



# Spatial Inequality of Urbanisation, Land Transformation and Environmental Quality in Bihar: A Remote Sensing and Socio-Spatial Vulnerability Framework

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**Abstract:** Bihar is among the least urbanised and most densely populated states of India, yet its urban growth is highly concentrated and its land base is under intense pressure. This paper develops an integrated remote sensing and socio-spatial vulnerability framework to measure how unevenly urbanisation, land transformation, and environmental quality are distributed across the state's 38 districts. The framework combines a satellite-based land-transformation module (land use/land cover classification, NDVI, NDBI, MNDWI, and land surface temperature) with three district-level composite indices built from Census of India 2011 data: an Urbanisation–Land Pressure Index (ULPI), a household Environmental Quality Index (EQI), and a Social Vulnerability Index (SVI). The indices are weighted by the entropy method and analysed with population-weighted Gini and Theil coefficients, global and local Moran's I, and a coupling coordination model. Urban households range from 3.8% of all households in Madhubani to 45.6% in Patna, a twelve-fold gap, and access to tap water varies more than twenty-fold. Between 49% and 73% of the Theil inequality in each indicator arises between the nine administrative divisions. ULPI and EQI are strongly correlated ( $\rho = 0.84$ ,  $p < 0.001$ ), and both are inversely related to social vulnerability. Local spatial statistics reveal a high-urbanisation, high-environmental-quality corridor along the Ganga around Patna and a low–low cluster in the Kosi–Seemanchal region, where Supaul and Araria form a significant hot spot of combined socio-environmental vulnerability. Fifteen districts, home to 38% of the state's population, fall in a rural-deprived priority class. Published remote sensing evidence for Patna, where built-up land expanded from 38% to 80% of the city area between 1988 and 2022, shows that where urbanisation is most advanced it is accompanied by rapid vegetation loss and surface warming. The framework offers a transparent basis for spatially targeted investment in sanitation, clean energy, piped water, and green infrastructure.

*Article impact statement: An integrated remote sensing and census-based vulnerability framework shows that urbanisation, household environmental quality and social vulnerability in Bihar are sharply and regionally unequal, and identifies fifteen priority districts for spatially targeted investment.*

**Keywords:** Bihar; Urbanisation; Land transformation; Environmental quality; Remote sensing; Social vulnerability; Spatial inequality; Moran's I; Coupling coordination

## 1. Introduction

### 1.1 Background

Urbanisation is one of the most powerful forces reshaping land and environment in the twenty-first century. Global forecasts suggest that urban land could expand by more than a million square kilometres between 2000 and 2030, with much of the

growth in Asia and Africa, and that this expansion will directly consume croplands and natural habitats (Seto et al., 2012). Cities concentrate economic opportunity, but they also concentrate environmental burdens, alter biogeochemical cycles, and modify local climate (Grimm et al., 2008). In developing countries, the speed of urban growth frequently outpaces the provision of basic services, so that urbanisation and environmental deterioration proceed together (Cohen, 2006).

Bihar illustrates these tensions in an extreme form. According to the Census of India 2011, the state had a population of about 104 million people living at an average density of more than 1,100 persons per square kilometre, one of the highest in the country, while only about 11.5% of its households were urban (Census of India, 2011). Urban growth is dominated by the capital, Patna, and a few divisional towns, whereas large parts of the flood-prone north remain overwhelmingly agrarian. Satellite studies of Patna show rapid conversion of vegetation and agricultural land to built-up surfaces and a corresponding rise in land surface temperature (Akram et al., 2025). At the same time, the state's population is highly exposed to floods, heat, and poor household environmental conditions, and exposure interacts with social disadvantage to create vulnerability (Cutter et al., 2003; Adger, 2006).

## 1.2 Research Gap and Objectives

Most studies of Bihar examine either the physical side of change (land cover and temperature in a single city) or the social side (poverty and deprivation), but rarely both at the scale of the whole state. Yet planning decisions are made at district level, and what planners need is a consistent picture of where urbanisation, land transformation, environmental quality, and social vulnerability coincide or diverge. This paper addresses that gap with four objectives:

- to design an integrated framework that links satellite-derived land transformation indicators with census-based socio-spatial indicators;
- to construct objective composite indices of urbanisation–land pressure, household environmental quality, and social vulnerability for all 38 districts of Bihar;
- to quantify the magnitude, regional structure, and spatial clustering of inequality in these indices; and
- to identify priority districts where low urbanisation, poor environmental quality, and high social vulnerability overlap.

Section 2 reviews related work, Section 3 describes the study area and data, Section 4 sets out the methodology, Section 5 presents and discusses the results, and Section 6 concludes the paper.

## 2. Literature Review

### 2.1 Vulnerability and Socio-Spatial Inequality

Vulnerability is commonly understood as a function of exposure, sensitivity, and adaptive capacity (Adger, 2006). Turner *et al.* (2003) proposed a framework in which vulnerability emerges from coupled human–environment systems, so that the same hazard affects places differently depending on their social and ecological conditions. Cutter *et al.* (2003) operationalised this idea in the Social Vulnerability Index (SoVI), which combines census variables such as income, education, age, race, and housing into a place-based score. SoVI-type indices have since been widely adapted, including in India, but most applications focus on a single hazard and do not integrate land-use change.

### 2.2 Remote Sensing of Urban Land Transformation in Bihar

Remote sensing has become the standard way to observe land transformation. Chettry and Surawar (2021) assessed the characteristics of urban sprawl in Patna, Ranchi, and Srinagar from satellite imagery and highlighted the dispersed, low-density form of growth in these cities. Mishra and Rai (2016) combined remote sensing with a multi-layer perceptron and Markov chain model to simulate and predict land use and land cover (LULC) change in Patna district. Akram *et al.* (2025) analysed Landsat imagery of Patna from 1988 to 2022 and found that built-up land rose from 38% to 80% of the city area while vegetation fell from 44% to 7%, accompanied by rising land surface temperature (LST). At the regional scale, Gogoi *et al.* (2019) showed that LULC change has measurably influenced surface temperature over eastern India. Thermal remote sensing more generally links impervious surfaces and vegetation loss to urban heat (Weng, 2009), and time-series analysis of Landsat data can separate urbanisation-induced warming from background trends (Fu & Weng, 2016).

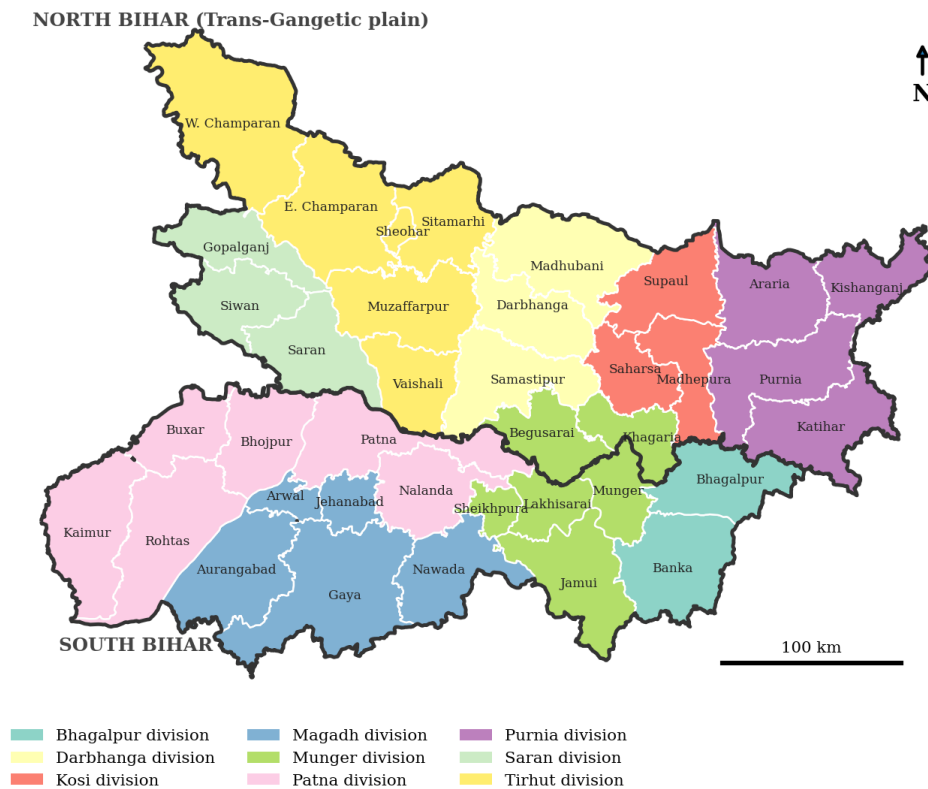
### 2.3 Urbanisation–Environment Coupling

Li *et al.* (2012) introduced a coupling coordination model to evaluate whether urbanisation and environmental quality evolve in harmony, and this approach has since become common in regional studies. It treats urbanisation and environment as two interacting subsystems and measures both their degree of interaction and their joint level of development. What remains less common is the combination of such coupling measures with explicit spatial statistics and social vulnerability, which is the contribution of this paper.

### 3. Study Area and Data

#### 3.1 Study Area

Bihar lies in the middle Ganga plain between about 24°20' N and 27°31' N latitude and 83°19' E and 88°17' E longitude. The Ganga divides the state into two physiographic regions (Figure 1). North Bihar, the trans-Gangetic plain, is crossed by the Gandak, Bagmati, Kamla, Kosi, and Mahananda rivers and is highly prone to floods. South Bihar is drained by smaller rivers and grades into the Chotanagpur plateau fringe in Kaimur, Rohtas, Gaya, Nawada, Jamui, and Banka. In 2011 the state comprised 38 districts grouped into nine administrative divisions, which form the spatial units of this study.



**Figure 1. Study area: the 38 districts and nine administrative divisions of Bihar, with the North–South Bihar divide (bold line) along the Ganga. District boundaries from Census 2011.**

#### 3.2 Data Sources

Socio-economic and household data were taken from the Census of India 2011 district tables (Census of India, 2011), namely the Primary Census Abstract and the Houselisting and Housing tables, covering 104.1 million people and 23.4 million households. District boundaries were obtained from the Census 2011 administrative boundary layer and projected to UTM Zone 45N (EPSG:32645) to compute district areas. The remote sensing module is designed around freely available Landsat 5 TM, Landsat 8/9 OLI–TIRS, and Sentinel-2 MSI imagery. Table 1 lists the 18 census indicators used, grouped into three dimensions, together with their direction of effect and entropy weights.

**Table 1. Indicator System, Direction of Effect, and Entropy Weights.**

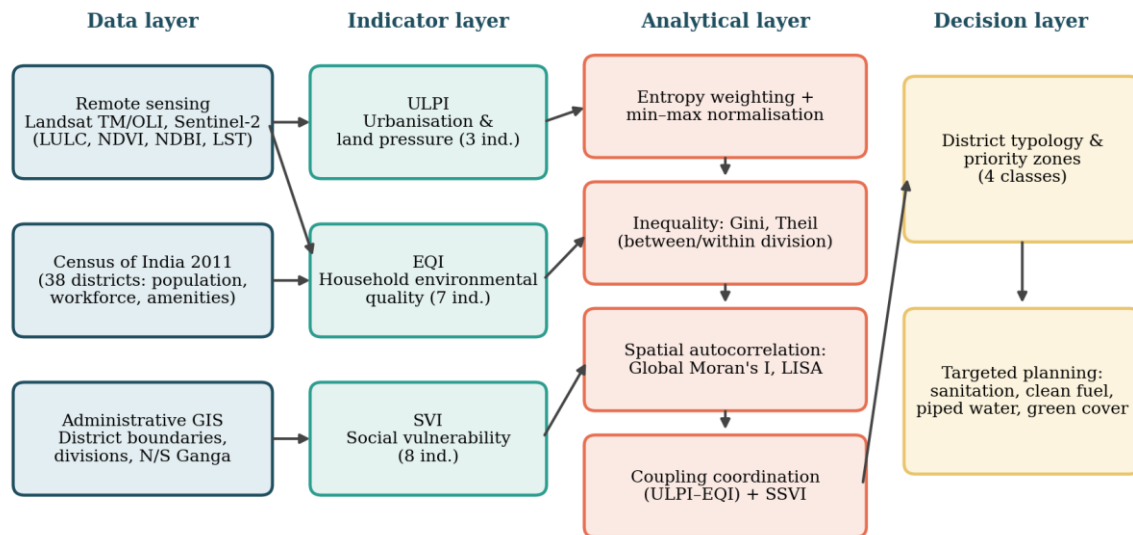
| Dimension | Indicator (% unless stated)                             | Dir. | Weight |
|-----------|---------------------------------------------------------|------|--------|
| ULPI      | Urban households in total households                    | +    | 0.522  |
| ULPI      | Main and marginal workers in non-farm (“other”) work    | +    | 0.288  |
| ULPI      | Population density (persons/km <sup>2</sup> )           | +    | 0.190  |
| EQI       | Households with tap water as main drinking-water source | +    | 0.306  |
| EQI       | Households using LPG/PNG for cooking                    | +    | 0.236  |
| EQI       | Households with latrine within premises                 | +    | 0.131  |
| EQI       | Households with electric lighting                       | +    | 0.121  |
| EQI       | Households practising open defecation                   | –    | 0.095  |
| EQI       | Dilapidated census houses                               | –    | 0.057  |
| EQI       | Households fetching drinking water from away            | –    | 0.055  |
| SVI       | Households with nine or more members                    | +    | 0.207  |
| SVI       | Female illiteracy                                       | +    | 0.145  |
| SVI       | Total illiteracy                                        | +    | 0.144  |
| SVI       | Scheduled Caste and Scheduled Tribe population          | +    | 0.142  |
| SVI       | Marginal workers in total workers                       | +    | 0.137  |
| SVI       | Agricultural labourers in total workers                 | +    | 0.084  |
| SVI       | Non-workers in total population                         | +    | 0.083  |
| SVI       | Households in lowest income-proxy class (< ₹45,000)     | +    | 0.058  |

Note: Dir. = direction of effect on the index (+ raises, – lowers); weights obtained by the entropy method; ULPI = Urbanisation–Land Pressure Index; EQI = Environmental Quality Index; SVI = Social Vulnerability Index.

## 4. Methodology

### 4.1 Integrated Framework

Figure 2 presents the framework. It has four layers. The data layer assembles satellite imagery, census data, and administrative boundaries. The indicator layer converts these into the three composite indices. The analytical layer measures inequality, spatial clustering, and coupling. The decision layer classifies districts into a policy typology. The design keeps the physical and social components separate until the final stage, so that each can be updated independently as new imagery or new census data become available.



**Figure 2. Integrated remote sensing and socio-spatial vulnerability framework used in this study.**

### 4.2 Remote Sensing Module for Land Transformation

Four spectral indices characterise land transformation: the Normalised Difference Vegetation Index (NDVI) (Tucker, 1979), the Normalised Difference Built-up Index (NDBI) (Zha et al., 2003), and the Modified Normalised Difference Water Index (MNDWI) (Xu, 2006), together with land surface temperature. They are computed from cloud-screened surface-reflectance scenes of the post-monsoon dry season, when crop and water contrasts are clearest, after masking clouds and shadows with the

Fmask algorithm (Zhu & Woodcock, 2012); all processing is carried out on Google Earth Engine (Gorelick et al., 2017). Using red (R), near-infrared (NIR), short-wave infrared (SWIR), and green (G) reflectance:

$$NDVI = \frac{(NIR - R)}{(NIR + R)} \quad (1)$$

$$NDBI = \frac{(SWIR - NIR)}{(SWIR + NIR)} \quad (2)$$

$$MNDWI = \frac{(G - SWIR)}{(G + SWIR)} \quad (3)$$

Land surface temperature is retrieved from the thermal band by converting at-sensor brightness temperature  $T_B$  (in kelvin) with an NDVI-based emissivity  $\varepsilon$  (Weng, 2009):

$$LST = \frac{TB}{[1 + (\lambda \cdot TB / \rho) \cdot \ln \varepsilon]} - 273.15 \quad (4)$$

where  $\lambda$  is the effective wavelength of the thermal band and  $\rho = 1.438 \times 10^{-2}$  m·K. Land cover is classified into built-up, agriculture, vegetation, water, and fallow/sand using a Random Forest classifier (Breiman, 2001) trained on the spectral bands and indices, and accuracy is assessed with stratified reference samples and area-adjusted estimators following good-practice guidance (Olofsson et al., 2014). The rate of land transformation between two dates  $t_1$  and  $t_2$  is expressed as the annual built-up expansion rate:

$$AER = \frac{\left[ \frac{(Bt_2 - Bt_1)}{Bt_1} \right]}{(t_2 - t_1)} \times 100 \quad (5)$$

#### 4.3 Normalisation and Entropy Weighting

Each indicator  $x_{ij}$  (district  $i$ , indicator  $j$ ) is rescaled to  $[0, 1]$  by min–max normalisation, reversing the scale for indicators with a negative effect. Weights are obtained objectively with the entropy method, which is based on Shannon's information entropy (Shannon, 1948) and gives more weight to indicators that discriminate more strongly between districts:

$$ej = -\left(\frac{1}{\ln n}\right) \sum_i pij \ln pij, \quad pij = \frac{zij}{\sum_i zij} \quad (6)$$

$$wj = \frac{(1 - ej)}{\sum_j (1 - ej)}, \quad Index_i = \sum_j wj zij \quad (7)$$

where  $n = 38$  is the number of districts and  $z_{ij}$  is the normalised value. A combined Socio-Spatial Vulnerability Index is defined as  $SSVI = 0.5 \cdot SVI + 0.5 \cdot (1 - EQI)$ , so that it rises with both social disadvantage and environmental deprivation.

#### 4.4 Inequality Measures

Inter-district inequality is measured with the population-weighted Gini coefficient and the Theil  $T$  index. The Theil index can be decomposed additively into inequality between groups and within groups (Shorrocks, 1980), which allows us to ask how much inequality lies between Bihar's nine divisions, or between North and South Bihar:

$$T = \sum_i si \left(\frac{x_i}{\mu}\right) \ln \left(\frac{x_i}{\mu}\right) = T_{between} + T_{within} \quad (8)$$

where  $s_i$  is the population share of district  $i$ ,  $x_i$  its indicator value, and  $\mu$  the population-weighted state mean.

#### 4.5 Spatial Autocorrelation

Tobler's first law of geography states that near things are more related than distant things (Tobler, 1970). This is tested with global Moran's  $I$  (Moran, 1950) and the local indicators of spatial association (LISA) of Anselin (1995), using a row-standardised queen-contiguity weights matrix  $W \sim ij \sim$ :

$$I = \left(\frac{n}{\sum_i \sum_j wij}\right) \cdot \frac{\sum_i \sum_j wij (xi - \bar{x})(xj - \bar{x})}{\sum_i (xi - \bar{x})^2} \quad (9)$$

Significance is assessed with 9,999 random permutations. LISA classifies significant districts ( $p < 0.05$ ) as High–High, Low–Low, High–Low, or Low–High clusters.

#### 4.6 Coupling Coordination Model

Following Li *et al.* (2012), the coupling degree  $C$ , the comprehensive development index  $T$ , and the coupling coordination degree  $D$  between the urbanisation ( $U_1 = ULPI$ ) and environment ( $U_2 = EQI$ ) subsystems are:

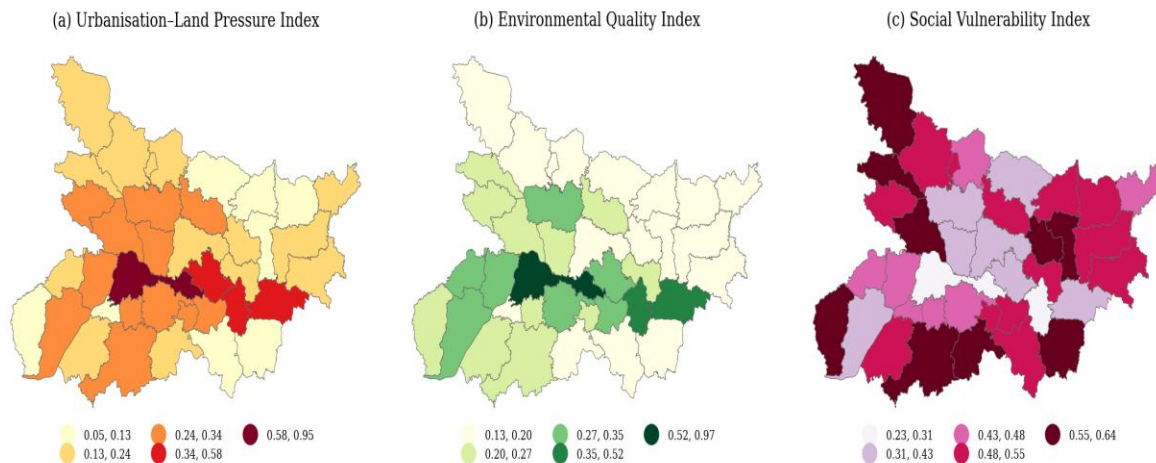
$$\frac{C}{(U_1 + U_2)} = \frac{2\sqrt{U_1 U_2}}{(U_1 + U_2)}, \quad T = 0.5U_1 + 0.5U_2, \quad D = \sqrt{C \cdot T} \quad (10)$$

Districts are classed as moderately imbalanced ( $0.2 \leq D < 0.3$ ), slightly imbalanced ( $0.3\text{--}0.4$ ), barely balanced ( $0.4\text{--}0.5$ ), in basic coordination ( $0.5\text{--}0.6$ ), or in good coordination ( $D \geq 0.6$ ). Finally, districts are placed in a four-class typology by comparing their ULPI and SSVI with the state medians.

## 5. Results and Discussion

### 5.1 Spatial Patterns of the Composite Indices

Figure 3 maps the three indices. Urbanisation–land pressure (Figure 3a) is concentrated in a narrow belt along the Ganga, from Bhojpur and Patna through Nalanda, Begusarai, and Munger to Bhagalpur. Patna stands far above every other district (ULPI = 0.95), followed by Munger (0.58), Begusarai (0.48), and Bhagalpur (0.45). The Kosi–Seemanchal districts of the north-east and the plateau-fringe districts of the south, such as Banka (0.05) and Kaimur (0.07), have the lowest values. Environmental quality (Figure 3b) follows almost exactly the same pattern, with Patna (0.97) and Munger (0.52) at the top and Jamui, Madhepura, Araria, and Banka at the bottom (0.13–0.14). Social vulnerability (Figure 3c) is broadly the inverse. It is highest in Nawada (0.64), West Champaran (0.64), Gaya (0.59), Kaimur, and Saharsa, and lowest in Patna (0.23) and Munger (0.31).



**Figure 3.** Spatial distribution of (a) the Urbanisation–Land Pressure Index, (b) the Environmental Quality Index, and (c) the Social Vulnerability Index across the districts of Bihar (natural-breaks classes).

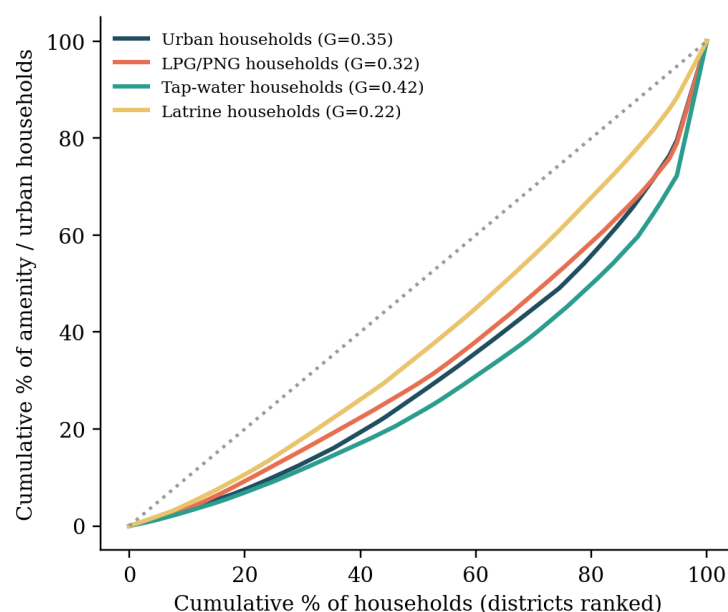
### 5.2 Magnitude of Inter-District Inequality

Table 2 and Figure 4 quantify inequality in eight key indicators. The largest disparities are in infrastructure-dependent amenities. Tap water reached 19.1% of households in Patna but only 0.9% in Supaul, a twenty-one-fold gap with a population-weighted Gini of 0.42. Electric lighting ranged from 1.5% in Arwal to 45.2% in Patna, and clean cooking fuel (LPG/PNG) from 2.0% in Supaul to 26.6% in Patna. The share of urban households varied twelve-fold, from 3.8% in Madhubani to 45.6% in Patna. In contrast, illiteracy and low income, although high everywhere, vary much less between districts (Gini 0.07 and 0.09). In other words, the basic condition of deprivation is widespread across Bihar, whereas access to modern urban services is concentrated in a few places.

**Table 2.** Inter-District Inequality of Key Indicators (n = 38).

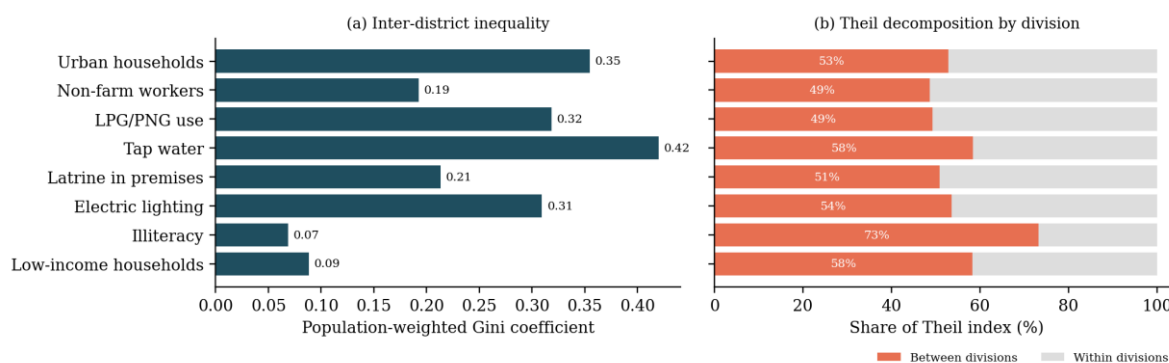
| Indicator             | Mean (%) | Min (%) | Max (%) | Max/Min | Gini  | Theil T | Between-division share |
|-----------------------|----------|---------|---------|---------|-------|---------|------------------------|
| Urban households      | 11.10    | 3.79    | 45.62   | 12.0    | 0.355 | 0.233   | 52.9%                  |
| Non-farm workers      | 21.72    | 11.10   | 46.08   | 4.2     | 0.192 | 0.060   | 48.7%                  |
| LPG/PNG use           | 6.02     | 2.02    | 26.55   | 13.2    | 0.319 | 0.211   | 49.2%                  |
| Tap water             | 3.25     | 0.90    | 19.11   | 21.3    | 0.420 | 0.359   | 58.4%                  |
| Latrine in premises   | 18.46    | 7.47    | 41.95   | 5.6     | 0.213 | 0.076   | 50.9%                  |
| Electric lighting     | 12.77    | 1.53    | 45.19   | 29.6    | 0.309 | 0.177   | 53.5%                  |
| Illiteracy            | 49.61    | 39.19   | 59.19   | 1.5     | 0.069 | 0.007   | 73.2%                  |
| Low-income households | 27.26    | 15.44   | 35.38   | 2.3     | 0.088 | 0.014   | 58.3%                  |

*Note:* Gini = population-weighted Gini coefficient; Theil T = Theil index; between-division share = share of Theil T arising between the nine administrative divisions.



**Figure 4. Lorenz curves of urban households and household amenities across districts (G = Gini coefficient over households).**

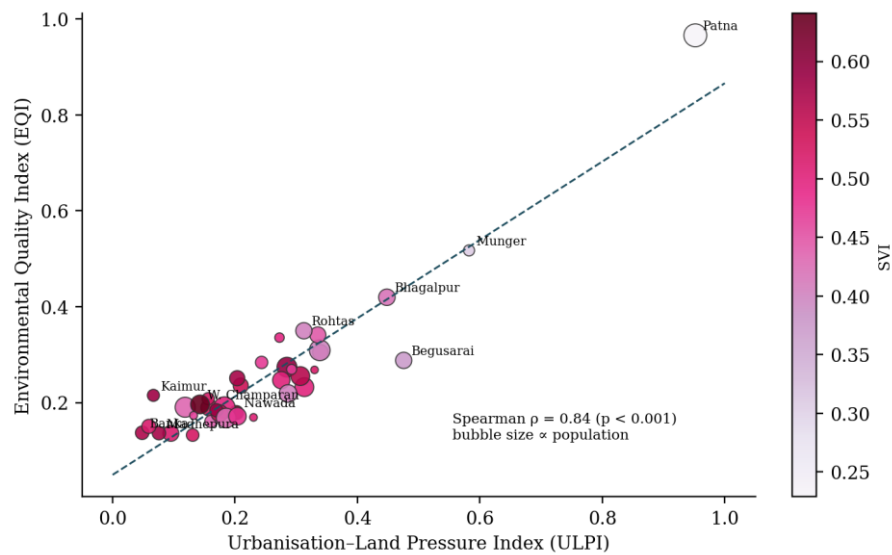
The Theil decomposition (Figure 5b) shows that inequality has a strong regional structure: 49–73% of the Theil index of each indicator arises between the nine divisions rather than within them. The North–South divide alone accounts for 20–41% of total inequality. On average, South Bihar districts have almost twice the urban household share of North Bihar districts (15.1% versus 7.8%), more than twice the tap-water coverage (4.8% versus 2.0%), and markedly higher LPG use (7.8% versus 4.6%) and latrine coverage (22.0% versus 15.6%). North Bihar, by contrast, is more crowded (1,308 versus 967 persons/km<sup>2</sup>), more illiterate (52.8% versus 45.6%), and poorer (29.5% versus 24.4% of households in the lowest income class). High density without urbanisation means that land pressure in the north is expressed as agrarian crowding on flood-prone land rather than as urban growth.



**Figure 5. (a) Population-weighted Gini coefficients of key indicators; (b) share of the Theil index arising between Bihar's nine administrative divisions.**

### 5.3 Relationships Among Urbanisation, Environment, and Vulnerability

Figure 6 plots environmental quality against urbanisation–land pressure. The relationship is strong and positive (Spearman  $\rho = 0.84$ ,  $p < 0.001$ ), which shows that in Bihar the household environment improves with urbanisation rather than deteriorating. The urban share of households alone correlates with LPG use at  $\rho = 0.75$ . Both indices are negatively associated with social vulnerability (ULPI–SVI  $\rho = -0.58$ ,  $p < 0.001$ ; EQI–SVI  $\rho = -0.46$ ,  $p = 0.003$ ). Population density by itself is not significantly related to environmental quality ( $\rho = 0.19$ ,  $p = 0.25$ ). What drives household environmental quality is therefore urban service provision, not the number of people per unit of land. Districts lying above the regression line, such as Kaimur, enjoy better environmental quality than their level of urbanisation would predict. Begusarai, an industrial district with a refinery and thermal power station, lies well below the line, which suggests that its non-farm growth has not yet been matched by household services.



**Figure 6. Environmental Quality Index versus Urbanisation–Land Pressure Index for the 38 districts; colour shows social vulnerability and bubble size is proportional to population.**

#### 5.4 Spatial Clustering

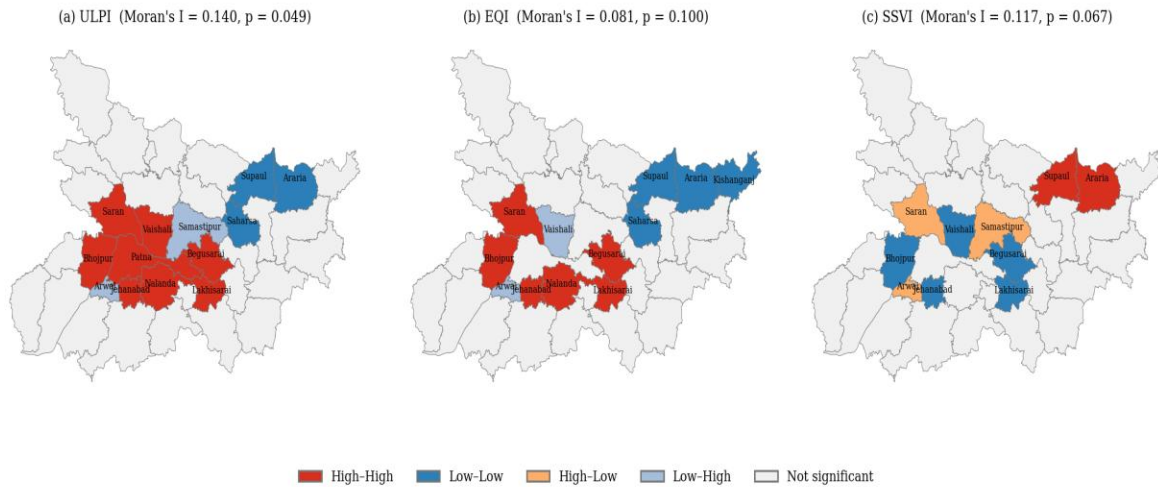
Table 3 reports global Moran's  $I$ . All indices show positive spatial autocorrelation, meaning that similar values tend to occur in neighbouring districts, although the global statistics are moderate, which is typical for a small number of large spatial units. Clustering is significant at the 5% level for ULPI ( $I = 0.140$ ,  $p = 0.050$ ) and the coupling coordination degree ( $I = 0.155$ ,  $p = 0.043$ ), and marginally significant for SVI and SSVI ( $p = 0.052$  and  $0.067$ ).

**Table 3. Global Moran's  $I$  of Composite Indices (Queen Contiguity, 9,999 Permutations).**

| Index                   | Moran's $I$ | z-score | Pseudo p-value | Interpretation         |
|-------------------------|-------------|---------|----------------|------------------------|
| ULPI                    | 0.140       | 1.74    | 0.050          | Significant clustering |
| EQI                     | 0.081       | 1.33    | 0.100          | Weak, not significant  |
| SVI                     | 0.150       | 1.70    | 0.052          | Marginally significant |
| SSVI                    | 0.117       | 1.62    | 0.067          | Marginally significant |
| Coupling coordination D | 0.155       | 1.84    | 0.043          | Significant clustering |

*Note: Queen-contiguity weights, row-standardised; pseudo p-values from 9,999 random permutations; SSVI = Socio-Spatial Vulnerability Index.*

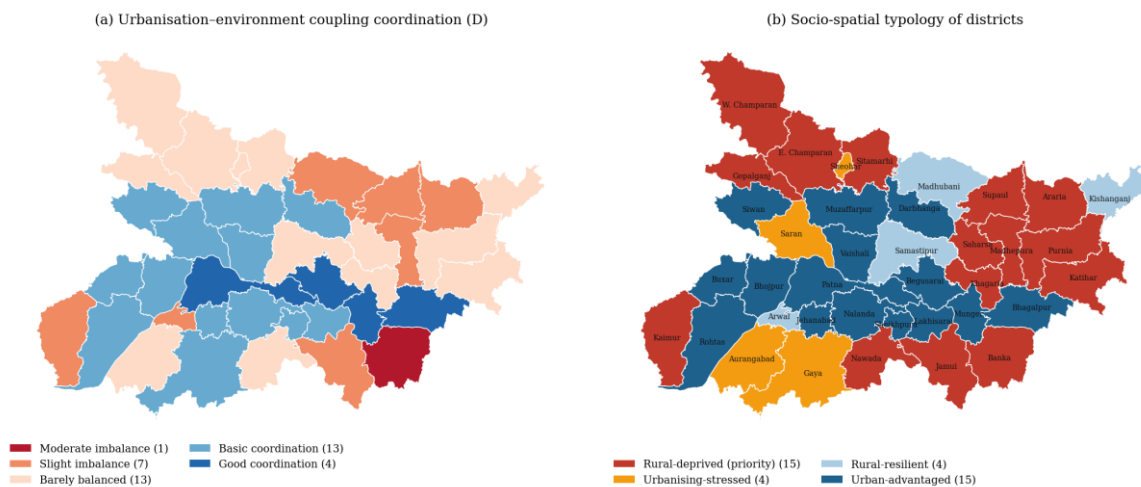
The LISA maps (Figure 7) are more revealing than the global statistics. A significant High–High cluster of urbanisation–land pressure runs through Saran, Vaishali, Bhojpur, Patna, Nalanda, Jehanabad, Begusarai, and Lakhisarai, which is the Patna-centred Ganga corridor. The environmental quality High–High cluster covers much the same districts. The mirror image is a Low–Low cluster in Supaul, Araria, Saharsa, and Kishanganj in the Kosi–Seemanchal region, the part of Bihar most exposed to Kosi floods. Most importantly, Supaul and Araria form the only significant High–High hot spot of the combined socio-spatial vulnerability index, whereas the Ganga-corridor districts form a Low–Low cold spot. Saran, Samastipur, and Arwal appear as High–Low outliers: vulnerable districts that sit next to better-off neighbours and could therefore benefit from spill-over if connectivity improves.



**Figure 7. LISA cluster maps ( $p < 0.05$ ) for (a) ULPI, (b) EQI, and (c) the combined Socio-Spatial Vulnerability Index.**

### 5.5 Coupling Coordination and District Typology

Figure 8a maps the coupling coordination degree between urbanisation and environment. Only four districts reach good coordination: Patna ( $D = 0.98$ ), Munger (0.74), Bhagalpur (0.66), and Begusarai (0.61). Thirteen are in basic coordination, thirteen are barely balanced, seven are slightly imbalanced, and Banka alone is moderately imbalanced ( $D = 0.29$ ). Because coordination here reflects the joint level of both subsystems, low values signal districts in which both urbanisation and household environment are underdeveloped. The typology in Figure 8b translates these results into policy classes. Fifteen districts are rural-deprived priority districts, with below-median urbanisation and above-median combined vulnerability, and together they hold 38% of Bihar's population. They are concentrated in the Kosi and Purnia divisions, the Champaran–Sitamarhi belt of Tirhut, and the southern plateau fringe (Nawada, Jamui, Banka, and Kaimur). Four districts (Saran, Gaya, Aurangabad, and Sheohar) are urbanising-stressed: they are relatively urbanised but still socially and environmentally vulnerable. Table 4 lists the ten most vulnerable districts, and Figure 9 summarises the gradient across divisions, from Kosi (mean SSVI 0.70) to Patna (0.51).

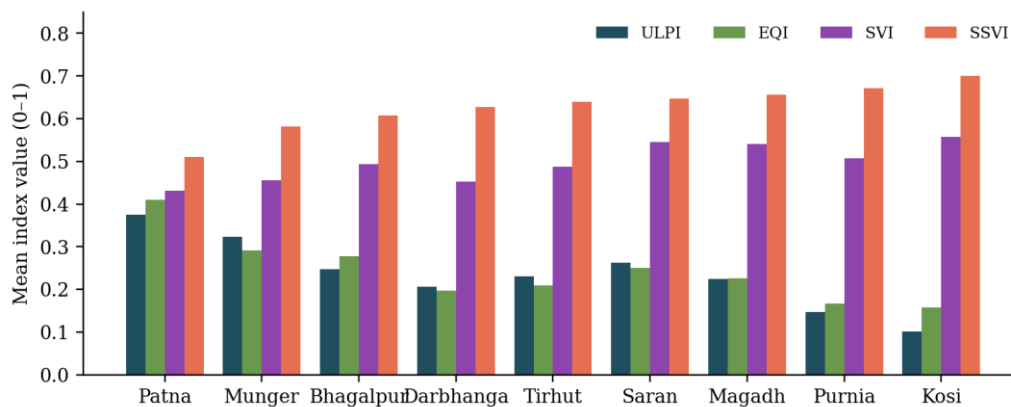


**Figure 8. (a) Coupling coordination degree between urbanisation and environmental quality; (b) socio-spatial typology of districts based on ULPI and SSVI relative to state medians.**

**Table 4. Ten Districts with the Highest Socio-Spatial Vulnerability.**

| Rank | District     | Division  | ULPI  | EQI   | SVI   | SSVI  | Coordination class |
|------|--------------|-----------|-------|-------|-------|-------|--------------------|
| 1    | Nawada       | Magadh    | 0.202 | 0.179 | 0.641 | 0.731 | Barely balanced    |
| 2    | W. Champaran | Tirhut    | 0.143 | 0.196 | 0.640 | 0.722 | Barely balanced    |
| 3    | Madhepura    | Kosi      | 0.076 | 0.136 | 0.576 | 0.720 | Slight imbalance   |
| 4    | Banka        | Bhagalpur | 0.048 | 0.137 | 0.567 | 0.715 | Moderate imbalance |
| 5    | Saharsa      | Kosi      | 0.169 | 0.184 | 0.582 | 0.699 | Barely balanced    |
| 6    | Jamui        | Munger    | 0.131 | 0.132 | 0.524 | 0.696 | Slight imbalance   |
| 7    | Araria       | Purnia    | 0.095 | 0.136 | 0.512 | 0.688 | Slight imbalance   |
| 8    | Purnia       | Purnia    | 0.175 | 0.178 | 0.546 | 0.684 | Barely balanced    |
| 9    | Kaimur       | Patna     | 0.067 | 0.215 | 0.583 | 0.684 | Slight imbalance   |
| 10   | Supaul       | Kosi      | 0.059 | 0.150 | 0.517 | 0.683 | Slight imbalance   |

Note: *ULPI* = Urbanisation–Land Pressure Index; *EQI* = Environmental Quality Index; *SVI* = Social Vulnerability Index; *SSVI* = Socio-Spatial Vulnerability Index.

**Figure 9. Mean composite index values by administrative division, ordered by increasing socio-spatial vulnerability.**

### 5.6 Remote Sensing Evidence of Land Transformation

The census indices show where urbanisation is advanced; satellite evidence shows what that urbanisation does to the land. Table 5 brings together published remote sensing findings for Bihar and the surrounding region. In Patna, the one district that dominates every urban indicator in this study, built-up land expanded from 38% to 80% of the city area between 1988 and 2022, while vegetation fell from 44% to 7%. Over the same period, maximum and minimum land surface temperatures rose by about 1.1 °C and 6 °C respectively, with LST strongly negatively related to NDVI and positively related to NDBI (Akram et al., 2025). This means that the high environmental quality score of Patna in household terms coexists with rapid loss of green cover and intensifying urban heat, an environmental cost that household amenity data cannot capture. Similar dispersed sprawl has been documented around Patna (Chetty & Surawar, 2021), and simulation studies project continued conversion of agricultural land in Patna district (Mishra & Rai, 2016). Across eastern India, LULC change has been shown to affect surface temperature at regional scale (Gogoi et al., 2019).

**Table 5. Published Remote Sensing Evidence on Land Transformation Relevant to Bihar.**

| Study                     | Area and period         | Data / method                                | Key finding                                                            |
|---------------------------|-------------------------|----------------------------------------------|------------------------------------------------------------------------|
| Akram et al. (2025)       | Patna city, 1988–2022   | Landsat; supervised LULC; LST, NDVI, NDBI    | Built-up 38% → 80%; vegetation 44% → 7%; LST rises, fastest after 2005 |
| Chetty and Surawar (2021) | Patna, Ranchi, Srinagar | Multi-date satellite imagery; sprawl metrics | Dispersed, low-density urban sprawl around the core city               |
| Mishra and Rai (2016)     | Patna district          | Remote sensing + MLP–Markov chain            | Simulated and projected continued LULC conversion                      |
| Gogoi et al. (2019)       | Eastern India           | Satellite LULC and surface temperature       | LULC change measurably alters surface temperature                      |

Note: *LULC* = land use/land cover; *LST* = land surface temperature; *NDVI/NDBI* = normalised difference vegetation/built-up index; *MLP* = multi-layer perceptron.

Taken together, the two strands of evidence reveal a double inequality. Most districts suffer from too little urbanisation: they lack the infrastructure that urban growth usually brings, and their land pressure takes the form of dense agrarian settlement on flood-prone plains. Patna and the Ganga corridor, on the other hand, face too rapid and poorly managed land transformation, with loss of vegetation and rising heat. A single state-wide urban policy cannot address both. The priority districts need basic service provision (piped water, sanitation, clean cooking fuel, and electrification), while the corridor districts need growth management, protection of green and blue infrastructure, and heat mitigation.

### 5.7 Robustness and Limitations

To test sensitivity to weighting, each entropy-weighted index was compared with an equal-weight version and with the first principal component of its indicators. Rank agreement with equal weights was high for all three indices (Spearman  $\rho = 0.95$  for ULPI, 0.86 for EQI, and 0.87 for SVI), and leaving out any single indicator did not reduce the correlation below 0.61. The first principal component agreed closely for ULPI ( $\rho = 0.98$ ) and EQI ( $\rho = 0.87$ ), but only weakly for SVI ( $\rho = 0.25$ ). This indicates that social vulnerability in Bihar is multidimensional and cannot be reduced to a single statistical axis, so SVI rankings should be read together with their component indicators. Four further limitations should be noted. First, the census indicators refer to 2011; later programmes such as rural sanitation and household electrification campaigns have changed several amenity levels, so absolute values are dated even though spatial patterns are likely to persist. Second, the district scale hides large intra-district contrasts, especially between Patna city and rural Patna. Third, the moderate global Moran's  $I$  values reflect the small number of spatial units. Fourth, district-wide satellite classification for all 38 districts is specified in the remote sensing module but is not reported here; land-transformation evidence is drawn from published Patna-region studies, and applying the module to the whole state is the most important next step.

## 6. Conclusion

This study proposed and applied a remote sensing and socio-spatial vulnerability framework to examine spatial inequality of urbanisation, land transformation, and environmental quality in Bihar. Four conclusions follow. First, inequality in urban services is severe: tap water, electric lighting, clean cooking fuel, and urban housing vary between twelve- and thirty-fold across districts, with Patna at the top in every case. Second, this inequality is strongly regional, with roughly half or more of it lying between administrative divisions and a clear North–South divide along the Ganga. Third, urbanisation and household environmental quality move closely together ( $\rho = 0.84$ ) and are both inversely related to social vulnerability, so the least urbanised districts are also the most environmentally deprived and socially vulnerable. Fourth, spatial statistics identify a significant Ganga-corridor cluster of advantage and a Kosi–Seemanchal cluster of disadvantage, with Supaul and Araria as the core vulnerability hot spot, and fifteen priority districts containing 38% of the population.

For policy, the results argue for spatially differentiated strategies: service-led development in the rural-deprived north-east and southern plateau fringe, and growth management with green-infrastructure protection in the Patna corridor, where satellite evidence shows rapid vegetation loss and surface warming. Future work will apply the remote sensing module to multi-date imagery for all districts, integrate satellite-derived air quality (van Donkelaar et al., 2021; Kawano et al., 2025), update the census indicators with the next census and national household surveys, and move to block or village scale to capture intra-district inequality.

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