, the present study will provide a vulnerability data to the policy makers at district for the state of Uttarakhand.

In brevity, the development of an efficient and well-connected roads network is recommended in far-flung districts like Uttarkashi and Pithoragarh. In the districts with high population density and better health facilities, preventive measures are needed to be taken, i.e. social distancing, compulsion of face masks. Health literacy and medical know-how are of key importance in coping with pandemic, and general public awareness is a must

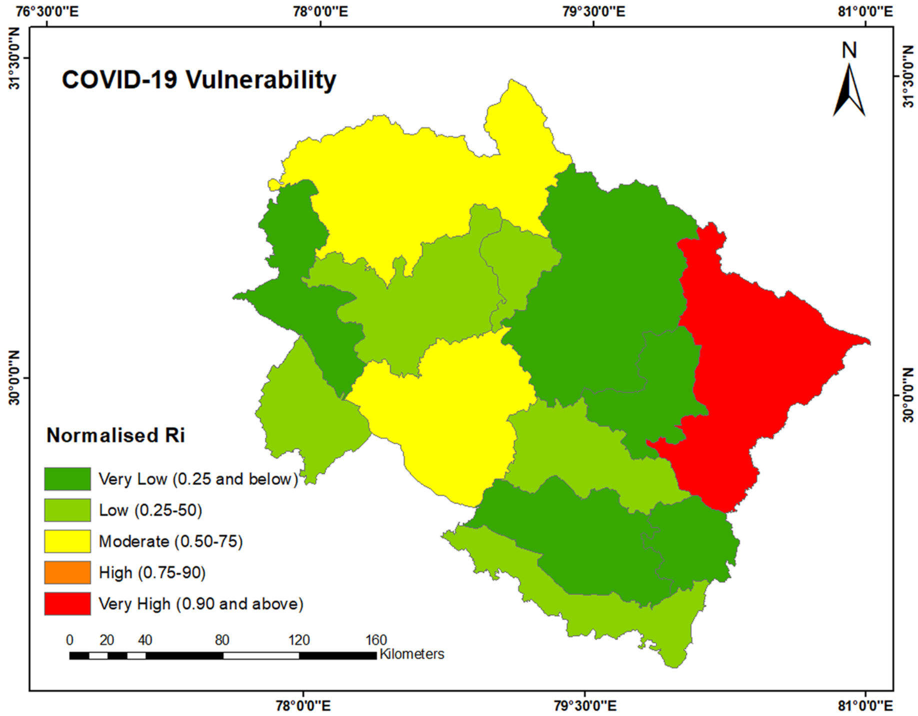

Fig. 12 Next COVID-19 variant (*Omicron BA.2*) vulnerability map of Uttarakhand

Table 2 Calculation of variable's weight using AHP

Variable codes	AHP weights (criteria weights)	Weighted sum	Ratio of weighted sum to criteria weights
V_1	0.109	7.255	66.332
V_2	0.104	7.723	74.199
V_3	0.078	4.928	63.341
V_4	0.075	4.314	57.741
V_5	0.069	3.200	46.599
V_6	0.065	3.186	49.399
V_7	0.053	2.464	46.603
V_8	0.049	2.057	41.714
V_9	0.060	2.685	44.852
V_{10}	0.045	1.421	31.892
V_{11}	0.040	1.256	31.092
V_{12}	0.056	2.549	45.207
V_{13}	0.068	2.592	38.198
V_{14}	0.038	0.983	25.674
V_{15}	0.015	0.168	11.496
V_{16}	0.043	1.176	27.416
V_{17}	0.034	0.538	15.949

Table 3 Internal assessment weighted average scores of all districts of Uttarakhand

Internal factors	AHP weights	Polarity	Weighted values (normalised values * AHP weights)												
			D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	D_{10}	D_{11}	D_{12}	D_{13}
I_1	0.109	–	0.047	0.040	0.039	0.068	0.000	0.084	0.031	0.026	0.031	0.109	0.063	0.079	0.069
I_2	0.104	–	0.006	0.000	0.006	0.002	0.104	0.045	0.032	0.011	0.004	0.003	0.010	0.031	0.006
I_3	0.078	–	0.078	0.022	0.022	0.008	0.004	0.016	0.000	0.047	0.034	0.012	0.038	0.009	0.010
I_4	0.075	–	0.020	0.008	0.001	0.009	0.047	0.075	0.018	0.013	0.003	0.006	0.013	0.054	0.000
I_5	0.069	–	0.024	0.006	0.014	0.004	0.057	0.069	0.031	0.034	0.017	0.000	0.026	0.061	0.011
I_6	0.065	–	0.038	0.012	0.030	0.011	0.033	0.029	0.036	0.065	0.032	0.000	0.041	0.028	0.028
I_7	0.053	–	0.009	0.016	0.037	0.011	0.011	0.001	0.002	0.015	0.053	0.000	0.001	0.009	0.040
I_8	0.049	–	0.000	0.008	0.013	0.000	0.000	0.019	0.000	0.001	0.040	0.000	0.049	0.002	0.037
I_9	0.060	+	0.060	0.003	0.004	0.026	0.013	0.007	0.008	0.004	0.000	0.001	0.008	0.004	0.000
I_{10}	0.045	+	0.045	0.022	0.013	0.044	0.025	0.022	0.035	0.022	0.000	0.012	0.038	0.011	0.002
I_{11}	0.040	+	0.018	0.000	0.028	0.001	0.015	0.021	0.036	0.032	0.001	0.012	0.040	0.015	0.024
I_{12}	0.056	+	0.000	0.041	0.041	0.051	0.054	0.045	0.056	0.022	0.032	0.047	0.029	0.050	0.049
I_{13}	0.068	+	0.005	0.000	0.003	0.000	0.043	0.068	0.011	0.006	0.004	0.000	0.004	0.043	0.001
I_{14}	0.038	+	0.004	0.005	0.007	0.002	0.024	0.038	0.006	0.007	0.007	0.000	0.001	0.025	0.002
I_{15}	0.015	+	0.009	0.008	0.012	0.009	0.015	0.000	0.014	0.011	0.011	0.010	0.001	0.000	0.002
Weighted Means			0.030	0.016	0.023	0.020	0.037	0.045	0.026	0.026	0.022	0.018	0.030	0.035	0.023

Bench mark value (mean of all weighted means) = 0.045303; Polarity: + for effective variables, - for cost variables; Consistency ratio for strengths and opportunities = 0.08815

I_1 to I_{12} indicate Population 19 and below, COVID-19 cases, Death Rate, Population Density, Fraction of population, area covered by 1 km distance from road, Unserved Area in sq.km. of Oxygen Plants (No Plant beyond 40 km), Unserved Area Hospitals (Area beyond 60 km), Service area Hospitals (Within 10 km range), Service area Hospitals (within 30 km range), Service area of Oxygen Plant (within 40 km range), and Recovery Rate, District Domestic product, Per capita Income, Literacy rates, respectively

D_1 = Almora, D_2 = Bageshwar, D_3 = Chamoli, D_4 = Champawat, D_5 = Dehradun, D_6 = Haridwar, D_7 = Nainital, D_8 = Pauri Garhwal, D_9 = Pithoragarh, D_{10} = Rudra Prayag, D_{11} = Tehri Garhwal, D_{12} = Udham Singh Nagar, D_{13} = Uttarkashi

Table 4 External assessment weighted average scores of districts of Uttarakhand

External Factors	AHP weights	Polarity	Weighted values (normalised values * AHP weights)												
			D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	D_{10}	D_{11}	D_{12}	D_{13}
E_1	0.043	−	0.000	0.000	0.006	0.000	0.019	0.043	0.004	0.003	0.000	0.002	0.002	0.001	0.001
E_2	0.034	+	0.000	0.000	0.034	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Weighted Means			0.00	0.00	0.000	0.000	0.020	0.000	0.009	0.021	0.002	0.001	0.000	0.001	0.001

Bench mark value (mean of all weighted means) = 0.031362;

E_1 and E_2 indicate Tourist Influx and Increased service area due to proposed oxygen plant, respectively.

Table 5 Coordinate values of Districts of Uttarakhand under the SWOT analysis

District codes	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	D_{10}	D_{11}	D_{12}	D_{13}
Coordinate values for internal factors[a]	0.003	−0.011	−0.005	−0.007	0.010	0.018	−0.001	−0.001	−0.005	−0.009	0.003	0.008	−0.004
Coordinate values for external factors[b]	−0.004	−0.004	0.015	−0.004	0.005	0.017	−0.002	−0.003	-0.004	−0.003	−0.003	−0.004	−0.004

[a] Coordinate value = Corresponding Weighted mean value – Benchmarking value; [b]Coordinate value = Corresponding Weighted average value – Benchmarking value.

Table 6 District-level vulnerability index

District codes	Cost indicators (Weakness and threats) Weighted mean[c]	Effective indicators (strengths and opportunities) weighted mean[d]	R_i	Min–max Normalisation of R_i
D_1	0.025	0.020	1.243	0.235
D_2	0.013	0.011	1.107	0.179
D_3	0.022	0.015	1.452	0.321
D_4	0.013	0.019	0.670	0.000
D_5	0.042	0.027	1.548	0.361
D_6	0.068	0.029	2.347	0.689
D_7	0.020	0.024	0.827	0.065
D_8	0.026	0.015	1.738	0.439
D_9	0.024	0.008	3.105	1.000
D_{10}	0.016	0.012	1.376	0.290
D_{11}	0.029	0.017	1.654	0.404
D_{12}	0.031	0.021	1.464	0.326
D_{13}	0.023	0.011	2.027	0.557

R_i= Weighted mean[c]/weighted mean[d]

to be promoted by government and non-government agencies. These measures are highly required in the remote rural area and in the districts with low literacy rates.

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Data Availability The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval The present study ensures that objectivity and transparency are followed in this research along with acknowledged principles of ethical and professional behaviour. The named authors confirm that the consent to participate is not applicable.

Consent for publication Not applicable.

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