Remote Sensing Applications: Society and Environment 31 (2023) 101007

Contents lists available at ScienceDirect

Remote Sensing Applications: Society and Environment

journal homepage: www.elsevier.com/locate/rsase

Mapping hotspot clustering: An approach to study the spatial pattern of quality of living households in India

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ARTICLE INFO

Keywords:
Household quality of living index
India
Census
Hotspots
GIS Maps

ABSTRACT

This study provides insight into the regional disparity of households' quality of living standards in India through the selective indicators. A household quality of living index (HQI) which is called a composite index was developed by integrating four indices which are housing facility index (HFI-1), basic facility index (BFI-2), financial asset index (FAI-3) and human capital index (HCI-4). These four indices have been developed from 23 census indicators through entropy techniques. The research findings indicate that the central (Chhattisgarh, Madhya Pradesh, Uttar Pradesh), eastern (Odisha, Jharkhand), and northeastern region (Arunanchal Pradesh and Nagaland) have poor living standards, and these are highly influenced by the basic facility index and financial asset index. Further, the indicators like concrete materials, radio, computer, two-wheeler, four-wheeler and drainage systems are totally in the poor category for almost 95% of the districts of India. Accordingly, hotspot GIS maps were generated and these maps explored that the 24.6% (157 districts) of the study region covered by hotspot showing poor quality of living. Nearly 14 states covered by hotspots, in which Bihar has the highest hotspot district (29), followed by Odisha (24), Madhya Pradesh (22) and Jharkhand (20). Additionally, three set of hotspot clusters were created for the developmental purpose: Cluster 1: (Odisha, Chhattisgarh and Madhya Pradesh), cluster 2: (Bihar, Jharkhand and West Bengal) and cluster 3: (Assam and Meghalaya). Where cluster 1 needs immediate attention followed by cluster 2 and 3. The current study results certainly assists the regional and national policy and decision makers to implement the development plan in hotspot clusters to enhance the quality of living.

1. Introduction

The measure of quality of living (QoL) will directly indicate the economic development of the region. In the 1960s, the thirst for quantitative analysis for QoL evolved in the aspect of improving the social disadvantages by employing development policies (Vitale, 2008). The view on QoL has to be observed holistically as its characteristics are multidimensional and dynamic (Kironji, 2008). The QoL and wealth development are mostly indicated through the gross domestic product (GDP) for a long period of time (Stiglitz et al.,

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https://doi.org/10.1016/j.rsase.2023.101007
Received 27 February 2023; Received in revised form 22 April 2023; Accepted 4 June 2023
Available online 7 June 2023
2352-9385/

2009; Behera, 2016). So, many researchers have attempted to analyse the QoL of people by considering the gross domestic production (Stiglitz et al., 2009), but later it was understood that the per capita income and its associate factors are not adequate for measuring QoL as it is multidimensional factor (Fleurbaey and Blanchet, 2013; Liao, 2009; Rojas 2011; Self, 2017). Over the period, the insight over the QoL was strengthened by considering the influencing factors like housing condition, health and communication services and basic amenities (Kitchen and Muhajarine, 2008). Study states that assessment and development of QoL is quite challenging task for government as well as researchers (Alkire, 2002; Hagerty et al., 2001; Rahman et al., 2011). There are two distinct perceptions of assessing the quality of life such as subjective and objective quality of life. Researchers must have strong insight into these perceptions before assessing the quality of life (Ihsan and Aziz, 2019). The factors related to psychological behavior of humans (e.g., mental wealth, perception and feeling of individual) are called subjective quality of life (Kingdon and Knight, 2006; Selim, 2008). Whereas in the objective perception, the physical factors like living standard, literacy rate, economic status, housing material and condition are measured (Zorondo-Rodríguez et al., 2014). Objective perception has more impact on the QoL than the subjective perception because the parameters determining the QoL are directly or indirectly connected with financial status. Thus, the present study opted the objective perception to analysis the QoL.

Through literature survey (Morris, 1982; Stanton, 2007) it is clearly highlights that there are two significant indices for measuring the QoL, which is widely practiced by several researchers. These are physical quality of life index (PQLI) and human development index (HDI). PQLI was developed by Morris (1982) through the factors such as literacy rate, child death rate and life expectancy, which explain the physical wealth of human. HDI was constructed by united nations development program (UNDP) (Stanton, 2007) to understand the well-being of individuals by considering the indicators like per capita income, literacy, health and educational services. Later on, the size indicator was increased, and analysing techniques was changed with respect to spatial region. Likewise, various researchers constructed unique indices based on the regional necessity and data constraints. Das and Mistri (2013) constructed household quality of living index (HQLI) by considering 20 indicators for India. Zorondo-Rodríguez et al. (2014) conducted a study on QoL with 30 indicators for a small region in Karnataka, India. Haque (2016) developed an overall infrastructure development index (OIDI) by utilising 19 significant indicators to analyse the infrastructure development in west Bengal, India. Das et al., (2020) attempted research related to the QoL for the central-east region of India by developing a composite index through 19 indicators. Mondal (2020) analysed the QoL in west Bengal-India by constructing a composite index (i.e., HQLI) by considering 21 indicators. In the early period, the indices for QoL were developed by averaging (i.e., mean value) the selected indicators. After understanding the significance of weighting techniques like principal component analysis (PCA), entropy, compound factor (CF) and factor analysis (FA), several researchers are utilising these techniques for constructing the composite index (Das and Mistri, 2013; Das et al., 2020; Mondal, 2020; Balasubramani et al., 2021). Likewise, the present study constructed the composite index (i.e., household quality of living index) through the entropy technique by considering 23 indicators.

Study (Das et al., 2020) identified uneven development across India's regions, such as in western and southern parts, which are quite good in development. On the other hand, regions like Uttar Pradesh, Bihar, Chhattisgarh remain backward for long temporal scale (Das et al., 202). It is also identified that states like Gujarat, Punjab, Maharashtra and Haryana are noted with a faster rate of development, about 7–10% (Parker and Kozel, 2007; Raychaudhuri and Haldar, 2009). At the same time, the main goal of 11th 5-year plan of India was to accelerate regional development (Planning Commission of India, 2011). This comprehensive development can be achieved by lessening the disparities in basic factors (e.g., employment opportunity, living standard, basic necessities and housing conditions) across the urban and rural areas (Mondal, 2020). In order to reduce the regional disparities in India few research studies were attempted for particular region in India, namely Karnataka (Zorondo-Rodríguez et al., 2014), west Bengal (Haque, 2016; Mondal, 2020), Dandakaranya region part of Chhattisgarh and Odisha (Das et al., 2020) and Uttar Pradesh and Bihar (Parker and Kozel, 2007). However, there was no study attempted for district wise of entire India which directly indicates the research gap exists. Thus, the present study attempted to analyse the district-wise QoL for entire India. In this study, the size of indicators was considered as 23, and the unique entropy technique was used to overcome the problem of weightage contribution. Hence, this study contributed to reduce the disparities in living quality by measuring the district-wise household quality of living in India. For which few objectives are followed, they are: (i) Around 23 indicators representing household quality of living were acquired from Census India in two form such as primary census abstract and house level primary census abstract. (ii) Selected indicators are grouped into four category and computed four indices, namely housing facility index (HFI), basic facility index (BFI), financial asset index (FAI) and human capital index (HCI) to measure the household quality of living, (iii) Household quality of living index (HQI) was computed by integrating the HFI, BFI, FAI and HCI using entropy technique, (iv) District-wise regional disparities were examined through HQI, (iv) The hotspot analysis was attempted to identify the hotspot (poor living quality) and cold spot (good living quality) over the districts, in order to implement the developmental strategies over the hotspot regions.

2. Study area

India, the most populated (first position) country in the world, has been selected for the study. It lies between 8^0 4′ 45″ to 36^0 18′ 9″ north latitude and 68^0 11′ 48″ to 97^0 24′ 20″ east longitude (Fig. 1) with an aerial extent of ~3.28 million Km^2. Making it the seventh-largest country, which accounts for 2.4% of the world with a coastline of 7567 km (Dimri et al., 2023). The population density of India is 382 persons per Km^2, which holds 17.5% of the world's total population, making it one of the highest population densities (Balk et al., 2019). According to the census of 2011, the country has twenty-eight states and eight union territories subdivided into 640 districts. Rajasthan is the largest state occupying 3,42,239 sq. km followed by Madhya Pradesh, Maharashtra and Uttar Pradesh. With 16.49% of the total population, Uttar Pradesh ranks first in population, followed by Maharashtra, Bihar and West Bengal (Census of India, 2011). The sex ratio was 940 females for 1000 males, and the overall literacy rate was 74.02% for entire India, male

Fig. 1. Spatial information of the study region selected for the study.

literacy was 82% and 65% for females (Census of India, 2011). Among all states, Kerala has the highest literacy rate of 94%. It is one of the most diversified lands in the world from economic and social aspects; apart from the many religions, many tribes also reside here with different economic disparities from region to region. India's GDP growth was 5.2% in 2011; it is a proven fact that the improvement in economic growth and GDP translates into high quality of life. The Indian economy primarily depends on agriculture, as 70% of the population lives in rural areas (Das and Mistri, 2013). The Indian economy has been diversified significantly, creating different social groups; disparities in the economy and different stages of social development across the regions have been major fallbacks for high living standards. For better analysis, the states have been grouped and converted into six regions: The Northern states containing Ladakh, Jammu and Kashmir, Himachal Pradesh, Punjab, Haryana and Uttarakhand, Central states contains Uttar Pradesh, Madhya Pradesh and Chhattisgarh; The eastern states contains Bihar, Jharkhand and Odisha; Northeastern states contains Sikkim, Meghalaya, Assam, Nagaland, Mizoram, Tripura and Arunachal Pradesh; The western states has Rajasthan, Gujarat and Maharashtra. Finally, the south states contains Telangana, Karnataka, Andhra Pradesh, Tamil Nadu and Kerala.

3. Materials and methods

3.1. Dataset

To assess the district wise household quality of living for entire India, census 2011 data was used. The Census of India acquired a various type of information (e.g., demography, economy and social data) and grouped into different section like Primary Census Abstract (PCA), District Census Handbook (DCHB) and House Level Primary Census Abstract (HLPCA) (Census of India, 2011). In which the data related to population, education and economic activities from PCA, and data related to elementary facilities and services (e.g., house condition, latrine, electricity and banking services etc.) from HLPCA was utilised for the study. Thus, PCA and HLPCA are significant data sources to estimate the disparities of regional development through composite index (Household quality of living index-HQI). Around 23 indicators were considered to analysis the regional disparities in districts of India as shown in Table 1. These indicators are grouped into four sections namely housing facility index (HFI), basic facility index (BFI), financial asset index (FAI) and human capital index (HCI). Through the entropy technique, four indices (i.e., HFI, BFI, FAI and HCI) and composite index (i.e., HQI) were developed to visualize the spatial pattern of regional disparities. Further, the hotspot analysis is attempted to identify the hot and cold spots in the district of India. A detailed methodological flowchart was prepared as shown in Fig. 2.

Table 1
Indicators selected for the study.

Section	Description	Indicator
Housing Facility Index (HFI)	Number of households with good condition of census house	House Condition
	Material of roof (concrete)	Concrete Material
	Number of dwelling rooms = > 2	Dwelling Room
	Own house	Own House
	Households by type of structure of census houses permanent	Permanent House
Basic Facility Index (BFI)	Tap water from treated source	Tap Water
	Location of drinking water source within premises	Drinking Water
	Main source of lighting (electricity)	Electricity
	Number of households having latrine facility within the premises	Latrine
	Waste water outlet connected to closed drainage	Drainage System
	Type of fuel used for cooking (LPG, electricity, biogas)	Cooking Fuel
	Cooking inside house (Kitchen facility)	Cooking Condition
Financial Asset Index (FAI)	Total number of households availing banking services	Banking Services
	Radio/Transistor	Radio
	Television	Television
	Computer/Laptop with internet	Computer
	Mobile only	Mobile Facility
	Scooter/Motorcycle/Moped	Two-Wheeler
	Car/Jeep/Van	Four-Wheeler
Human Capital Index (HCI)	Literates population person	Literacy Rate
	Literates population male	Male Literate
	Literates population female	Female Literate
	Total worker population person	Working Population

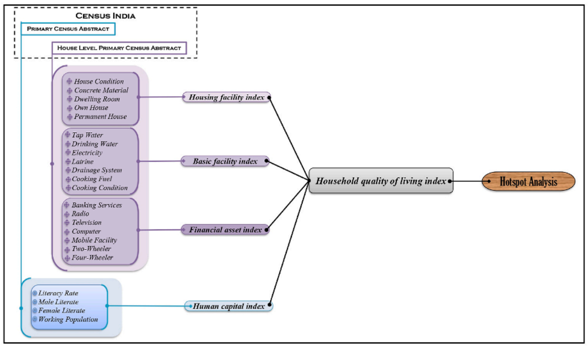

Fig. 2. Methodological flowchart.

3.2. Analysing methods

3.2.1. Entropy technique

Entropy technique has been used to analyse the spatial pattern of household quality of living among districts of India. Entropy is one of the Multiple-criteria decision-making (MCDM) methods which was widely used in assigning the objective weights to factors. This technique was primarily introduced by Shannon (1948), which is mostly used for assigning weights to multiple criteria when the researches have conflicting opinion over the weights (Abdul Rahaman and Venkatesh, 2020; Goswami and Behera, 2021; Thilagaraj et al., 2021; Kantamaneni et al., 2022). Further, entropy technique is used to compute the entropy (i.e., Uncertainty information) based on probability theory (Chodha et al., 2022). The advantage of this technique is that the weight computation will be achieved in a short period by measuring the degree of dispersion (Bhowmik et al., 2018). The weights for 23 indicators were computed through the following steps.

Step1 The initial values of the indicators were normalised through equation (1).

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{1}$$

Whereas, r_{ij} is the normalised values of indicator, x_{ij} is the actual or initial value of ith alternative jth indicator and m is the total number of indicators.

Step2 Computation of entropy values (e_j) through the following equation 2

$$e_j = -h \sum_{i=1}^{m} r_{ij} \ln\left(r_{ij}\right), h = \frac{1}{\ln(m)} \tag{2}$$

Where, j = 1,2, …,n and i = 1,2, …,m.

Step3 Equation (3) is used to calculate the degree of dispersion (D_j).

$$D_j = 1 - e_j \tag{3}$$

Step 4: The objective weights (w_j) of each indicator was computed by using following formula (eq. (4))

$$w_j = \frac{D_j}{\sum_{j=1}^{n} D_j} \tag{4}$$

3.2.2. Development of a composite index

In this study, 23 indicators were used to construct four indices, namely HFI, BFI, FAI and HCI through entropy techniques. The objective weights for 23 indicators were obtained through equation (4), as mentioned in Table 2. Utilising the local weights of the indicators (w_j), the 4 indices (i.e., HFI, BFI, FAI and HCI) are computed through equation (5). Composite index is the multi-dimensional view of multiple information in a single variable (Das et al., 2020). Thus, the HQI composite index was constructed by assessing the global weights (g_j) through the formula mentioned in equation (6).

$$I_j = \sum_{j=1}^{m} w_j \times i_j \tag{5}$$

Where, w_j is the local weightage and i_j is indicatior value

$$HQI = \sum_{j=1}^{m} I_j \times g_j \tag{6}$$

Where, $I_{1,2,3\ \&\ 4} = HFI, BFI, FAI\ and\ HCI$ and g_j is global weights of the index I_j.

3.2.3. Hotspot analysis

The normalised value of HQI were used to perform a hotspot analysis (Getis-Ord Gi*) to identify the hot and cold spot for each district of India. For which, the hotspot analysis tool in ArcMap was utilised and the spatial relation of “contiguity edges corner” was assigned (Sánchez-Martín et al., 2019; Mondal, 2020; Venkatesh et al., 2020; Ravichandran et al., 2022). Based on the HQI value of the district, the spatial autocorrelation will work with the neighbouring districts. Getis-Ord Gi* statistics measure the spatial concentra-

Table 2
Entropy objective weights for the selected indicators.

Section	Indicator	Local weights (w_j)	Global weights (g_j)
Housing Facility Index (HFI)	House Condition	0.204	0.25
	Concrete Material	0.186	
	Dwelling Room	0.205	
	Own House	0.206	
	Permanent House	0.199	
Basic Facility index (BFI)	Tap Water	0.137	0.247
	Drinking Water	0.146	
	Electricity	0.148	
	Latrine	0.145	
	Drainage System	0.131	
	Cooking Fuel	0.140	
	Cooking Condition	0.153	
Financial Asset index (FAI)	Banking Services	0.151	0.248
	Radio	0.147	
	Television	0.146	
	Computer	0.125	
	Mobile Facility	0.151	
	Two-Wheeler	0.144	
	Four-Wheeler	0.136	
Human Capital Index (HCI)	Literacy Rate	0.250	0.252
	Male Literate	0.251	
	Female Literate	0.249	
	Working Population	0.250	

tion between HQI values and produce the Z-scores and p-values for each district (Getis and Ord, 1992). Whereas the Z-values used to group the district into different categories of hot and cold spots and the P-value is used to differentiate it with the confidence interval (e.g., 90%, 95% and 99%) of the hot and cold spots. The district with dissimilar values from neighbouring districts is considered insignificant. The Getis-Ord G* statistics was performed through the formula mentioned below (Eqs. (7) and (8)).

$$G_i^* = \frac{\sum_j^n w_{i,j}\, x_j - \bar{X}\sum_j^n w_{i,j}}{s\sqrt{\frac{\left[n\sum_{j-1}^n w_{i,j}^2 - \left(\sum_{j-1}^n w_{i,j}\right)^2\right]}{n-1}}} \tag{7}$$

$$\bar{X} = \frac{\sum_{j=1}^n x_j}{n}, S = \sqrt{\frac{\sum_{j=1}^n x_j^2}{n} - \left(\bar{X}\right)^2} \tag{8}$$

where x_j is the attribute value for spatial feature j, $\omega_{i,j}$ is the spatial weight between feature i and j, n is the total number of features (Getis and Ord, 1992; Ord and Getis, 1995).

4. Results

The findings of the study resulted from the account of various indicators taken from census data to calculate four major indices: HFI, BFI, FAI and HCI. The HFI is the composite of house condition, concrete material, dwelling room, own house, permanent house indicators. The BFI is calculated from 7 indicators i.e., tap water, drinking water, electricity, latrine, drainage system, cooking fuel, cooking condition. Then the FAI is calculated by considering seven indicators: banking services, radio, television, computer, mobile facility, two-wheeler, and four-wheeler. The four indicators like literacy rate, male literate, female literate, and working population, are combined to compute the HCI. Additionally, the HQI was calculated by integrating all four significant indices (i.e., HFI, BFI, FAI and HCI). These indices are computed by assigning the weights to the indicators through the Entropy technique. Finally, the hotspot analysis is mapped from the HQI values to demarcate the hotspot zone (poor quality of living). Table 3 explains the descriptive statistics of indicators. In which 640 observations (districts) of 23 indicators were considered. The minimum values represent the districts with less percentage of facility/services, and the maximum value indicates that the district has a higher percentage of facilities/services.

Table 3
Descriptive Statistics of indicators.

Indicators	Observations	Poor Quality of Facility		Good Quality of Facility	
		Min	Location	Max	Location
House Condition	640	13	Debagarh, Odhisa	88.1	Diu, Daman&Diu
Concrete Material	640	0.1	Anjaw, Arunanchal Pradesh	83.1	Chandigarh, Chandigarh
Dwelling Room	640	11.9	Dhalai, Tripura	96.5	Mahe, Puducherry
Own House	640	13	New Delhi	99	Pulwama, Jammu&Kashmir
Permanent House	640	1.2	Leh (ladakh), Jammu&Kashmir	99	Diu, Daman&Diu
Tap Water	640	0.9	Kishanganj, Bihar	99.6	Yanam, Puducherry
Drinking Water	640	2.4	Longleng, Nagaland	93.9	Srinagar, Jammu&Kashmir
Electricity	640	1.9	Arwal, Bihar	99.7	Lakshadweep, Lakshadweep
Latrine	640	5.6	Bijapur, Chhattisgarh	98.9	Aizawl, Mizoram
Drainage System	640	0.4	Bijapur, Chhattisgarh	96.5	Hyderabad, Andhra Pradesh
Cooking Fuel	640	0.7	Kiphire, Nagaland	92.4	East Delhi, NCT of Delhi
Cooking Condition	640	33.2	Kishanganj, Bihar	99.6	Mahe, Puducherry
Banking Services	640	10.5	Tamenglong, Manipur	93.9	Kangra, Himachal Pradesh
Radio	640	2.8	Srikakulam, Andhra Pradesh	77.2	Srinagar, Jammu&Kashmir
Television	640	5.8	Madhepura, Bihar	95.4	Chennai, Tamil Nadu
Computer	640	0.2	Alirajpur, Madhya Pradesh	24.2	New Delhi
Mobile Facility	640	8	Bijapur, Chhattisgarh	79.6	Daman, Daman&Diu
Two-Wheeler	640	1	Kiphire, Nagaland	57.4	South Goa, Goa
Four-Wheeler	640	0.5	Gajapati, Odhisa	29	Gurgaon, Haryana
Literacy Rate	640	28.7	Alirajpur, Madhya Pradesh	88.7	Pathanamthitta, Kerala
Male Literate	640	16.5	Alirajpur, Madhya Pradesh	54.5	Daman, Daman&Diu
Female Literate	640	12.1	Alirajpur, Madhya Pradesh	47.4	Mahe, Puducherry
Working Population	640	25.8	Malappuram, Kerala	66.9	Kinnaur, Himachal Pradesh

4.1. Spatial pattern of housing facility index (HFI) and its indicators

House condition depicts the percentage of households living in good house condition. The result shows that the households in the Diu district of Diu and Daman have better housing conditions (88.10%), whereas the Debagarh district of Odhisa have poor housing conditions (13%). The spatial pattern of house condition depicts (Fig. 3a) that most of southern states (e.g., Tamil Nadu, Kerala, Andhra Pradesh) and part of north (e.g., Himachal Pradesh and Uttarakhand) falls under good housing condition (>60%). Almost two third states in eastern region and most of the districts of Assam falls in poor condition (<40%), particularly entire Odisha were falls in very poor category (<30%). The rest of the district follows a mixed pattern. **Concrete material** is the prime factor in defining a household's house roof material (e.g., Pucca or Kuccha). Fig. 3b depicts a negative indication that except southern states (i.e., Tamil Nadu, Kerala and Andhra Pradesh) entire study region was noted as poor class (<30%). Anjaw, Arunachal Pradesh is the district with the lowest number (0.10%) of concrete roof structure, in contrary to this Chandigarh have the highest number (83.10%) of household's buildings with concrete material.

Dwelling room facility represents the percentage of households with more than two rooms available. The good room facility (> 70%) are noted over the north, northeast, part of central states and Kerala (Fig. 3c). Two-third districts of India come under the inadequate-to-poor category. In entire India, Dhalai district of Tripura was marked as a poor dwelling facility (11.9%), whereas Mahe, capital of Union Territory Puducherry indicates a good dwelling facility (96.5%). **Own house** (i.e., House ownership) represents the percentage of household's having own house (Fig. 3d), which is closely related to financial wealth. New Delhi is the place where India's lowest percentage (13%) of own houses. On the other hand, Pulwama, Jammu Kashmir households have the highest own house (99%). Except few districts, entire India has good facilities (>60% of households have their own house). **Permanent house** (i.e., formal settlement) indicates the construction of a house for a longer period with basic amenities is considered as a good standard of living. Ladakh, Jammu and Kashmir account for the lowest number of permanent house (1.20%) and Diu, Daman and Diu have the highest number of permanent houses in the country (99%). The households in central, east and northeast states have poor facilities (<40% of households have permanent houses) as shown in Fig. 3e.

The housing facility index (HFI) determines the housing condition of households, which is the composite of above mentioned five indicators (i.e., house condition, concrete material, dwelling rooms, own house and permanent house). HFI is classified into five categories: poor, low, moderate, high and good, which implies the development level of the district's households as shown in Fig. 3. Around 63 districts in India falls under poor class, following 233 in low, 220 in moderate, 103 in high and 21 districts in good class as shown in Table 4. The spatial distribution of HFI portrays a diverse pattern over the region. Thus, the good category of HFI was achieved by most of the districts of Kerala, Uttarakhand and Himachal Pradesh. Then the states like Gujarat, Delhi, Punjab, Chandigarh, Goa were noted under high category of HFI. More than half of the districts of Tamil Nadu, Maharashtra, Rajasthan and Andhra Pradesh were in the moderate category. One-third of Indian districts (233) experiencing a low category of HFI. Entire eastern zone

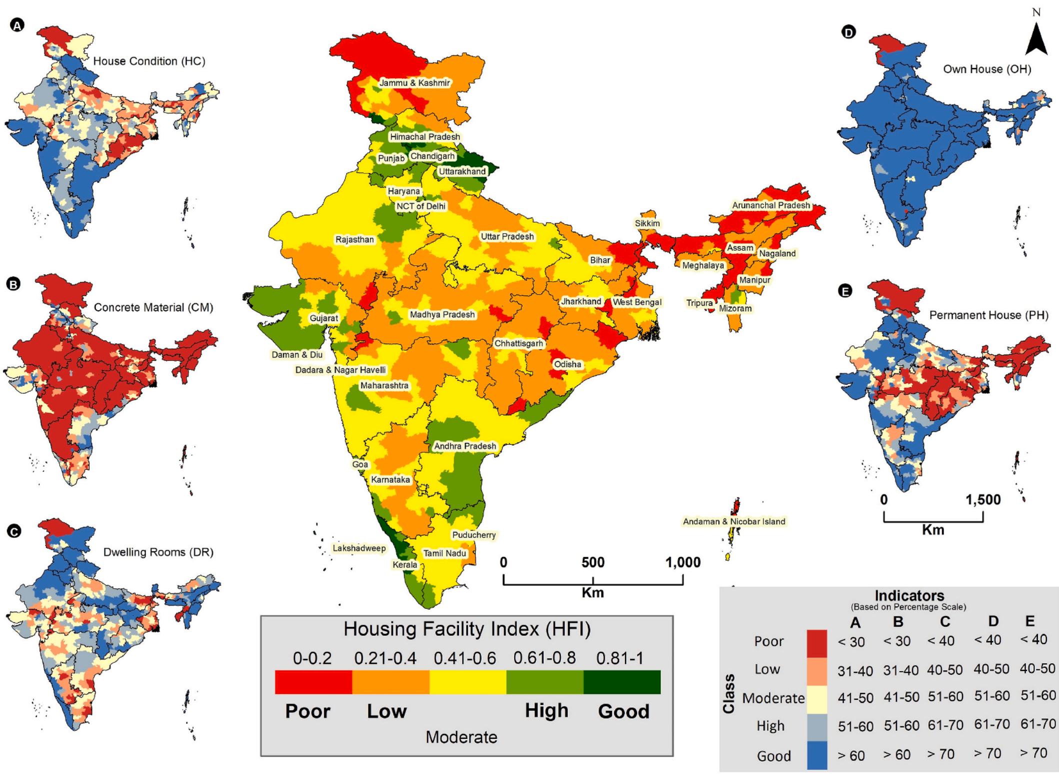

Fig. 3. Spatial pattern of housing facility index (HFI) and its indicators.

Table 4
Number of districts falls under different class in sub-indices and composite index.

Class					
Index	Poor	Low	Moderate	High	Good
HFI	63	233	220	103	21
BFI	146	223	169	77	25
FAI	86	193	215	117	29
HCI	34	140	214	193	59
HQI	93	228	179	104	36

(e.g., Chhattisgarh, Odisha, West Bengal and Sikkim) and part of central and north-eastern region (e.g., Madhya Pradesh and Uttar Pradesh, Meghalaya, Mizoram, Manipur and Nagaland) were noted as low HFI class. The poor housing facility was concentrated in the districts of Assam, Arunachala Pradesh and Meghalaya and few districts are scattered along central and eastern zones. The HFI results show that central, eastern, and north-eastern regions need immediate improvement in the housing facility. The overall HFI distribution portrays that the districts of India were positioned in the moderate-to-low category of housing facilities, which needs possible action to improve the facility.

4.2. Spatial pattern of basic facility index (BFI) and its indicators

Tap water denotes the percentage of households has the accessibility of tap water facility and it is mapped in Fig. 4a. The result represents that the poor (<20%) and inadequate tap water facility (21–30%) are mostly concentrated over the central, eastern and northeastern states of India, which includes Madhya Pradesh, Chandigarh, Odisha, Uttar Pradesh, Bihar Jharkhand, West Bengal, Sikkim, Assam and Nagaland. Following this, the moderate (31–40%) and good tap water facility (41–50%) are scattered over entire India. In contrast, the good facility (>50%) is mostly distributed over the northern and southern states. Out of 640 districts of India,

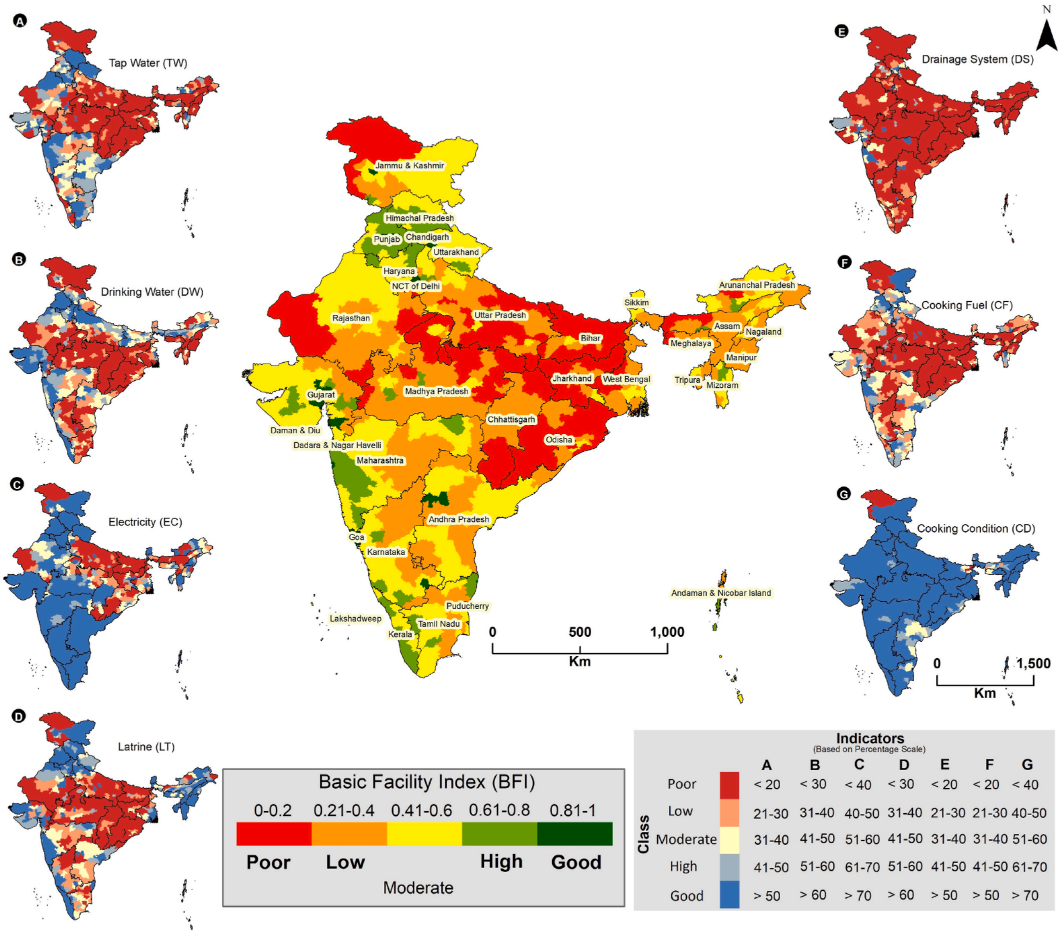

Fig. 4. Spatial pattern of basic facility index (BFI) and its indicators.

Kishanganj, Bihar was marked as poorest tap water facility (0.9%), in contrast Yanam, Puducherry has good facility (99%). **Drinking water** represents the availability and accessibility of drinking water for the households as in Fig. 4b. More than 60% of India districts have poor drinking water facilities (<30%), including central, eastern and southern states. Then, the good drinking water facility (>60%) was marked over the northern states. India's poorest and most good drinking water facility was noted at Longleng, Nagaland (2.4%) and Srinagar, Jammu and Kashmir (93.9%).

Electricity indicates the percentage of households are accessible to electricity facility. The Arwal district in Bihar was marked as the poorest electricity facility (1.9%) and households in Lakshadweep have access to good facility (99.7%). The result infers that the poor (<40%) and inadequate electricity facility (40–50%) was only marked over the Uttar Pradesh, Bihar, Jharkhand and Assam (Fig. 4c). Whereas 70% of India (i.e., entire south, west and northern states) holds a good electricity facility (>70%). **Latrine** denotes the availability of toilet facilities for the district households. Bijapur district in Chhattisgarh has the record of India's poorest latrine facility (5.6%), where Aizawl in Mizoram has the good latrine facility (98.9%). The poor latrine facility (<30%) constituted over entire west, central and eastern state as shown in Fig. 4d. In contrast, northern states, part of northern east and south Kerala have good latrine facilities (>60). In southern states, the households have mixed classes like adequate and moderate facilities. **Drainage system** signifies the availability of proper drainage system for the households. The result shows that 80% of the study area falls under the poor drainage facility (<20%) and few portions of India's districts represent the other classes of drainage system as shown in Fig. 4e. In which, the minor portion of Himachal Pradesh, northern most portion of Gujarat, western portion of Maharashtra and Madhya Pradesh are falling under adequate (41–50%) and good drainage facilities (>50%). Hyderabad in Andhra Pradesh has the best drainage facility (96.5%), and the Bijapur district in Chhattisgarh having the worst drainage facility (0.4%).

Cooking fuel represents the percentage households using cooking fuel (Fig. 4f). The spatial pattern of cooking fuel was similar to latrine and drinking water facility pattern. The poor (<20%) and inadequate facility (21–30%) are mostly dominant over the central, eastern and northern eastern states of India and some minor portions in the western and southern parts. It is marked that the very few portions of area falls under other classes like moderate to good facility and is sparsely distributed rather than the mentioned portions of very low region. The worst cooking fuel facility prevails over Kiphire district, Nagaland (0.70%), but the East Delhi of NCT of Delhi has the record of a good facility (92.4%). **Cooking condition** denotes the percentage of households having proper kitchen facility inside the house (Fig. 4g). The result shows that 90% of the study area falls under good condition of cooking facility (>70%). Then the few districts of Andhra Pradesh and Tamil Nadu has moderate cooking facility (51–60%). Only 33.2% of households in Kishanganj district of Bihar have good cooking condition, where Mahe district in Puducherry has 99.6% of households has good facility.

The basic facility index (BFI) is the most significant index to evaluate the accessibility and availability of basic household services and assets. BFI is computed by integrating seven indicators (i.e., tap water, drinking water, electricity, latrine, drainage system, cooking fuel and cooking condition) through entropy weights. Fig. 4 and Table 4 represents the spatial pattern of BFI along with the number of districts in each categorised, such as poor (146), low (223), moderate (169), high (77) and good (25). The poor BFI class are highly concentrated in the eastern states (e.g., Odisha, West Bengal, Jharkhand and Bihar) and part of central states (e.g., Chhattisgarh, Madhya Pradesh and Uttar Pradesh). The distribution low BFI class were closely associated with the poor class and some portion in north-eastern states (e.g., Assam, Meghalaya, Manipur and Nagaland) and southern states (e.g., Karnataka, Andhra Pradesh and Tamil Nadu), it covered 35% of the study region. The moderate BFI classes were distributed all over the region, except in central and eastern states. Further, the high BFI class covers 12% of study region in northern states (e.g., Punjab, Himachal Pradesh, Chandigarh and NCT of Delhi) and southern states (e.g., Kerala and Tamil Nadu). Whereas the good BFI class are highlighted in Gujarat and Delhi. The observation of BFI indicates that more than half of the study region falls under the low and poor BFI class, it needs more attention from multi-aspects.

4.3. *Spatial pattern of financial asset index (FAI) and its indicators*

Banking Services denotes the percentage of households accessible to banking service. The poor banking facility (<40%) is highly concentrated in east and northeast states and entire Madya Pradesh as shown in Fig. 5a. Whole northern states and some southern and western states has good baking facilities (>70%). The moderate banking facility (51–60%) was only dispersed over the minor regions of the study area. Further, the worst and best banking facilities were found in the Tamenglong district of Manipur (10.9%) and Kangra district of Himachal Pradesh (93.9%). **Radio facility** represents the percentage of households uses radio/transistor as a broad communication. The result of radio shows that the 70% area of India is distributed with poor facilities (<20%) over the central, north, eastern, western and northern portions (Fig. 5b). Following this, inadequate facilities (21–30%) were noted in Uttar Pradesh, Tamil Nadu and Kerala and moderate facilities (31–40%) were highlighted in few districts of the same states. Households in Srikakulam distrcit in Andhra Pradesh has the worst radio facility (2.8%) and households in Srinagar district in Jammu and Kashmir has the best radio facility (77.2%).

Television facility is considered as a mandatory asset like other electronic gadgets and the percentage of households holding was mapped in Fig. 5c. The results of television portray the good (>60%) and adequate television facility (51–60%) is mostly concentrated over the northern, southern and patches of western states. Whereas the households in Chennai, Tamil Nadu, has best television facility (95.4%). Entire central, east and northeast states were concentrated with poor (>30%) to inadequate television facility (31–40%). Then the worst television facility (5.8%) was distributed in Madhepura district, Bihar. **Computer** is one of the notable high-end electronic gadgets in recent decades and the percentage of households holding computers was mapped in Fig. 5d. The result of the computer infers that 90% of the study region falls under the poor computer facility (<5%). Then the inadequate (6–10%) and moderate facility (11–15%) are scattered in very small patches covering only 5% of the study region. Only 0.2% of households of Alirajpur district, Madhya Pradesh have a computer facility. On other hand, households in New Delhi have 24.2% of computer facility.

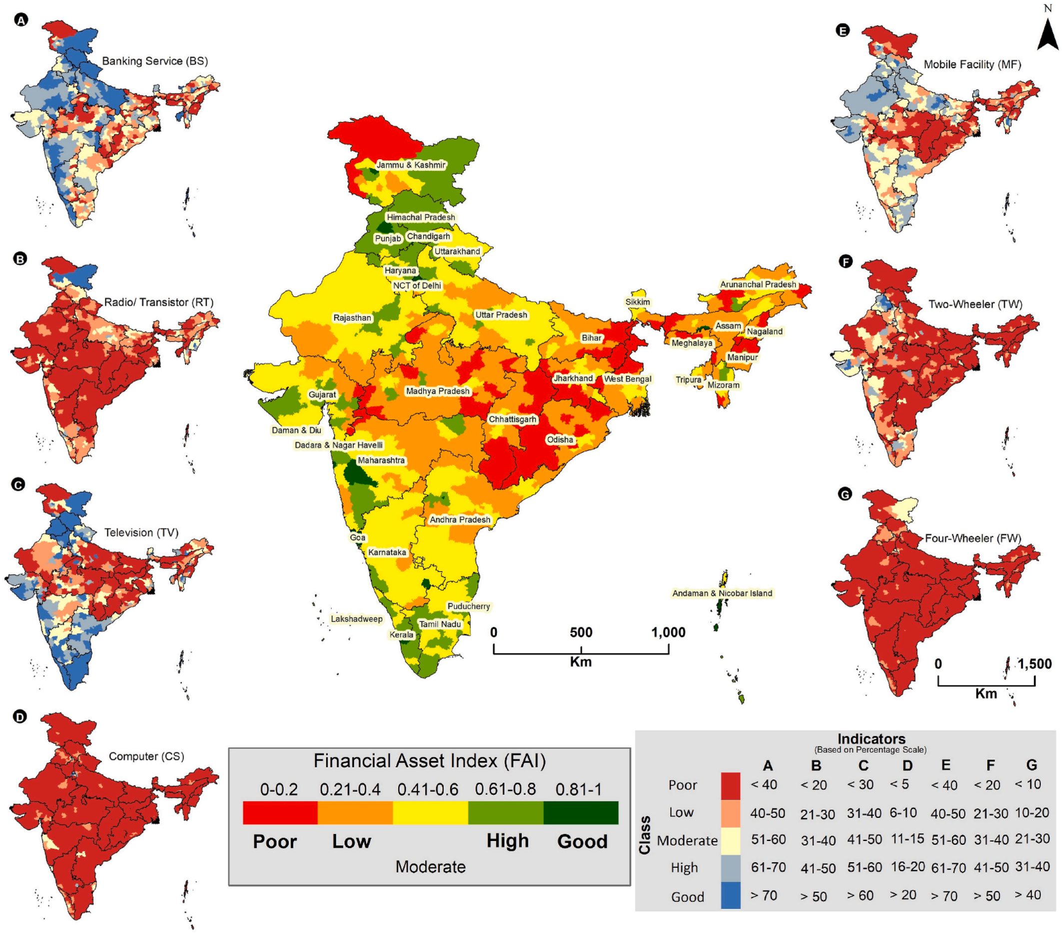

Fig. 5. Spatial pattern of financial asset index (FAI) and its indicators.

Mobile Facility is also considered as high-end electronic gadgets similar to computer. The percentage of household mobile users in the district was mapped in Fig. 5e. Here, the poor mobile facility (<40%) was noted in central, eastern and northeastern states. Then the inadequate facility (40–50%) is associated with poor mobile facility distribution. Further, the good (>70%) and adequate facility (61–70%) is distributed over entire northern states, parts of Rajasthan and some southern states like Karnataka and Tamil Nadu. The best mobile facility (79.6%) was found in households of Daman, Daman and Diu and the worst facility (8%) was founded in Bijapur district of Chhattisgarh.

Two-Wheeler represents the percentage of households in a district using two-wheeler were mapped in Fig. 5f. The result depicts that poor two-wheeler facility (<20%) is distributed as the major category throughout the study area covering almost 75% of the study area, along with this inadequate facility (21–30%) is distributed closer. Then the moderate (31–40%) to good two-wheeler facility (>50%) are spread over the minor portions of Punjab, Rajasthan, Gujarat and Tamil Nadu. In South Goa, Goa households use more two-wheeler facilities (57.4%), whereas the Kiphire dustrcit, Nagaland has the poorest two-wheeler facility (1%). **Four-Wheeler** denotes the household percentage using four-wheeler. The result shows the poor four-wheeler facility (<10%) is distributed over almost 90% of the study region as indicated in Fig. 5g. The inadequate (10–20%) and moderate four-wheeler facility (2–30%) is sparsely distributed along the study region and the other class are not distributed. Gajapati district in Odhisa has 0.5% of households have a four-wheeler (worst four-wheeler facility). In contrast, 29% of households in Gurgaon, Haryana use a four-wheeler (good four-wheeler facility).

Financial asset index (FAI) was computed with the base of seven indicators (i.e., banking services, radio, television, computer, mobile facility, two-wheeler and four-wheeler). It determines the household's level of financial assets and services at district level. Here, the FAI map (Fig. 5) categorised into five classes (e.g., poor, low, moderate, high and good) and number of districts falls under each class are in consecutive order (86, 193, 215, 117 and 29) (Table 4). The FAI results imply that poor FAI class is concentrated in eastern states (e.g., Odisha, Chhattisgarh, Jharkhand, Bihar) and some Madhya Pradesh and Assam districts. Almost 25% of study region (e.g., entire districts of central, eastern and northeast states) was falls into low FAI class and its distribution are associated with poor FAI class. The poor and low FAI class regions have to be improved immediately as the economic and social wealth of these regions is at low where it is estimated with these FAI results. Then the major portion of the moderate FAI class distributed all over the study region, where the high concentration was noted in Rajasthan, Gujarat, Uttar Pradesh, Andhra Pradesh, Karnataka and Tamil

Nadu. The high FAI class was highly concentrated over the northern states (e.g., Jammu and Kashmir, Himachal Pradesh, Panjab, Chandigarh and Haryana) and sparsely distributed in Tamil Nadu, Kerala and Maharashtra. Similarly, good FAI class were noted in a few districts of Delhi, Kerala and Maharashtra. Here the vulnerability is moderate at this time, but these areas will become vulnerable in future if they are not considered for planning and improvement towards a financial asset.

4.4. Spatial pattern of human capital index (HCI) and its indicators

Literacy Rate is an index that measures the strength of primary education in the country and the strength of the human capital. According to the 2011 census, a person aged seven or above who can read, write and understand any language is considered literate. Overall, India has a 74.04% of literacy rate. In which Pathanamthitta district from Kerala has the better literacy rate (88.7%), whereas Alirajpur from Madhya Pradesh has the lowest among all the districts (28.7%). The good literacy rate (>70%) was concentrated mostly in northern states, Kerala and part of Karnataka and Tamil Nadu (Fig. 6a). Accordingly, adequate literacy rate class (61–70%) was distributed closely. Rajasthan, Uttar Pradesh and Andhra Pradesh have moderate literacy rates (51–60%). Moderate to poor literacy rates (<40%) can be seen in many parts of central India. States like Rajasthan, Bihar, Jharkhand and Andhra Pradesh are greatly affected. **Male Literate** indicates the percentage of male literate in district wise. Around 65% of the study region falls under adequate literacy rate (31–40%) and 25% in good literacy rate (>40%) (Fig. 6b). However, some patches of moderate literacy rate (21–30%) can be seen in the eastern states. Around 10% of district falls under the moderate (21–30%) to poor male literate rate (<10%). Then Alirajpur of Madhya Pradesh have the lowest (16.5%) and Daman from Daman and Diu have the highest male literacy (54.5%). Whereas some parts of Kerala, Maharashtra, Jammu, and Kashmir have a very good male literacy.

Female Literate indicates the percentage of female literate in district wise. The condition of female literates is unsatisfactory compared to male literates. However, both follow the same spatial pattern, but female literates mostly range from moderate (21–30%) to poor literacy rate (<10%) as in Fig. 6c. Almost 40% of the study region falls under the moderate to poor literacy rate (<10%). The patch of the adequate female literacy rate (31–40%) was noted along the west coast district and few districts in Tamil Nadu, where Kelera have the good literacy rate (>40%). Alirajpur in Madhya Pradesh ranks lowest in female literates (12.2%), whereas Mahe in Puducherry has the highest female literates (47.5%). **Working Population** denotes the percentage of households engaged in working. The result shows that most of the study region falls under the adequate (41–50%) to good working population rate (>50%), where the moderate working population is distributed in Uttar Pradesh, Bihar and part of Kerala (Fig. 6d). Then the poor working population rate (<20%) is marked in Uttar Pradesh and Bihar. Whereas the Malappuram district of Kerala has the weak working population rate (25.8%) and the high working population rate (66.9%) noted in Kinnaur, Himachal Pradesh.

The human capital index (HCI) is noted to be a significant index in representing the education and working status of households in a district. The HCI calculation needs four indicators: literacy rate, male literate, female literate and working population. The result of the HCI is categorised into five classes (Fig. 6) associated with a number of district falls in each category namely (Table 4), poor (34),

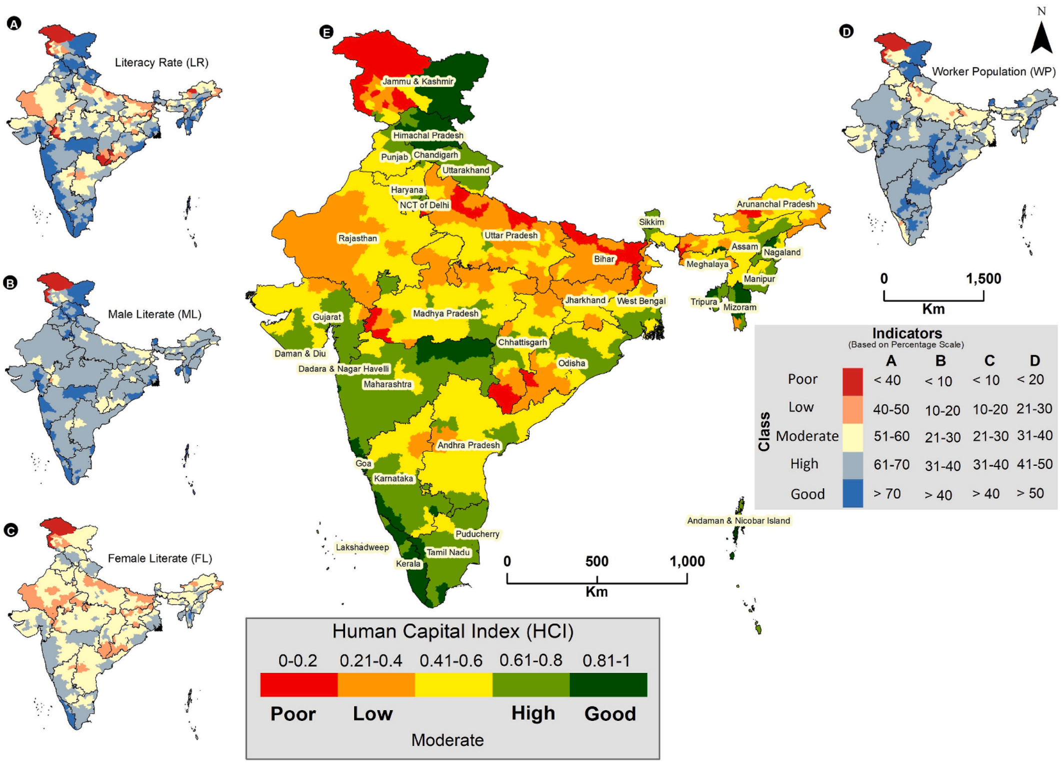

Fig. 6. Spatial pattern of human capital index (HCI) and its indicators.

low (140), moderate (214), high (193) and good (59). It is inferred from the HCI result that the good HCI class were distributed to the entire Himachal Pradesh and Kerala and in few districts of Karnataka, Maharashtra, Mizoram, Tripura and Jammu and Kashmir. Where high HCI class is highly concentrated in Tamil Nadu, Karnataka, Maharashtra, Uttarakhand and NCT of Delhi and sparsely noted in Andhra Pradesh, Odisha and Punjab. Nearly 40% of study regions were under moderate HCI class, distributed in all directions except north and southern states. Entire Bihar is highlighted with low HCI class and followed by Uttar Pradesh, Rajasthan, Odisha and Madya Pradesh, Jammu and Kashmir are noted. Whereas poor HCI class noted in few districts of Bihar, Uttar Pradesh, Chhattisgarh and Jammu and Kashmir. These results resemble the combined result of literacy rate and working population where these factors show very low values. These regions of India are vulnerable towards HCI and have to be given higher concern in development. Then the moderate HCI class distributed over other parts of the study region has to be marked for the implementation of development plans as it is at risk of becoming vulnerable in the near future.

4.5. Household quality of living index (HQI)

The quality of living/living standard of households is quantified for India in the present study through the composite index called household quality of living index (HQI). HQI is a complex factor to analyse as it involves several influencing indicators. Thus, the HQI is computed as a composite index by integrating four sub-indices (i.e., housing facility index, basic facility index, financial asset index and human capital index) with the help of entropy weights. Fig. 7a shows the spatial pattern of district-wise household quality of living index (HQI) for India, which is the represents the influence of 23 indicators. Further, the HQI results varies from 0 to 1, which is categorised into five classes as poor (0–0.2), low (0.21–0.4), moderate (0.41–0.6), high (0.61–0.8) and good (0.81–1) respectively. HQI map signifies that very less area of 5.6% (36 districts out of 640) in the study region was noted as a good HQI class, which is spatially distributed as few districts in Kerala, Maharashtra, Gujarat, NCT of Delhi, Punjab, Himachal Pradesh, Mizoram and Uttarakhand. Then the spatial pattern of high HQI class was distributed in association to good HQI class, nearly 104 districts of India (16.3%) were marked in entire Kerala, Punjab and Himachal Pradesh, following to this many district in Tamil Nadu, Maharashtra, Uttarakhand, Haryana and Gujarat was noted to this class. The moderate HQI class is significantly distributed in southern and western states, where Andhra Pradesh is highly concentrated, followed by Karnataka, Maharashtra, Tamil Nadu, Gujarat, and Rajasthan. The scattered pattern of Moderate HQI class was noted in central, eastern and northeastern states. Exactly 30% of the study region (179 districts out of 640) was covered in moderate class. The dominant category of HQI map is the moderate class, which covers 35.6% of the study area; nearly 228 districts of India comes under this class. Entire central (e.g., Maharashtra, Uttar Pradesh, Chhattisgarh), eastern (e.g., Odisha, Jharkhand, Bihar and West Bengal) and northeastern states (e.g., Meghalaya, Manipur, Arunachal Pradesh, Nagaland, Assam and Tripura) was highly concentrated with HQI moderate class. Minor patches were noticed in the southern states of Karnataka and western states of Maharashtra, Gujarat and Rajasthan. The rest of the 14.6% of the study area was occupied by the poor HQI class, that is 93 districts of India. The high concentration of the poor class was noted in Odisha, Jharkhand and Chhattisgarh. Followingly, one-third of the district in West Bengal, Bihar and Assam was noted. Then minor patches were highlighted in Madhya Pradesh, Uttar Pradesh, Rajasthan, Arunanchal Pradesh and Nagaland. The HQI result shows that central, eastern and northeastern regions have poor living standards. These marked regions of poor and low HQI class have to be monitored consistently to implement appropriate management plans by the government organization in the developmental aspect. These portions are at risk towards household quality and will become vulnerable towards the quality of households in the future. Thus, these regions must be noticed, and plans should be implemented sooner.

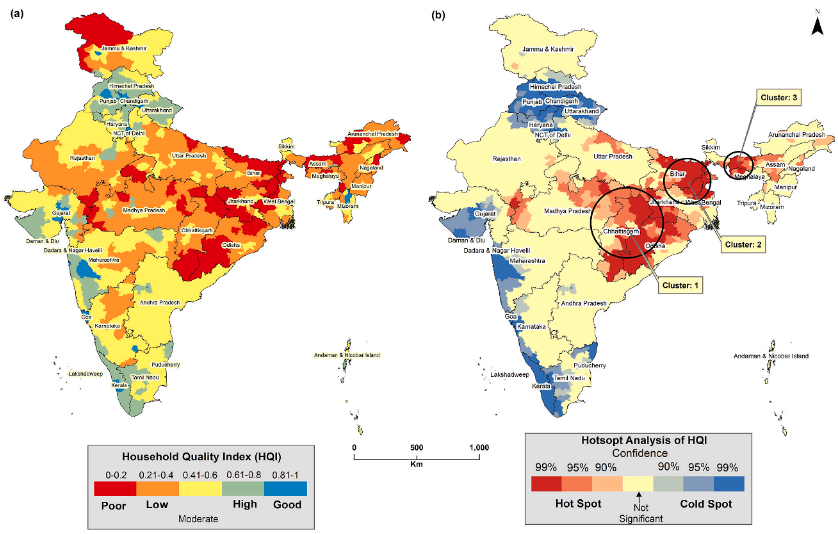

Fig. 7. Spatial distribution of (a) Household Quality of Living Index (HQI) and (b) Hotspot mapping.

5. Discussion and recommendations

In India, regional disparities are the significant challenges faced by the regional planner, government organization and policymakers. Particularly, in the socio-economic condition (e.g., QoL) we can experience this disparity as intra-states and intra-districts all over India. The main reasons behind this condition are unequal distribution of resources and lack of services due to natural barriers and anthropogenic influence. This is the basic challenge of socio-economic researchers and policymakers to solve this regional disparity among the selected areas. But the size of the study area is the primary barrier to planning and managing. Over the period, the emergence of GIS technology and data availability (e.g., multi-scale demographic information, agricultural data and health information) made the assessment of regional disparities on a larger scale easier. Thereafter, the impact and pattern of regional disparity on a household's quality of living played a significant role in the development aspect. Many researchers attempted to evaluate the reason behind the disparity and its pattern over the region using various indicators. According to UNDP, human development mostly depends on the availability of basic assets and services, which are considered important indicators of quality of life (Lind, 2004). It is clearly indicated through the study conducted by Kurian (2000) that based on the social sector's investment, the regional disparities will vary; for example, economically and industrial-rich advanced region (district/state) holds a good standard of living.

A research study performed by Ohlan (2013) states that the districts falls in the central and eastern states have low QoL for household compared with south and north states, which directly indicates huge disparities on the accessibility of services and availability of basic needs among the states. Dasgupta (1971) reveals from his PCA-based household's quality of living analysis that many households are facing a lack of basic necessities. Das and Mistri (2013) conducted study on census data-based household quality of living index (HQLI) estimation for Indian States, which concludes that Uttar Pradesh in central and Chhattisgarh, Odisha in eastern region have poor HQLI due to lack of basic amenities and necessary services. Das et al., (2020) performed a QoL study in Dandakaranya region, and the results say huge intra-state and intra-district disparities for basic amenities and services. Mondal, (2020) attempted to study the spatial pattern of household living quality in West Bengal. It concludes that the QoL is influenced by urban and city regions, making internal disparity among the state. Similarly, the spatial inequality study in urban regions indicates that the households in the periphery of the city are poor in assets holding and have a low standard of living, and vice versa in the city centre (Dutta and Das, 2019).

Apart from these kinds of studies, many researchers considered education status as a deciding factor for living standard. Edgerton et al. (2012) describe the importance and relationship between education status and quality of life. Kiran and Devi (2017) state that education gap is the common reason for regional disparity among the region. Similarly, in this study, several indicators were utilised including education status. The present study attempted to analyse the district-level spatial pattern of household's quality of living for India. From HQI results it is clearly indicating that the central (e.g., Chhattisgarh, Madhya Pradesh, Uttar Pradesh), eastern (e.g., Odisha, Jharkhand) and the northeastern region (e.g., Arunanchal Pradesh and Nagaland) have poor living standards. Except the human capital index (HCI), all three indices (i.e., HFI, FAI, BFI) influence these regions towards the poor category. Particularly, the basic facility index holds high priority, followed by the financial asset index. In examining the BFI and FAI, the influencing indicators for those regions are tap water, drinking water, latrine, cooking fuel, radio, television, computer, mobile facility, vehicles facility. Out of 23 indicators, 9 were in poor stage of development at central, eastern and northeastern states. Further, the indicators like concrete materials, radio, computer, two-wheeler, four-wheeler and drainage system are in poor category for almost 95% of the district in India. So, rapid development should concentrate on indicators like concrete materials, computer and drainage system. In order to implement the development in weaker areas (i.e., poor living quality), there is a need to demarcate the zone of weaker sections (hotspots) and stronger sections (cold spots).

Thus, the hotspot analysis helps to understand the clustering phenomenon and spatial pattern of hotspots and cold spots. Here the hotspot analysis has been mapped to identify the hotspot region (cluster of worst living quality) of HQI. From the hotspot analysis, the outcome was ranked and classified into three statistical categories (e.g., hotspot, cold spot and not significant) with different confidential intervals like 99%, 95% and 90% as shown in Fig. 7b. It is inferred from the result that 24.6% (157 districts) of the study region was covered by hotspots, 22.7% (146 districts) of the region with cold spots and the rest of 52.7% (337 districts) region filled with not-significant category as shown in Table 5. Where the cold spot is marked over northern (e.g., Himachal Pradesh, Punjab, Uttarakhand, Haryana, NCT of Delhi and Chandigarh), western (Gujarat and Maharashtra) and southern states (e.g., Kerala, Tamil Nadu, Karnataka and Andhra Pradesh), these regions are having good living quality for households. The not-significant category covers the dominant portion of the study region and extends all over the parts of the study region. Then the high concentration of hotspot was marked over eastern states (e.g., Odisha, Jharkhand, West Bengal and Bihar) and northeastern states (e.g., Assam and Megha-

Table 5
Distribution of district on hotspot classification.

Classification/Confidence interval		No. Of Districts
Hot Spot	99%	61
	95%	52
	90%	44
Not Significant		338
Cold Spot	90%	20
	95%	40
	99%	86

laya), followed by central states (e.g., Chhattisgarh, Madhya Pradesh, Uttar Pradesh, Gujarat and Rajasthan) are noted in decreasing order of concentration.

Several researchers (Edgerton et al., 2012; Kiran and Devi, 2017; Dutta and Das, 2019; Das et al., 2020; Mondal, 2020), studied the household quality of living on different scales to identify the reason behind the regional disparities and to suggest policy implementation. But those studies failed to address the spatial phenomena in applying the recommended policy. This study identified the spatial location through hotspot analysis by filling this research gap. The districts that comes under the hotspot category were demarcated in Table 6 to suggest the policy implementation according to spatial location. Around 157 district of 14 states were marked as hotspot in three confidence interval of 99%, 95%, 90% like Bihar (18, 6, 5), Odisha (13, 6, 5), Jharkhand (11, 4, 5), Chhattisgarh (7, 4, 4), Assam (5, 7, 3), Madhya Pradesh (1, 12, 9), Uttar Pradesh (0, 5, 5), West Bengal (4, 3, 1), Rajasthan (1, 1, 2), Meghalaya (1, 2, 0), Arunanchal Pradesh (0, 0, 3), Nagaland (0, 1, 1), Gujarat (0, 1, 0) and Jammu and Kashmir (0, 0, 1). In which Bihar holds the highest hotspot district (29), followed by Odisha (24), Madhya Pradesh (22) and Jharkhand (20). From spatial observation, three set of hotspot clusters were found, cluster 1: (Odisha, Chhattisgarh and Madhya Pradesh), cluster 2: (Bihar, Jharkhand and West Bengal) and cluster 3: (Assam and Meghalaya). Primarily, the policy implementation and development plan should be imposed on these clusters in order. Where the cluster 1 needs more and immediate attention followed by cluster 2 and 3.

Therefore, these above results and information will assist the policy maker, regional planner and designer in framing the policy/plan to be implemented in weaker zones. Based on study outcome and location specified information the following recommendation are framed: (1) Specific family welfare programmes and social schemes should be imposed over the hotspot region, (2) Proper communication and adoptable transportation facility should strengthen in the region with dominant regional disparities (e.g., central, eastern and northeastern part), (3) Initiate the social investment activities in order to maintain the stable economy status over city core and peripheral, (4) The distribution of basic amenities and services should maintained equally among the region especially at the central and eastern region (5) Compulsory education system (e.g., Class 1 to any science/technology degree), must imposed in rural part, (6) Immediate scheme of standard education for women's should be implement for all the states, because the female literacy is weaker than male in all over India, (7) Sanitation facilities like latrine and drainage system need a special attention in implementation and management in weaker zone, (8) Production and distribution of electricity are facing huge intra-state disparities, which should be reach to government concern (9) Advance policy like technological investment (e.g., compute and mobile), and infrastructure development (e.g., city planning) must be initiated, (10) More districts has low housing facility, for which government need to implement special scheme, (11) Annual and intra-annual employment scheme should be called from government side, (12) Policy implementation or management doesn't matter, the authority should check the whether the scheme/policy reached the concern group or not. In every new scheme/policy, three barriers are always left: education, communication and transportation.

Table 6
Distribution of district and state in Hotspots at different confidence intervals.

State	Hotspot district with confidence intervals		
	99%	95%	90%
Arunanchal Pradesh	Nil	Nil	Anjaw, Lohit, Upper Subansiri
Assam	Baksa, Bongaigaon, Dhubri, Goalpara, Kokrajhar	Karimganj, Barpeta, Chirang, Kamrup, Nagaon, Dima Hasao, Sonitpur, Udalguri	Darrang, Karbi Anglong
Bihar	Araria, Banka, Bhagalpur, Darbhanga, Jamui, Katihar, Khagaria, Kishanganj, Madhepura, Madhubani, Munger, Muzaffarpur, Purba, Champaran, Purnia, Saharsa, Samastipur, Sitamarhi, Supaul	Gaya, Nawada, Patna, Rohtas Sheikhpura, Sheohar	Begusarai, Gopalganj, Lakhisarai Nalanda, Pashchim Champaran
Chhattisgarh	Bastar, Dakshin Bastar Dantewada, Jashpur, Narayanpur, Raigarh, Raipur, Surguja	Bilaspur, Korba, Koriya, Mahasamund	Bijapur, Dhamtari, Uttar Bastar Kanker, Kabeerdham
Jharkhand	Deoghar, Dumka, Godda, Gumla, Latehar, Pakur, Palamu, Pashchimi Singhbhum, Ranchi, Sahibganj, Simdega	Garhwa, Jamtara, Khunti, Saraikela-kharsawan	Chatra, Giridih, Kodarma, Lohardaga, Purbi Singhbhum
Odisha	Anugul, Balangir, Bargarh, Bauda, Kalahandi, Kandhamal, Kendujhar, Koraput, Nabarangapur, Nuapada, Rayagada, Subarnapur, Sundargarh	Baleshwar, Bhadrak, Dhenkanal, Gajapati, Mayurbhanj, Sambalpur	Debagarh, Jajapur, Jharsuguda, Malkangiri, Nayagarh
Madhya Pradesh	Satna	Alirajpur, Anuppur, Ashoknagar, Chhatarpur, Jabalpur, Jhabua, Panna, Ratlam, Sagar, Shahdol, Sidhi, Singrauli	Barwani, Damoh, Dhar, Dindori, Katni, Mandla, Rewa, Shivpuri, Umaria
Uttar Pradesh	Nil	Bahraich, Banda, Gonda, Kheri, Sonbhadra	Chitrakoot, Farrukhabad, Lalitpur, Shahjahanpur, Shrawasti
West Bengal	Birbhum, Maldah, Murshidabad, Uttar Dinajpur	Barddhaman, Dakshin Dinajpur, Koch Bihar	Pashchim Medinipur
Rajasthan	Banswara	Pratapgarh	Dungarpur, Karauli
Meghalaya	East Garo Hills	South Garo Hills, West Garo Hills	Nil
Nagaland	Nil	Tuensang	Mon
Gujarat	Nil	Dohad	Nil
Jammu & Kashmir	Nil	Nil	Rajouri

6. Conclusion

Entropy-based household quality of living index (HQI) and hotspot mapping provided insight over the regional disparities. HQI result infers that the several central and eastern and northern states are having poor living standard, around 14.6% of study area was occupied by the poor HQI class that is 93 districts of India. The hotspot mapping identified that 157 districts of 14 states were marked as hotspot zone (worst living standard). In which 4 states are in the very worst condition as follows; Bihar has the highest hotspot district (29), followed by Odisha (24), Madhya Pradesh (22) and Jharkhand (20). Through the spatial observation of hotspot clustering, three clusters are formed, cluster 1: (Odisha, Chhattisgarh and Madhya Pradesh), cluster 2: (Bihar, Jharkhand and West Bengal) and cluster 3: (Assam and Meghalaya) to implement the development strategies accordance with cluster order. These clusters need to be monitored and managed in the developmental aspect. The districts covered in cluster 1 are the concentrated hotspot, where the housing, financial, basic amenities and services are at the worst level. So, immediate and special attention is needed for cluster 1, followed by cluster 2 and 3. When these hotspots improve their QoL, the surrounding region (e.g., district) will be influenced socially and economically. The results of this study will assist the policy makers, planners and regional and national governments to initiate adequate action in the selected cluster region to enhance the QoL.

Credit and authorship contribution statement

Venkatesh Ravichandran: Conceptualization, methodology, software, validation, writing—original draft preparation, writing—review and editing. **Komali Kantamaneni:** methodology, software, writing—review and editing. **Aditya Singh:** software, validation, writing—original draft preparation. **Aishwarya Nair:** validation, writing—original draft preparation. **Janakiraman A:** methodology, software, validation. **Sukumar Prem Kumar:** software, validation **Shubham Dhar Choudhury:** software. All authors have read and agreed to the published version of the manuscript.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Ethical statement

The authors declare that all ethical practices have been followed in relation to the development, writing, and publication of the article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

The authors would like to acknowledge the Department of Geography, Bharathidasan University, Tamil Nadu-India and Department of Civil Engineering, Indian Institutes of Technology–Guwahati, Assam, India for their coordinative involvement and support in utilising the laboratory facilities, and also thank the faculty members of the respective departments.

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