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Heat Vulnerability Index for Urban Heat wave Risk Adaptation for Indian Cities: A Case Study of Akola

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ABSTRACT

According to IPCC report 2012, the intensity, duration, and frequency of heat wave are going to increase in the upcoming future (IPCC 2012) and from past experience shows that heatwave has a strong relation to human health. (Meteorological Bulletins 2003)(NDMA 2016)(Climate Council 2016). However, in India to tackle heat wave, Heat Action Plan (HAP) was prepared involving do's and don'ts strategy in which spatial pattern of vulnerability have not been addressed and excludes the role of an urban planner (Anjali Jaiswal, 2013). A Heat Vulnerability Index (HVI) was proposed using the GIS-based spatial information system which presents an overall vulnerability considering three more indices based on sensitivity, exposure, and adaptive capacity. This study entails a comprehensive method for preparing HVI which is constructed based on data extracted from census tract and remote sensing data assessed via Principal Component Analysis (PCA). The study also describes the criteria for selecting the indicators for constructing three indices and overall HVI taking weightage factor by variance in the context of Indian cities. The objective of the study is to perform a comparative analysis of vulnerability considering the indices and their interrelationship study at a local scale in India. These indices will further help in resource distribution, urban planning measures and also for proposing the specific policies which can help in risk adaptation of heat hazards in the dynamic nature of urban areas in a more accurate way.

Introduction

Heat wave does not have a universally accepted definition but defined by different countries in a different manner. In India, National Disaster Management Authority (NDMA) defines heat wave as a *"condition where the maximum temperature at a grid point is 3˚C or more than the normal temperature, consecutively for three days or more"* (NDMA 2016). In European countries, heat wave is defined by a combination of three criteria that is a minimum duration of heat event, relative humidity and threshold based on maximum and minimum temperature (WHO Europe 2009). While Australia has succeeded in establishing location-specific criteria in defining heat wave as *"a period of at least three days where the combined effect of excess heat and heat stress is unusual on the local climate"*. Both maximum and minimum temperatures are used in this assessment (Nairn and Fawcett 2013). Heat Index (Mohan et al. 2014) was not constructed in this study but rather is adopted by Meteorological Department of India which defines threshold temperature at 45ºC for plain areas and 30ºC for hilly areas (NDMA 2016). However, in India, the maximum temperature was found alone for constructing Heat Index and

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previous research have laid the importance of incorporating minimum temperature as a factor of accumulating heat load in defining heatwave (ARUP 2014)(Pattenden et al. 2003).

Heat wave is regarded as a silent killer where its intensity, duration and frequency is going to increase in future (Steffen et al. 2014). It's impact on mortality can be understood from past experiences like European heat wave, 2003 and Russian heat wave, 2010 which took 70,000 and 56,000 lives respectively (Climate Council 2016). The situation is similar in India where heat wave has taken more than 15,000 lives during the year 2000 to 2014 (NDMA 2016). Several pilot projects such as Climate Change and adaptation strategies for human health and Euro HEAT had established the heat-health relationship to understand and evaluate the impact of extreme heat and proposed the need for adaptation strategies to tackle heat wave implications (World Health Organization and World Meteorological Organization 2014).

For adaptation strategies, several countries including India have prepared Heat Action Plan. Reports suggests that rise in global average temperatures from 1.5 degrees Celsius to 2 degrees will lead to non-linear increases in mortality risks across Indian cities, according to a study by the Council on Energy, Environment and Water (CEEW), Indian Institute of Management Ahmedabad and Indian Institute of Technology Gandhinagar. Rising to the challenge of climate change, the Ahmedabad Municipal Corporation (AMC) prepared the 2013 Heat Action Plan, which was the first comprehensive early warning system and preparedness plan to tackle extreme heat events. Similarly, Heat Action Plan of Greater Manchester, UK and Australia have defined vulnerable population to heat hazard in terms of socio-economic profile, spatial distribution of facilities and past experience of heatwave impact (Kazmierczak 2012)(Met Office 2015)(The Office of Environment and Heritage 2016)(Trundle et al. 2015). While in India, identification of vulnerable population is based on health perspective only with laid emphasis on do’s and don’ts strategies. Moreover in Indian scenario, vulnerability pattern is unequally distributed within the cities because of their composite character having socio-spatial segregation based on caste, religion, income and type of occupation (Dupont 2004)(Singh and Vithayathil 2012) linked to the availability of amenities like water supply (Sidhwani, 2015). Due to this socio-social segregation phenomenon like developing of slum and squatters took place in environmentally prone areas whose dwelling solution are not enough to cope with the growing climate impact (World Health Organization 2010).

Heat Vulnerability Index is the spatially explicit method which offers the solution to identify spatial pattern of vulnerability as done in the case of Santiago (Chile), London and various cities (Inostroza et al. 2016)(Wolf and Mcgregor 2013)(Bao et al. 2015)(Johnson and Wilson 2009). HVI can be quantified by three component indices that are sensitivity, exposure and adaptive capacity as defined by IPCC report (IPCC 2012) for a better understanding of vulnerability and deploying location-specific measures. There is a need to understand the spatial pattern of vulnerability in India which are not covered in heat action plan considering the following objective: 1) To explore the spatial pattern of heat vulnerability within the urban area. 2) To identify hotspot clusters of heat vulnerability formed spatially and understand their constituting factors.

Methods and Materials

Case Study Area

Akola (20.7059° N, 77.0219° E) is a city in the Vidarbha region of Maharashtra state in central India situated at 925 ft (300 m) above mean sea level. It has a municipal area of 27 sq. km. and a population of 4,25,817 as per census of India, 2011. Akola has extreme weather conditions with very cold winter & hot summer with annual temperatures ranging from 5.6 ºC to 45.9 ºC (Akola District Gazetteers 2016). The population density of the city varies from 86.362 to 1512 persons per hectares and average being 326 persons per hectares for the continuous urban area. There are total 194 slums of which 92 are notified consisting of about 32% of the total city population (Municipal Corporation, Akola).

As per the census of India, Akola consists of 71 wards which have been used as the spatial unit of exploration for an understanding pattern of vulnerability. The fringe areas of the city remain undeveloped though city limits are extended to open or agriculture land, thus affiliating household census data at the actual urban and peri-urban area. This un-continuous urban area can produce biases in results of pixel based indexes. To avoid such an error, the study focused on the spatial assessment of continuous urban area demarcated based on an evaluation of Google map image of Akola city.

Heat Vulnerability Index (HVI)

HVI is the approach for vulnerability characterization and its consequent mapping. The purpose of the index is to identify areas with increased vulnerability so that specific adaptation and mitigation tactics can be implemented to reduce the probability of severe heat related impacts such as illness, death, damage to infrastructure and property (Loughnan et al. 2013). The approach to developing vulnerability index was first introduced by Cutter, 2003 (Cutter et al. 2003). It was applied for the first time at a spatial level based on the best knowledge of the concern of heat hazard (Wolf and McGregor 2009) in UK and Reid (Reid et al. 2009) in the US country level.

In this study, a HVI is developed using an inductive approach (Tate, 2012) in which principal component analysis is used to identify the principal components representing the group of covariant of factors related to the heat risk. This method was adopted to reduce the complexity of the indicators defined and further reduce it to a smaller set of indicators representing most of the variance (Wolf and Mcgregor 2013)(Inostroza et al. 2016).

HVI was developed using the geographic information system platform and calculated as shown in equation (1). Vulnerability is defined as a function of exposure, sensitivity and adaptive capacity as per 12th IPCC assessment report (IPCC 2012) and is used for the classification of indicators. Each component of vulnerability was quantified to form individual indices which then combined to form overall HVI to understand the spatial pattern of vulnerability. Vulnerability indices are convenient tools for a better understanding of the underlying cause of vulnerability for suggesting appropriate measures to natural hazards for example heatwaves (Loughnan et al. 2013). HVI was calculated using the in the equation:

$$V_j = E_j + S_j + A_j \qquad (1)$$

Where V is a vulnerability, E is exposure, S is sensitivity, and A corresponds to the adaptive capacity calculated at census tract *j* (IPCC 2012).

Data collection and identification of indicators

Heat vulnerability can be measured by specific set of factors that have an impact on human health, and these factors can be determined through literature, referring relevant experts, and related research work. Multiple studies conducted in London (Wolf and Mcgregor 2013), Phildadelphia (Weber et al. 2016), Chile (Inostroza et al. 2016) and New York (Nayak et al. 2017) have assessed vulnerability of urban populations to deadly heat wave health impacts. At the same time several studies have used readily available data from census tract such as in case of developing HVI for London, Santiago (Chile) and USA (Inostroza et al. 2016)(Wolf and Mcgregor 2013)(Schmidtlein et al. 2008)(Bao et al. 2015). In this particular study, the criteria for defining indicators is based on data extracted from the Census of India, Municipal Corporation and remote sensing data that are considered as a determinant of risk before and after being impacted by the heat hazard. Indicators are reclassified in three domains of vulnerability that are sensitivity, exposure and adaptive capacity which are considered as a function of vulnerability in diverse research works (Inostroza et al. 2016)(Wolf and Mcgregor 2013)(Cutter et al. 2003). Further, in this study adaptive capacity is taken as a component to increase vulnerability as all of its indicators are defined regarding teh reduction in capacity with an incraese in values.

Exposure to climate phenomena is the degree to which the system or community comes in contact with that threat (Climate Proof Cities Consortium 2014). In this study, Land Surface Temperature (LST) was used to represent exposure. LST was extracted from the remote sensing data which stored thermal emissivity of the land surface. Landsat imagery band six was processed based on standard procedure mentioned by United States Geological Survey (USGS). The image was then clipped along the municipal boundary using GIS platform. (Refer Table 3 for quantification method).

While sensitivity to the outcome of climate threat concerns the degree to which a community is influenced by the changing climatic condition. Unlike exposure, sensitivity portrays the intrinsic features of a system (Climate Proof Cities Consortium 2014). There are total five indicators used to quantify sensitivity (Table 2). Intrinsic factors broadly refer to the physical condition of individuals (typically called susceptibility factors or sensitivity in public health literature) that make them more sensitive to heat hazard due to a different thermoregulatory system and also depends upon behavioural characteristics of the individual (Milan and Creutzig 2015).

The IPCC Fourth Assessment Report has defined adaptive capacity as "*the ability or potential of a system to respond successfully to climate variability and change and includes adjustments in both behaviour and in resources and technologies*" (Barker 2007). IPCC also laid stress on the unequal distribution of adaptive capacity within the urban area (Barker 2007). There are total fourteen indicators used to quantify adaptive capacity in this study. Many indicators are defined considering a situation having high level of vulnerability such as lack of water supply, electricity and galvanised iron roof material are taken as roof material as it accounts high thermal conductivity.

Selection of Indicators

Further for selection of indicator chosen at a broader level, fourteen case studies including research papers on heat and social vulnerability were analysed. Indicators used in more than four studies were selected for further analysis. This shows the availability of necessary data required for constructing HVI in which out of possible 44 indicators, 20 indicators are selected for further analysis (Table 1).

Table 1. Indicators selection validation through case studies

	Case studies																
No	Indicators	1	2	3	4	5	6	7	8	9	10	11	12	13	14	NO	SL
1	Old population	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y			Y	Y	12	Y
2	South facing top flat	Y			Y		Y									3	
3	Pre-medical condition	Y		Y	Y	Y	Y			Y			Y			7	
4	Occupational group	Y		Y	Y									Y	Y	5	Y
5	Poverty	Y	Y		Y	Y			Y	Y	Y	Y		Y	Y	10	
6	Young population	Y	Y	Y	Y	Y		Y	Y	Y	Y			Y	Y	11	Y
7	Urban heat island		Y			Y										2	
8	Rented housing		Y			Y	Y			Y				Y	Y	6	Y
9	Social infrastructure		Y			Y		Y		Y				Y	Y	6	Y
10	Green space distribution		Y						Y							2	Y
11	Transient/Communal/ Slum communities		Y	Y			Y							Y		4	Y
12	Bus railway passengers			Y												1	
13	Pregnant or nursing mothers				Y											1	
14	Condition to regulate body temperature				Y											1	
15	Heat intolerant condition				Y											1	
16	Living alone				Y	Y	Y					Y	Y			5	Y
17	People with disability				Y	Y		Y								3	
18	People without air conditioning				Y								Y			2	
19	Homeless people				Y											1	
20	People with limited access to transport				Y									Y		2	Y
21	Not have access to health services because of culturally and linguistically diverse background				Y		Y									2	
22	Population density		Y			Y	Y		Y					Y	Y	6	Y
23	Single pensioner households						Y									1	
24	Land surface temperature					Y		Y				Y				3	Y
25	Education level							Y	Y		Y		Y	Y	Y	6	Y
26	Unemployment							Y					Y	Y	Y	4	Y
27	Access to communication technologies							Y								1	Y
28	Access to water supply							Y								1	Y
29	Material index							Y	Y							2	Y
30	NDVI							Y								1	Y
31	Roads km per sq. km							Y								1	

32	Land cover vegetation abundance								Y							1	Y
33	Mortality: Heat as primary cause of death									Y						1	
34	Mortality: Heat as one of the cause									Y						1	
35	Heat wave intensity and duration									Y						1	
36	Zoning and land use											Y				1	Y
37	Living units in building					Y							Y			2	Y
38	Ceiling Height												Y			1	
39	Outside wall material												Y			1	
40	People per housing unit							Y		Y				Y	Y	4	Y
41	Social Security recipients													Y		1	
42	Housing density					Y						Y		Y		3	
43	Recent immigrants													Y		1	
44	Ethnic group					Y	Y		Y	Y	Y	Y	Y	Y	Y	9	

Note-The pre-medical condition being necessary excluded from PCA because of data unavailability. Y, No and SL depict indicator, repetition and selection respectively.

Indicators Quantification

Most of the indicators selected are quantified in unit per hectares to avoid the biases in results produced due to variation in ward sizes of the census tract (Table 2). The values of indexes guide to determine the comparable level of vulnerability between the wards which could be wrongly interpreted due to the high variation in scale and density. Afterwards, due to the different unit, each indicator is converted into unit less quantity using standardisation method.

Table 2. Indicator quantification and classification method

Domain	Indicators	Method to quantify	Data Source and Year
Sensitivity	Population below 6 years (UNU-EHS 2014)	Wardwise population below six years of age per hectare.	Census of India Website: http://www.censusindia.gov.in/2011census/HLO/HL_PCA/Houselisting-housing-HLPCA.html. Year: 2011
	Single household size (M. Loughnan et al. 2012)	Inhabitants per hectares who live alone.	
	Education (UNU-EHS 2014)	Inhabitants per hectares who are illiterate.	
	Age above 60 years (Kenny, Yardley, Brown, Mph and Jay, 2010)	Inhabitants per hectares whose age are equal or greater than the age of 60.	
Exposure	LST (Inostroza et al. 2016)	It was computed by average temperature plus one standard deviation for each census tract to provide a conservative estimation of LST.	Landsat TM band 6. Source: https://www.usgs.gov/ Year: 2013
Exposure because of condition	Slum (Johnson and Wilson 2009)	Number of slums in each ward.	Data collected from MunicipalCorporation, Akola.Year: 2016
	Rented (Kazmierczak 2012)	Wardwise rented household per hectare.	Census of India Website: http://www.censusindia.gov.in/2011census/HLO/HL_PCA/Houselisting-housing-HLPCA.html Year: 2011
	Temporary structure (Johnson and Wilson 2009)	Wardwise household per hectare of a temporary structure.	
	Roof material (Kendrick 2009)	Wardwise household per hectares with GI/metal as a roof material.	

Adaptive capacity	Congestion (Tate 2012)	Single household X average household size ≥ 5 for each ward giving population per hectare living in congestion.	
	Infrastructure facilities- electricity & water supply (Mooventhan and Nivethitha 2014)	Wardwise household per hectare that are not covered with electricity. Wardwise household per hectare has water facility away premises.	
	No communication facilities	Wardwise household per hectare that has no landline and mobile phone.	
	No personnel vehicle (Wilhelmi et al. 2004)	Wardwise household per hectare having no personal vehicle.	
	No bank account, factor to predict poverty (Johnson and Wilson 2009)	Wardwise household per hectare availing no banking facilities.	
	Residual green space (Oliveira, Andrade and Vaz, 2011)(Upmanis, Eliasson and Lindqvist 1998)	Standard 9 sq.m. per person per person required as per WHO. Residual Green area per hectares = (area required– existing green area)/ward area.	Remote sensing and data gathered from MC. Year: 2016
	NDVI (Kendrick 2009)	NDVI was computed as the average NDVI value per census tract plus one standard déviation.	Landsat TM band 6. Source: https://www.usgs.gov/ Year: 2013
	Health facilities (M. Loughnan et al. 2012)	The distance of centroid of the continuous urban area in each ward to the nearest government hospitals.	Remote sensing and data gathered from MC. Year: 2016
	Social facilities- religious facilities & schools (Kazmierczak 2012)	The distance of centroid of the continuous urban area in each ward to the nearest social facilities.	

Statistical analysis:

Detail procedure for HVI calculation

Heat vulnerability pattern is not explained uniformly by selected indicators and prior assumptions related to their importance can produce biases. Also, there is a strong correlation between the indicators defining the socio-economic condition (Wolf and Mcgregor 2013). To avoid this co-linearity issue the complications of selected indicators have been further reduced to a smaller set of principal components (PCs) that describe most of the variance in the selected indicators. As PCA is highly sensitive to the input values, it is of paramount importance to standardise the data into the same magnitude. This criterion was achieved by converting the values in z-score using equation (2).

$$Z_i = (Xi - \eta)/SD \quad (2)$$

where Z_i is z-score for each ward of respective indicator, X_i is original value, η is mean of all the values of the individual indicator and SD is standard deviation of all the values of the individual indicator. Standardization of data also avoid biases that are produced by low and very high variance level. This will result in centering and scaling of dataset with mean 0 and standard deviation 1 on which PCA can be performed (Schmidtlein et al. 2008). Both tests are required to check the appropriateness of using PCA (Wolf and Mcgregor 2013). The number of components to be retained in PCA is done using Kaiser criteria and scree test where only those components are selected whose eigenvalues are greater than one as they explained maximum of the variance.

For improving interpretation, varimax rotation developed by Kaiser was performed on eigenvectors in revealing the simple structure (Abdi and Williams 2010). Afterwards, PC scores were generated for n retained components, so that each 71 wards possessed the n-PC scores. These retained PCs are then weighted according to the variance explained and combined to get overall PC score for each ward results to form vulnerability index on which PCA was performed (Wolf and Mcgregor 2013). This method was applied to reduce any prior assumptions related to the importance of indicator which can produce biases in the results. While doing this, weight as well as a sign of each score were retained. XLSTAT an extension of Excel was used for performing PCA calculation. Partial results of each index that is sensitivity, exposure, and adaptive capacity were then normalised using equation (3) to get values in 0 to 1 range.

$$\alpha = \left\lfloor \frac{\mathrm{X-Xmin}}{\mathrm{Xmax-Xmin}} \right\rfloor \tag{3}$$

Where α is normalized value, X_{max} is maximum value and X_{min} is minimum value of the input dataset. Normalized values are then grouped in five categories based on equal interval to understand spatial pattern of vulnerability for each index. HVI is then calculated using eq. (1) and then normalized using eq. (3).

Cluster Analysis

Cluster analysis was performed using Hot Spot Analysis by Getis-Ord Gi tool within the ArcGIS 10.4 software from ESRI to understand the spatial pattern of vulnerability for all four indexes. This tool identifies whether low, or high values tend to form cluster using Getis-Ord Gi statistics (Ord and Getis 1995). The output of the operation gives the z-score for all 71 wards. In this method, the statistical significance of clustering was represented by the z-score at a specified distance where values less than -1.96 were classified as cold spots and greater than 1.96 formed hotspots at 0.05 level of significance. In this analysis, only the hot spot clusters were considered for further analysis.

Results and Analysis

Outlier identification and error correction

Ward 67 having density 1512 persons per hectare is much higher than the city average density and seemed to be behaving in an unexpectedly different manner with much higher values for all variables creating dominance in PCA. So to reduce error induced by Ward 67, it was excluded from PCA analysis. Based on results of PCA performed with its inclusion while the highest value was assigned on one to five scales for calculation of sensitivity and adaptive capacity index.

The spatial pattern of heat hazard exposure

Land surface temperature (LST) has an average temperature within the municipal limit of value 27.12ºC. LST has minimum value 23.68ºC found in the south-west of the city, and the maximum value is 31.23ºC located in the core or old area in the town with a standard deviation of 1.011. The difference between the highest and lowest value of LST was found to be 7.55ºC. Analysing the spatial relationship between the values of LST and slum location shows the significant link between the socio-economic condition and exposure level.

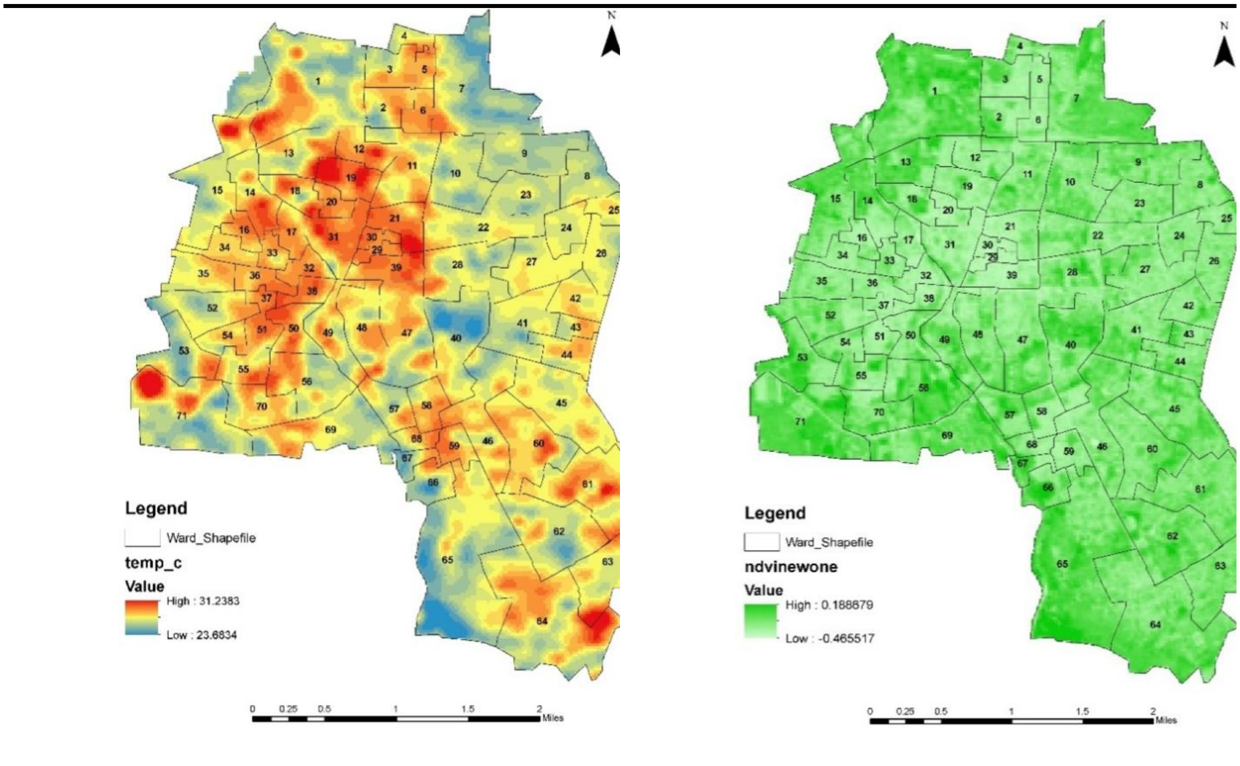

Figure 1. (i) Land surface temperature (LST) (ii) Both are calculated using the LANDSAT-TM image, 2009 band 6 acquired from the USGS

Also, the average ward value plus one standard deviation of LST is found highly correlated with the values of NDVI (r Pearson = -0.7434, $p < 0.05$). LST is found to have a negative correlation with NDVI values which tend to the significant positive correlation with the increase in open, green area and area with high vegetation. This result shows the influence of parks, open space, and areas with high vegetation on temperature. Analysing the results of the exposure shows the average city value of 0.472 at five level scales with a standard deviation of 0.23. The correlation of exposure with distance from the city centre is not significant (r Pearson = -0.0955, $p < 0.05$) but found be important with population density (r Pearson = 0.4505, $p < 0.05$). The weight of exposure with HVI is found to be 0.705.

Analysis and results for indicators of sensitivity

Bartlett's sphericity test result shows value less than 0.0001, so one should accept the alternative hypothesis depicting that atleast one of the correlations between the variables is significantly different from 0. Based on kaiser rule and scree test, two PC's were retained. The first PC has considerably large eigenvalue (3.492) and the second PC has eigenvalue very close to 1 (0.885) explaining the 69.85% and 17.71% of the total variance respectively. These two retained PCs explaining the 87.56% of total variance captured most of the data. The variables which dominate in PC 1 are illiteracy (0.51), children (0.516), living alone (0.385) and unemployment (0.518). PC 1 is interpreted as the "ability to respond" by considering the dominant variable while PC 2 having one variable elderly population (0.960) is interpreted as "dependency" (Table 3). The biplot axes depicting the z-score dispersion along with magnitude and correlation (sign) of eigenvectors after varimax rotation are shown in Fig 2.

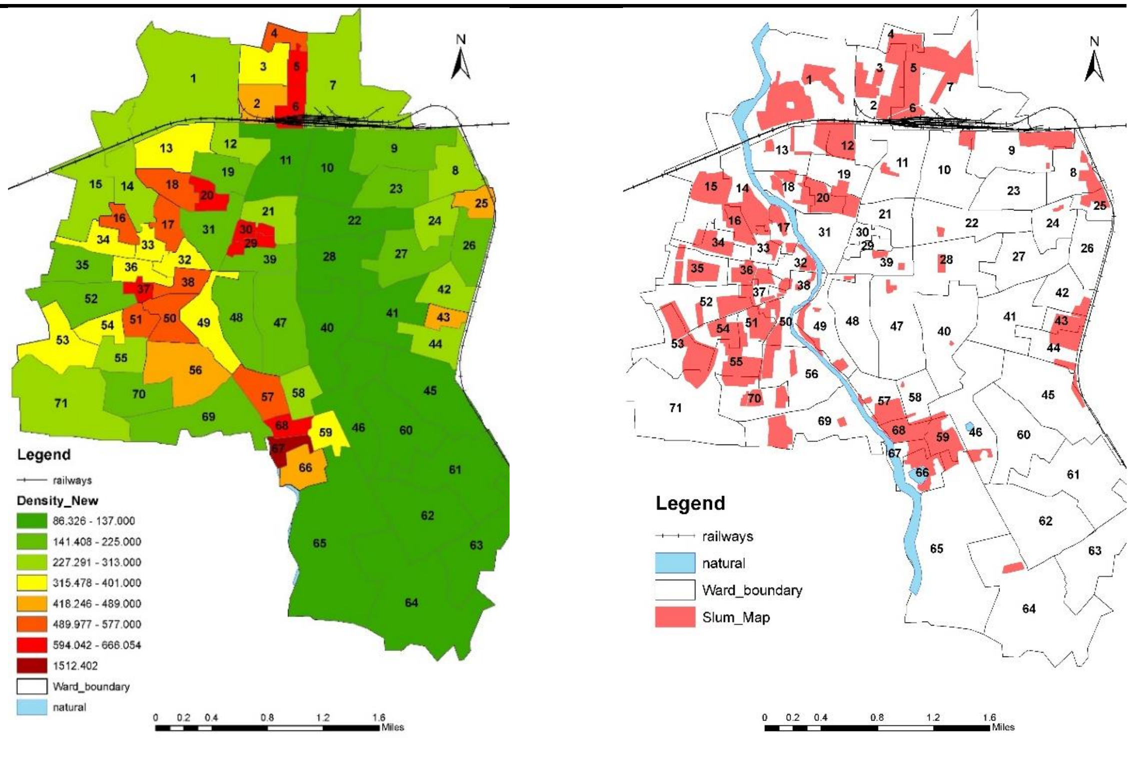

Figure 2. (i) Density map based on continuous urban area (Census 2011) (ii) Slum location map prepared using GIS 10.4 platform based on information acquired from Municipal Corporation, Akola

The asymmetric sensitivity profile was seen in ward number 65 while wards that are close to the centre have shared properties *(Note: Ward 67 was excluded from analysis).* The normalized sensitivity has a mean value of 0.34 (moderate according to scale from 0 to 1) and standard deviation (SD) of 0.264. The sensitivity found highly correlated with density (0.897) while showing a negative correlation with ward area (-0.485), means smaller wards are more sensitive than a larger one. Sensitivity show minimal and adverse relation (-0.11) with distance from the city centre depicting the non-relevance of centrality issue. Moreover, the weight of sensitivity (0.944) with HVI is found to be very high than any other index.

Table 3. PC loading following Varimax rotation for sensitivity

	PC 1	PC 2	PC 3	PC 4
Population Illiterate	**0.966**	-0.105	-0.136	-0.189
Population below 6 years	**0.965**	-0.057	-0.250	0.009
Population living alone	**0.721**	-0.228	0.654	0.008
Non workers population	**0.970**	-0.050	-0.155	0.177
Population above 60 years	0.409	**0.904**	0.125	-0.010

Note: Bold depicts statistically significant values.

Analysis and results for indicators of adaptive capacity

Bartlett's sphericity test results shows value less than 0.0001. As the computed p-value is lower than the significance level alpha=0.05, one should accept the alternative hypothesis that at least one of the correlations between the variables is significantly different from 0. Based on kaiser Rule, four PC retained for adaptive capacity (Ward 67 excluded from the calculation). The four retained PC has eigenvalues 6.128, 1.657, 1.383 and 1.044 explaining 43.77%, 11.84%, 9.88% and 7.457% of the total variance respectively. Together all four PC explain 72.949% of the total variance is retaining much of the data structure. The left out PCs do not satisfy Kaiser rule and for the same reason not included for further analysis.

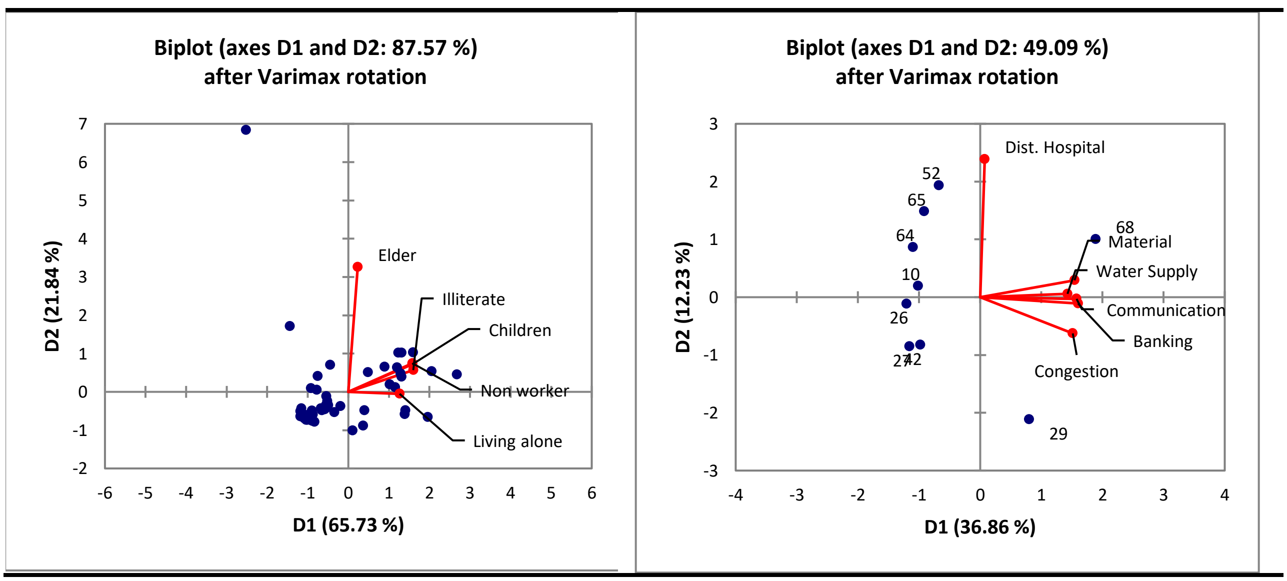

Figure 3. Scatter plot depicting the z values for sensitivity (left) and adaptive capacity (right). Principal components (PC) load are shown in red.

After varimax rotation, considering the values of squared cosines, a total of seven variables are dominant in PC 1. Variables dominant in the first PC are no banking facilities (0.879), no communication (0.853), roof material (0.817), congestion (0.787) and water supply away premises (0.70) while two more variables that are rented household (0.40) and temporary structure (0.26) but having little dominance.

The dominant variables in the second PC are the distance from the hospital (0.529), school (0.216) and social facilities (0.454)and NDVI (0.371). The dominant variables in the third PC are a residual green area (0.684) and no personal vehicle (0.436). While there is only one variable no electricity (0.820) that is dominant in the fourth PC.

Table 4. PC loading after Varimax rotation for adaptive capacity

	PC1	PC2	PC3	PC4
Rented	**0.400**	0.061	0.311	0.040
Temporary structure	**0.260**	0.007	0.093	0.001
Roof material	**0.817**	0.008	0.035	0.014
No water supply	**0.700**	0.000	0.009	0.001
No electricity	0.022	0.010	0.000	**0.820**
No communication	**0.853**	0.000	0.054	0.004
No personal vehicle	0.258	0.007	**0.436**	0.000
No banking facilities	**0.879**	0.001	0.059	0.000
Congestion	**0.787**	0.036	0.065	0.005
Hospital distance	0.002	**0.529**	0.165	0.018
School distance	0.059	**0.216**	0.000	0.140
Religious facilities distance	0.021	**0.455**	0.012	0.001
Residual green area	0.015	0.010	**0.685**	0.005
NDVI	0.087	**0.372**	0.205	0.162

Bold depicts statistically significant values.

The first PC is interpreted as socio-economic condition, the second PC as natural and built environment. The biplot axes are depicting the z-score dispersion of eigenvectors after varimax rotation shows asymmetric profile while the ones which are present near the centre of the plane shows average values of adaptive capacity. The normalised index for adaptive capacity has an average city value of 0.453 with SD of 0.270. Adaptive capacity shows a negative and less necessary relation with distance from the centre (-0.139) and highly significant correlation with population density (0.782). The weight of adaptive capacity with HVI is found to be 0.890.

Though weight of adaptive capacity index is smaller than that of sensitivity index still it is the crucial index which includes socio-economic status in its principal component (Table 4).

The HVI for Akola, Maharashtra

Statistical analysis results show that the inner structure of HVI is uneven, where sensitivity (0.944), adaptive capacity (0.890) weight more than the exposure (0.705). HVI has a high correlation with population density (0.846) as expected (Table 5).

Table 5. List of 17 wards with HVI value greater than 0.6

Ward No	Adaptive index	Sensitivity index	Exposure index	HVI index
4	0.919795	0.67983	0.337833	0.708771
5	0.973635	1	0.625968	1
6	0.900615	0.865831	0.665359	0.926199
14	0.654587	0.371494	0.670937	0.603019
16	0.689653	0.596543	0.675348	0.719365
17	0.912177	0.682927	0.740431	0.883856
18	0.787476	0.679473	0.626719	0.777476
20	0.612946	0.72411	0.745456	0.77257
29	0.553146	0.7425	0.806767	0.781323
30	0.567687	0.739983	0.846876	0.804252
37	0.853287	0.809305	0.784825	0.933065
38	0.587209	0.608735	0.921257	0.787827
43	0.80192	0.591454	0.357371	0.62665
50	0.87568	0.782062	0.761853	0.920828
51	0.737515	0.59862	0.738352	0.769041
56	0.706011	0.614858	0.708745	0.749304
67	1	1	0.560972	0.983009
68	1	0.722023	0.496401	0.832347

The normalised Heat Vulnerability Index (HVI) has an average value of 0.416 and the standard deviation is 0.287 (moderate on a five-point scale). Among the 71 wards, 18 wards have HVI greater than 0.6 (Table 4). Out of them, five wards have very high HVI value greater than 0.9 namely ward number 5, 6, 37, 50 and 67. All these wards have high values for adaptive capacity index than sensitivity index. These 17 wards have a total area of 187.72 hectares which account 9.6% of the total continuous urban area. Lower HVI values are mainly in the eastern and southern part of the city.

Table 6. Pearson correlation matrix between four indexes at 0.05 level of significance

Variables	Centre Distance	Ward Area	Density, 2011	Adaptive index	Sensitivity index	Exposure index	HVI index
Centre Distance	**1**	0.224	-0.066	-0.140	-0.118	-0.096	-0.139
Ward Area	0.224	**1**	**-0.546**	**-0.414**	**-0.485**	**-0.457**	**-0.530**
Density, 2011	-0.066	**-0.546**	**1**	**0.782**	**0.898**	**0.451**	**0.846**
Adaptive index	-0.140	**-0.414**	**0.782**	**1**	**0.873**	**0.350**	**0.890**

Sensitivity index	-0.118	**-0.485**	**0.898**	**0.873**	**1**	**0.505**	**0.944**
Exposure index	-0.096	**-0.457**	**0.451**	**0.350**	**0.505**	**1**	**0.705**
HVI index	-0.139	**-0.530**	**0.846**	**0.890**	**0.944**	**0.705**	**1**

Note: Values in bold are different from 0 with a significance level alpha=0.05

Cluster analysis of heat vulnerability

Cluster analysis was performed using Getis-Ord Gi tool in Arc-GIS which shows that the wards with low adaptive capacity also tends to show high sensitivity. Cluster formation took place in core area and areas at the fringes. Analysing this pattern of clustering with the location of slums defined the relation of vulnerability with their socio-economic status of the city. It was also interpreted that the two barriers within the city limit are not only physically dividing the city but also affecting vulnerability. Total 19 wards are forming two hotspots clusters based on values of HVI. Cluster 1 in the north consists of 3 wards of 44.38 hectares of the continuous urban area while Cluster 2 in the core area in the west consists of 16 wards of 235.71 hectares of area. It was analysed that the density of all wards in cluster 1 and 14 out of 16 wards in cluster 2 are higher than the city average density (309.65 per/hectares, excluding Ward 67). Average density of cluster 1 is 496.35 per hectares and cluster 2 is 437.30 per hectares. The average HVI values are high in both clusters that are 0.721 and 0.678 for cluster 1 and 2 respectively (Table 5).

Spatial structure of four indexes

For the analysis of the spatial distribution of four indices namely exposure, sensitivity, adaptive capacity and HVI, correlation matrix test was performed between indices, the density of continuous urban area and distance from city centre (Table 6). It was found that centrality is not a major factor for analysing vulnerability which was unevenly distributed within the city. While the density which was not taken in the initial set of indicator, a significant correlation was found with all the indexes having sensitivity (0.86) and HVI (0.84) being the highest. High-population density areas mainly lie in the core area of the city having a greater number of slums with the low-income group as residents.

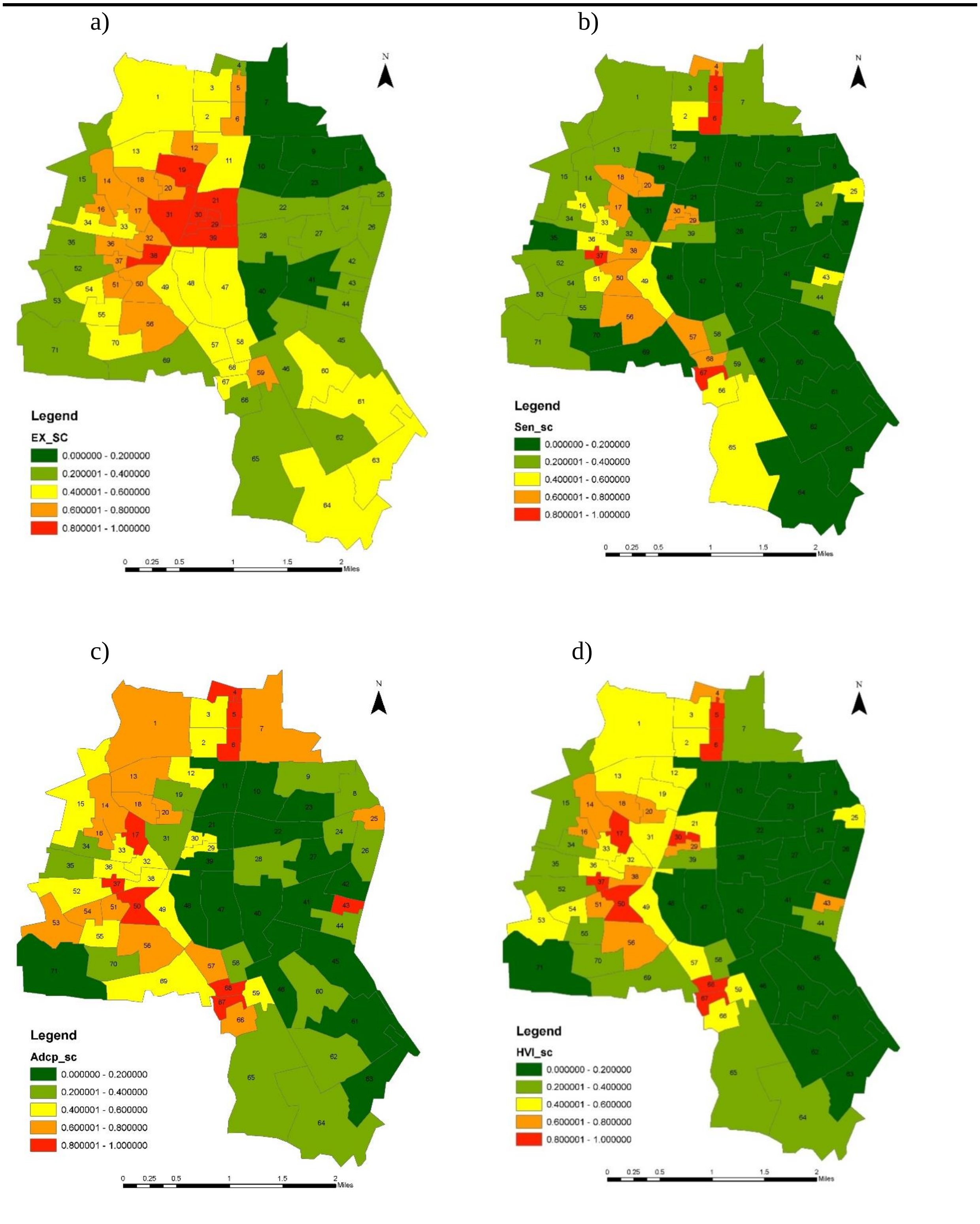

Figure 4. Results for a) Exposure index, b) Sensitivity Index, c) Adaptive capacity index and d)Heat vulnerability index for 71 wards, Akola

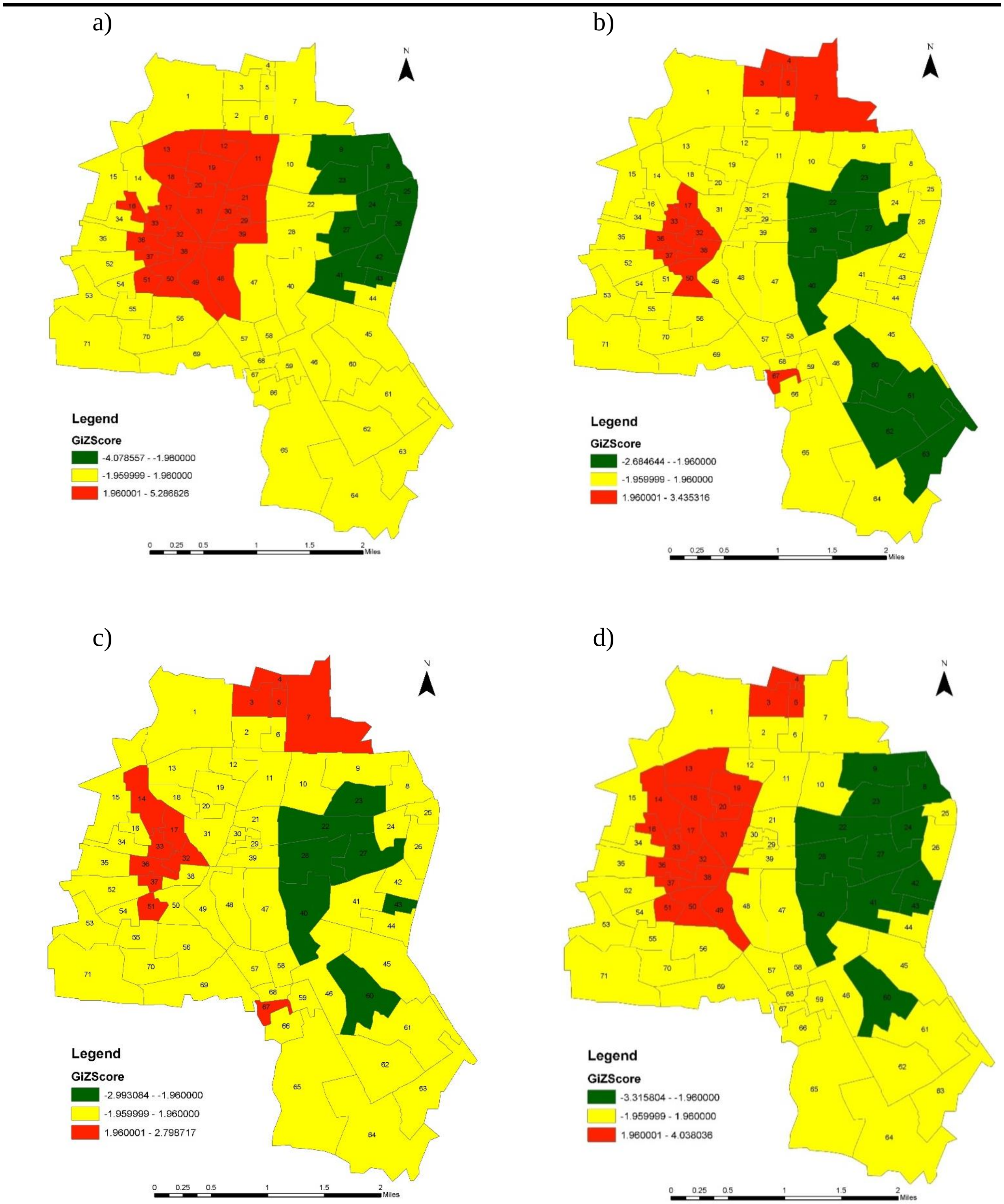

Figure 5. Cluster Analysis. Getis-Ord Gi for a) Exposure, b) Sensitivity, c) Adaptive capacity and d) HVI. Two clusters are statistically significant hotspots in HVI considering z value greater than 1.96 at 0.05 level of significance.

Overall, HVI is found to be highly correlated with all other indexes and are governed by the socio-economic pattern of the city (Table 7).

Table 7. List of 19 wards contained in the two identified hotspots cluster

Cluster	Ward No	Density	Adaptive	Sensitivity	Exposure	HVI
1	3	333.0292	0.57226	0.362727	0.426455	0.455424
	4	489.9771	0.919795	0.67983	0.337833	0.708771
	5	666.0543	0.973635	1	0.625968	1
2	13	315.4782	0.601559	0.329057	0.594368	0.527354
	14	312.6835	0.654587	0.371494	0.670937	0.603019
	16	511.4344	0.689653	0.596543	0.675348	0.719365
	17	535.6377	0.912177	0.682927	0.740431	0.883856
	18	529.3337	0.787476	0.679473	0.626719	0.777476
	19	211.2655*	0.241536	0.199961	1	0.490635
	20	614.9244	0.612946	0.72411	0.745456	0.77257
	31	179.2951*	0.384048	0.137058	0.82316	0.44787
	32	368.0168	0.53279	0.37029	0.743121	0.580669
	33	372.1265	0.549774	0.46348	0.598377	0.565464
	36	384.6699	0.437833	0.439285	0.696269	0.548643
	37	661.253	0.853287	0.809305	0.784825	0.933065
	38	532.1908	0.587209	0.608735	0.921257	0.787827
	49	385.7516	0.597613	0.482754	0.430269	0.521043
	50	544.828	0.87568	0.782062	0.761853	0.920828
	51	537.9299	0.737515	0.59862	0.738352	0.769041

**Wards' density which are lower than city average are marked with asterisk.*

Discussion and Conclusion

Major Findings

Prior identification of vulnerability to extreme heat events can guide public health efforts ahead of, during, or in the aftermath of the event. In this study, we created a fine-scale cumulative HVI for Akola city using census tract level information to identify communities that are most likely to be impacted during extreme heat events. In HVI results, 18 critical wards were identified having HVI value greater than 0.6. While results of HVI cluster analysis show 11 out of 18 critical wards tends to form cluster excluding ward numbers 6, 29, 30, 43, 56, 67, and 68. Average HVI values for these seven wards are quite high (0.8). Comparing these wards with the slum location reveals that more than 90% of the area of four wards namely 6, 43, 67 and 68 are under slum which consists of low income group and having very low average adaptive capacity (0.93) as compared to other two clusters. As these four wards have similar socio-economic character and adaptive capacity, they can form one different cluster with special need other than the clusters formed by spatial location. For all three clusters, urgent urban planning measures are required to deal with heat vulnerability.

Strength, Added Value and Limitations

Though cumulative HVI aids in swiftly recognizing susceptible communities with to extreme heat, it is of paramount importance in understanding underlying basis of vulnerability. This in turn is equally important for targeted and strategic public and community health efforts. Furthermore, interventions can then be structured for and disseminated to the appropriate target groups. A systematic group of indicators taken collectively provide a general assessment of the vulnerability of urban populations to extreme heat events. By understanding the distinct components of vulnerability (exposure, sensitivity, and adaptive capacity), policy makers can better understand what contributes to vulnerability and can decide how best to plan adaptation solutions. Decision makers can opt to consider the details of each component, or simply focus on high-level vulnerability results through longer-term responses such as urban tree planting, or identify short-term solutions such as social services for the most sensitive populations.

Specific indicators such as exposure and sensitivity are designed to provide decision makers a clear picture of immediate significance regarding historical and recent exposures to high temperatures. To look at longer term trends, adaptive capacity indicators can provide incremental and additive changes made to the urban environment targeted at urban greening and cooling. The use of indicators for monitoring and evaluation of adaptation programs can help to assess results, and will feature the most relevant policy interventions.

Implication on Practice and Research

Future research could test the satellite datasets at a much higher resolution to better capture the urban landscape and further enhance the resultant local vulnerability models. Studies could also undertake costs and benefits to evaluate the importance of urban greening and vegetation programmers while making the indicators more accountable. The spatial configuration of exposure, sensitivity, adaptive capacity and heat vulnerability indexes can be better used to inform urban planning and management and as a platform for public discussions for community awareness. Location of heavy heat intensive infrastructures such as urban parks, public facilities large commercial centres or parking lots, should take into account their impact in terms of HVI values. Results and findings can be used to improve urban planning and land policy regulations in coping with heat stress while reforming energy efficient building codes and regulations. Institutional, infrastructural, financial and social adaptation strategies must be homogenized to reduce heat stress.

Conclusion

India has worked in this direction to develop Heat Action Plan which was not enough as it does not include the understanding of the spatial pattern of heat vulnerability and also did not assign the role of urban planner. In this study, with the aim to spatially understand the pattern of heat risk factor, HVI was proposed which is a spatially explicit index composed of three indexes namely, exposure, sensitivity and adaptive capacity following the IPCC vulnerability method. Through HVI, one can explore the patterns of spatial distribution of vulnerability by identifying clusters of hotspots and determine their driving factors at ward level as the smallest spatial unit in India. The heat vulnerability index developed in this study observed geographical variability with heat vulnerability due to differences in land cover and local socio-demographic characteristics. The study offers an inclusive approach in identifying, quantifying and mapping heat-related vulnerability for use by public health officials, policy makers, and data users as they prepare climate change adaptation plans for their communities. In the event of an extreme heat event, identification of these vulnerable areas can help streamline efforts toward mitigation of the effect of heat on health.

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