

Constructing a Spatial Public Service Availability Index (PSAI) for a Developing-Country Context: Development and Spatial Application in Bangladesh

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Abstract

Distribution of public services varies from place to place, yet it cannot be measured where information is limited. In this research, an index of public service availability (PSAI) is developed based on 64 districts of Bangladesh that includes education, healthcare, transportation, electricity, gas supply and water supply. Household level data of census are aggregated with OpenStreetMap data about facilities and networks. Indicators are scaled by population or area, normalized and then summed with equal weight. They reflect relative ranking in the district space and not the degree of adequacy of each indicator. The values range between 0.451 (Rangamati) and 5.598 (Dhaka) with a mean of 1.975. Districts having similar index values might have completely different profiles in terms of domains. Gas supply and water supply have high correlation (Pearson $r = 0.81$) as well as education and healthcare ($r = 0.71$). Moran's I statistic is quite low ($I = 0.137$). It is not statistically significant based on analytical method ($p = 0.063$), yet it becomes significant when permutation method is used ($p = 0.027$). Only two districts remain significant for local cluster class after false discovery rate correction. There is thus only weak evidence for central cluster of districts with high PSAI value.

1. Introduction

In many nations, place determines access to various services. Schooling, healthcare services, roads, power, natural gas, and water supply are distributed unevenly. Some areas have fallen behind in multiple sectors. Territorial inequality is both a planning issue and a matter of assessment since service delivery is multidimensional (D'Inverno & De Witte, 2020; Khasuev et al., 2025). The area may perform well in some sectors and poorly in others. Therefore, no sector-specific metric can assess all aspects of service delivery (Muhanguzi et al., 2025). Separate indicators reveal all gaps. However, they fail to show how an area performs overall in various sectors (Mansour, 2016).

At the same time, using a composite score entails risks, too. It masks the role of specific sectors in forming the area's performance. A composite index is therefore only useful when its components remain visible. Normalization, weighting, and aggregation define the meaning of the final score (Greco et al., 2019; Paruolo et al., 2013). An appropriate methodology must ensure that a clear-cut score can be associated with an explicit description of indicators used. This study addresses this challenge. It devises a Public Service Availability Index (PSAI) for Bangladesh's districts.

There are already many such composite indicators of service delivery available today. D'Inverno and De Witte (2020) developed a composite indicator of municipal service delivery levels. Muhanguzi et al. (2025) created a composite index of regional service delivery in Uganda. Khasuev et al. (2025) evaluated the effectiveness of social services using an index. Huang et al. (2024) relied on multisource geospatial information for assessing the availability of public services facilities in poor regions of China. All these examples illustrate how composite indicators can be applied in local planning and decision-making. In addition, they all have the same problem – each index needs indicators, denominators, weights, and an aggregation rule. The choices are never neutral (OECD, European Union, & European Commission Joint Research Centre, 2008; Saisana et al., 2005). Thus, a new index should reveal all the construction steps.

As regards application, the task is relevant for a wide range of policies. The 2030 Agenda connects health, education, water, energy, infrastructure and settlements (United Nations, 2015). It also calls for monitoring at lower levels than the national one because national averages may conceal great district inequalities (Huang & Lan, 2026). Even so, a district service index is not a measure of the Sustainable Development Goals. This study asks a narrower question. It asks how selected services and household connections are spread among districts.

This is because, being a study on territory, there will be the focus on spatial inequalities. There are different resources available in different places and varying connections between places. Most studies on health care and public services have found clustering and core periphery differences (Mansour, 2016; Singh & Guite, 2023; Tickamyer, 2000). Sun et al. (2017) look at how lack of services and housing conditions affect inequality in Chinese cities. Inequality is also found in other sectors and for county level public service availability (Huang & Lan, 2026; Wang et al., 2024). The current study is narrower. It looks at district level inequality and spatial patterns. It does not give reasons for these inequalities.

In this light, geographical perspective offers what will be lost with six independent sector indicators. This is because there is the question whether there is a centre and a periphery in the organization of services. Public service infrastructure hardly develops one district at a time in isolation from other places. Rather, it develops around privileged centers and transport routes (Tickamyer, 2000). If there were no spatial structure among the domains, this means fragmented service delivery. If higher-scoring districts clustered together, that would point to a centre-periphery pattern like those found elsewhere (Sun et al., 2017). The spatial statistics in Section 2.3 let this study address that question.

In order to measure such patterns, spatial autocorrelation statistics are often used. Global Moran's I measures the likelihood that similar values are close to each other within an area (Moran, 1950). LISA highlights cluster and outlier regions (Anselin, 1995). Local tests pose a statistical problem. The more districts being tested together, the more likely it is that some of them will be found to be significant by chance. Such uncorrected local maps would overestimate the extent of clustering. FDR correction provides a solution to this problem (Benjamini & Hochberg, 1995). Caldas de Castro and Singer (2006) describe how to apply such correction to dependent local tests.

Prior to measuring these patterns, however, the notion of availability needs to be defined. Penchansky and Thomas (1981) distinguish between availability and other aspects of access such as affordability and proximity. Accessibility, rather than availability, is measured in GIS-based studies (Abeyrathna et al., 2025; Luo & Wang, 2003; Mansour, 2016). In this paper, availability refers to documented facilities and networks per unit of population or territory. Availability can also include the number of connections to selected utilities in households. A mapped hospital counts regardless of its staff or quality. A road counts without showing travel time or cost. The PSAI therefore measures recorded provision, not effective access. Each component is also normalized against the extremes of the 64 districts. A score thus shows a district's relative position within this system, not absolute adequacy.

Similarly, the concept of public services needs to be clearly delimited. The facility databases do not distinguish between ownership by government, private and non-profit entities. Public services here refer to selected public services irrespective of who runs them. These are not an audit database of government-owned facilities. This is important since the extent of measured coverage changes with the inclusion of private service providers (Abeyrathna et al., 2025). As a result, PSAI measures a wider concept of provision of service open to residents, and not a narrow measure of government public services.

Another aspect of using this index is concerned with the data itself. In many developing countries, facility data from the government sources is difficult to access at a common scale. OpenStreetMap presents an open-source platform for mapping facilities and networks. However, the completeness of OpenStreetMap data varies from place to place (Haklay, 2010). Barrington-Leigh and Millard-Ball (2017) estimated that the global road database was more than 80% complete, but there were considerable differences between countries. Herfort et al. (2023) have found significant data deficiencies in buildings across cities, connected with human development. It should treat low scores as prompts for checking rather than as final facts.

With these definitions established, the example of Bangladesh fits the analysis. Previous studies reveal the relevance of service indices in Bangladesh. In particular, Hossain et al. (2021) constructed a Service Infrastructure Index for the Greater Dhaka Region and discovered spatial inequalities. Parvez (2020) studied the facility thresholds in Pabna. Hasan et al. (2021) assessed service deficiencies in Rangpur City Corporation. Ahmed et al. (2021) revealed a geographical south-north disparity in household water, sanitation and hygiene services. Robin et al. (2019) illustrated the use of GIS mapping in district-level planning in Habiganj. However, the above studies differ in scope, scale and indicators compared to a national-level study with six domains.

Furthermore, Bangladesh has unique characteristics regarding service measurement. Populations in districts range from less than half a million to nearly fifteen million people. The population density in the district of Dhaka exceeds 10,000 people per km². The coverage rate of electricity among households approaches 100% in all districts. Conversely, only some districts provide piped gas and piped water to the households. One indicator would be insufficient in such situation. A district judged on electricity could look well served, while the same district judged on gas could look deprived. A multi-domain index can show both views at once.

All in all, the research gap is in scope, integration and transparency. No national district-level framework for Bangladesh that would integrate six service domains was reported in existing literature (Hasan et al., 2021; Hossain et al., 2021; Parvez, 2020). It should also ensure transparency of the information on each of the sectors used along with a transparent composite score (Greco et al., 2019; Muhanguzi et al., 2025). Network accessibility and floating catchment area models can help to address a similar problem, but they require additional data that this research does not have (Abeyrathna et al., 2025). This study will have three objectives. First, it will develop a reproducible six-domain PSAI for Bangladesh. Second, it will analyze differences in the sectorial and composite PSAI values at district level. Finally, it will test global and local spatial autocorrelation patterns. The following section describes the methodology used.

2. Materials and methods

2.1. Study area and data

To achieve these objectives, the study employs the administrative district as the spatial unit of analysis. All 64 districts have been used, and the eight divisions remain only for regional summaries. The total of the population data is 165,158,616 people. This is the enumeration number given in the census report in July 2022. An aggregate number of 169,828,911 people was released in February 2023 following the post-enumeration check process. This number was not disaggregated into individual districts and thus not used in this analysis. District populations are between 481,106 in Bandarban and 14,734,701 in Dhaka. District areas range from 705.85 to 5,646.37 km². Hence, the districts differ by about thirty times in population size and by eight times in area. This must be considered while interpreting the district-level findings (Fotheringham & Wong, 1991; Openshaw, 1984).

Data for these districts have been collected from three sources. Population and the percentages of household electricity, gas, and water are taken from the 2022 census (Bangladesh Bureau of Statistics [BBS], 2022). Education, health care, and transportation data have been extracted from OpenStreetMap facility and network records. Administrative codes and area fields support joining and mapping. Table 1 lists each domain, its inputs and its limits. Table S2 gives the source and treatment of each indicator. The denominator follows the intended users of each service. Facilities that serve people are divided by population. Networks that serve territory are divided by area. Household utilities stay as household percentages.

Table 1
Service domains and indicators

Domain	Recorded inputs and source	Calculation	Measurement boundary
Education	Mapped primary and secondary schools and colleges or universities (OpenStreetMap-derived records)	Counts per 1,000 people; two-stage normalization	Recorded institutions, not enrolment, capacity or quality
Healthcare	Mapped hospitals (OpenStreetMap-derived records)	Hospitals per 1,000 people; single-stage normalization	Recorded hospitals, not beds, staffing or all care providers
Transportation	Mapped road length, railway length and railway stations	Lengths per km ² ; stations per 1,000 people; two-stage normalization	Selected infrastructure, not travel time, frequency or all modes
Electricity	Household grid-supply percentage (census-based project table)	Direct min-max normalization	Recorded connection category, not reliability or total energy access
Gas supply	Household government-gas percentage (census-based project table)	Direct min-max normalization	Specific gas category, not all clean cooking fuels
Water supply	Household piped or tap-water percentage (census-based project table)	Direct min-max normalization	Specific supply category, not safely managed drinking water

Census data are from BBS (2022). Facility and network data are from OpenStreetMap.

Apart from these data, the key numerical dataset is a workbook consisting of 64 rows. The data includes the number of objects, length of networks, denominators, normalized components, domains and the final index. The polygons of the districts include identical codes as the districts. The Global and Local Moran's I statistics are extracted from the Python code. Districts codes match the workbook with the outputs. All the numbers were verified manually and were never extracted from the map colours.

Nevertheless, the inputs do not include one date. The census relates to 2022 while GIS calculations were performed in June 2025. The date of the extraction of the OpenStreetMap data and queries are unknown. Codes of the original census table are also unknown. Thus, the facility ratios include the OpenStreetMap numbers for approximately 2025 combined with the census populations of 2022. This combination is legitimate, but it is not a snapshot at one date. The PSAI should be considered a hybrid evaluation for the period between 2022 and 2025. The discrepancy is the most important issue in rapidly changing districts.

Within these constraints, there are 6,670 schools either primary or secondary and 867 colleges/universities. There are also 2,348 hospitals and 428 railway stations. The network contains 213,358.920 km of roads and 2,715.913 km of rail tracks. These statistics only reflect the retained components and could not have exhausted the total stock of the country. Capacity, staffing, ownership and

operational status are poorly documented. Hence, the research has to distinguish between map-based availability and service capacity.

Also, two problems in terms of quality were revealed. First, the count of colleges for Habiganj was missing and represented by zero. Second, there are four districts where railways stations were recorded but the railway length was zero. They are Netrakona, Habiganj, Moulvibazar and Sunamganj. The values were not imputed. As a result, there is a practical implication here since the normalized value of zero reflects the actual minimum (section 2.2). However, zero coding suggests that the college component for Habiganj is a verified zero. The railway cases raise the same concern. Both issues are treated as data limits, not as proof of missing services (Table S2). The next subsection explains how the index was built.

2.2. Construction of the Public Service Availability Index

Figure 1 below depicts the entire process of constructing the index. The index is developed from six categories of services. In all cases, the measures move in the same direction, hence, the higher rate, density, and percentage yields high values. Education relies on school and colleges or universities. Healthcare relies on hospitals. Transportation relies on road, railroads, and stations. The three utility services remain unchanged and continue to use the household-percentage measure. All 64 districts have domain scores available. The index does not rely on any external adequacy cut-off.

First of all, the raw figures are converted into ratios. If we let P = district population, and A = district area, in km^2 , schools, colleges, hospitals and railway stations are ratioed against population, and multiplied by 1,000. Roads and railway networks are ratioed against area. Both of these ratios are given by Eq. (1). Household access to electricity, gas and water remain as percentages.

$$R_{ik} = \frac{1,000 N_{ik}}{P_i} ; \quad D_{ik} = \frac{L_{ik}}{A_i}$$

1

In the Eq. (1) above, N represents the observed number, L represents the observed length while k represents the facility or network type. R and D represent the population rate and area density respectively.

Secondly, normalization of all the variables is done using the Min-Max approach among the 64 districts as per the Eq. (2) below. In this normalization approach, the minimum observed value is given a value of zero while the maximum value is given one. All the variables have a non-zero range. The technique drops the unit of measure but retains the relative distance and there is no outside criterion.

$$M(x_i) = \frac{x_i - \min(x)}{\max(x) - \min(x)}$$

2

Based on this rule, education is created in two steps, as depicted in Eq. (3). The school index and the college index are individually normalized. Their normalized indices are summed. The sum is once again

normalized to create the education index. The sum varies between 0.046580 and 1.316188. In the second step, education is brought onto the same zero to one scale as the other indexes.

$$E_i = M [M(s_i) + M(c_i)]$$

3

Here, in Eq. (3), “s” represents the rate for schools and “c” represents the rate for colleges or universities per 1,000 people.

Likewise, transportation consists of a two-stage process with three components as described in Eq. (4). First, road density, railway density, and stations per 1,000 people are normalized. Then, their total is normalized. The total varies between zero and 2.116577. This avoids the addition of kilometre-based and people-based variables in their units. The component fields stored affirm this process.

$$T_i = M [M(r_i) + M(l_i) + M(t_i)]$$

4

In Eq. (4), r stands for road density, l for railway density and t for stations per 1,000 inhabitants.

On the other hand, health and the three utilities have only one normalization procedure. Health is the normalized number of hospitals. Electricity is grid electricity. Gas is government gas. Water is piped/tap water. These are narrower than reliable electricity, cooking fuel or safely managed drinking water. The World Health Organization (WHO) and the United Nations Children’s Fund (UNICEF) conduct a Joint Monitoring Programme for household water supply. This defines water services as more than just a piped system (WHO & UNICEF, 2021). This determines the way the utilities domains are interpreted.

Once the six domains are ready, the composite index is the sum of these domains as presented in Eq. (5). All the domains have the same weight of one and range from zero to one. This means that the range of the theoretical index is between zero and six. A simple average of the six domains would yield the same ranking order but the additive scale is maintained. The composite index is compensatory since a high value in one domain may compensate a low value in another. The domain profile must therefore always be read with the total. Geometric aggregation would limit this offsetting (Munda & Nardo, 2009). It is not used here, because the study keeps the implemented additive scale.

$$PSAI_i = \sum_{d=1}^6 Z_{id} ; \quad 0 \leq Z_{id} \leq 1$$

5

In Eq. (5), Z is the final normalized score for domain d in district i.

Two more decisions require discussion. First, the weights assigned to different domains are the same. All the domains are considered equally important for everyday living. The decision is very simple and easily understandable by planners. The effects of this decision will be discussed in Section 4. Second, min-max

normalization makes each score relevant only for the particular extremes observed. In other words, the score for Bangladesh is not comparable with a score for any other country and for any other point in time. The methodological framework may be used in other countries, but the scores cannot be compared.

Moreover, the workbook includes the rescaled index PSAI_N calculated using Eq. (6). PSAI_N represents the application of min-max normalization to the observed composite scores. PSAI_N provides the composite in a zero to one range for the purpose of comparison. The index is not the additive index divided by six. The lowest district has PSAI_N equal to zero even though the additive index is positive. PSAI_N has the same ranking as the additive index. Both the indices can be found at Table S1.

$$PSAI_N_i = \frac{PSAI_i - \min(PSAI)}{\max(PSAI) - \min(PSAI)}$$

6

Lastly, the implementation audit ensures that the values calculated can be derived from the stated method. The six domain values stored in the database accurately reproduce the additive index to 0.000001. Recalculated domain scores tally with the stored domain scores for the six domains. The maximum difference is 0.000013 for the domain of health care, which arises because of the few decimal places in the exported hospital rate value. The audit validates the computation of the index but does not validate the source inventories.

2.3. Spatial analysis and multiple testing

The construction of the index is then followed by two statistics for testing the geographical pattern. Global Moran's I statistic is for the general spatial association (Moran, 1950). Local Moran's I statistic indicates local similarities and local outliers (Anselin, 1995). This is the only local statistic, as it identifies both the clusters and the outliers. Both statistics were derived from the polygons of the district boundaries. These have been based on the Queen contiguity weights, such that the districts are regarded as neighbors if they are adjacent or touching corners. The weights are row standardized, and the inference uses 999 conditional permutations.

For the global statistic, the statistic was defined using Eq. (7). Its expected value under the condition of spatial randomness is $-1/(n-1)$, which for 64 districts is -0.015873 . The alternative hypothesis in this case is positive spatial autocorrelation. There are two p-values in this test. The analytical p-value is two tailed, which is the default option of the software employed. The permutation p-value, on the other hand, is one tailed. The two p-values are not equivalent tests. Both are reported so that the effect of the inferential approach is visible.

$$I = \frac{n}{S_0} \frac{\sum_i \sum_j w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2}$$

7

In Eq. (7), x refers to index value, $\bar{x}$ to its mean, w to the spatial weight, and S_o is the sum of all weights.

Coming to the local tests, the local version of the test is conducted on the additive index using the Queen contiguity weights and 999 conditional permutations. The number of neighbours differs among districts. Central districts have more neighbours than coastal and border districts. When a local statistic is estimated using few neighbours, only a few values are used for comparison, and thus the information is restricted.

Indeed, Local Moran classes require interpretation. High-high and low-low classes indicate districts that are similar to their neighbours, whereas high-low and low-high classes denote local contrasts. Local contrast classes depend upon values in relation to their mean values, and on the neighbourhood structure. The classes are not simply based on the ranking of the values within districts. The local p-values represent one-tailed permutation values. Given 999 permutations, the lowest pseudo p-value is 0.001. The local permutations used a fixed random seed (12345), while the seed for the global test was not fixed.

Since 64 local tests are performed at the same time, some of the results may be significant due to randomness. For this reason, Benjamini-Hochberg correction has been applied to all 64 Local Moran p-values (Benjamini & Hochberg, 1995). This approach takes all the 64 district tests as one group, with 5% threshold. Formula (8) demonstrates the correction. Since local tests may be spatially correlated, the correction should be interpreted cautiously (Caldas de Castro & Singer, 2006).

$$p_{(i), \text{adj}} = \min\left\{1, \min_{j \geq i} \left[\frac{m p_{(j)}}{j} \right]\right\}; \quad m = 64$$

8

For Eq. (8), $p(i)$ is the i th ordered original p-value. The adjusted values are then put back into their original district order.

Finally, all spatial statistics were calculated using Python by employing libpysal and esda libraries. The entire procedure for calculation of spatial statistics from raw indicators is hence reproducible using only one documented program. The following section shows the results.

3. Results

After describing the methods, the results section will proceed in three steps. Section 3.1 analyzes the six service domains. Section 3.2 analyzes the composite index and its regional distribution. Section 3.3 tests for any spatial distribution. Table S1 contains the complete index scores for each district.

3.1. Differences among service domains

First, there are vast variations in terms of distribution between the six domains. This can be seen from Table 2 that presents the district background as well as the raw indicator scores. Table 3 presents the normalized scores while Fig. 2 presents the range. The most heterogeneous data set comes from the

utilities sector. The average district access to electricity services stands at 95.795%. However, the average access to gas and piped water is 5.893% and 5.330%, respectively.

Table 2
Descriptive statistics of district indicators

Variable	Unit	Mean	SD	Minimum	Maximum
Total population	persons	2,580,603	2,134,836	481,106	14,734,701
Area	km ²	2,279.62	1,145.47	705.85	5,646.37
Population density	persons per km ²	1,303.34	1,321.88	104.72	10,033.04
Schools	per 1,000 people	0.039581	0.040046	0.001695	0.235444
Colleges / universities ^a	per 1,000 people	0.004122	0.003438	0.000000	0.013845
Hospitals	per 1,000 people	0.011387	0.009594	0.001023	0.050215
Road density	km/km ²	1.528321	1.030241	0.127907	5.474207
Railway density	km/km ²	0.021793	0.023398	0.000000	0.082628
Railway stations	per 1,000 people	0.002609	0.002667	0.000000	0.012607
Electricity	% of households	95.795	10.438	47.540	99.660
Gas supply	% of households	5.893	13.234	0.000	69.170
Piped / tap water	% of households	5.330	9.161	0.310	61.500

SD standard deviation. Statistics are unweighted across the 64 districts.

^a Habiganj's missing college count is coded zero.

Starting with education, there are two types of institutions in combination. Following normalization through two steps, Dhaka has the highest index, 1.000. Bhola and Chattogram follow next in line. The lowest score is for Rangpur, as it has the lowest index when combining the two types of institutions. However, that does not mean that Rangpur does not have any schools. High scores can be attained in the case of the education domain in districts that do not have the highest population.

As opposed to the above results for the education sector, the healthcare sector has another set of indices. Bagerhat has the highest rate of hospitals per capita. Apart from Bagerhat, Dhaka, Khulna, Satkhira and Tangail have a high score. On the other hand, Narayanganj has the lowest score. This index simply represents the mapped ratio between the number of hospitals and the population. There is nothing much about the healthcare services provided within the district.

The transportation domain is characterized by two types of denominator. Rajbari tops the list due to high rates of railways and stations. Following Rajbari are Chuadanga, Dinajpur, Dhaka, Pabna and Faridpur. Rangamati ranks last because of low road density and lack of rail. The result is relative, and it does not

imply that Rangamati has no roads. The domain does not include waterways, service frequency, and road condition. The railway inconsistency discussed in Section 2.1 adds additional concern.

In comparison with the other two domains, utilities have more extremes. More than 90% of districts have electricity coverage, and Gazipur has the highest one. Only five districts have less than 90% electricity. In Rangamati, the least electricity exists at 47.54%, then Khagrachhari and Bandarban. Since the minimum is Rangamati, the domain of electricity has the highest mean of the three domains (Table 3). The distribution of gas is much more extreme. More than half of the districts have zero gas coverage, and only ten districts have more than 10%. The maximum is Dhaka, then Narayanganj and Gazipur. The piped water is also similar; Dhaka has the maximum coverage. These results relate to particular supply categories only; they do not indicate availability of cooking fuels and drinking water.

Table 3
Normalized domain and composite scores

Domain or index	Mean	SD	Minimum	Maximum
Education	0.325	0.274	0.000	1.000
Healthcare	0.211	0.195	0.000	1.000
Transportation	0.346	0.232	0.000	1.000
Electricity	0.926	0.200	0.000	1.000
Gas supply	0.085	0.191	0.000	1.000
Water supply	0.082	0.150	0.000	1.000
Additive PSAI	1.975	0.704	0.451	5.598
Normalized composite (PSAI_N)	0.296	0.137	0.000	1.000

Domain scores range from 0 to 1. PSAI has a theoretical range of 0 to 6. PSAI_N rescales the observed PSAI range to 0 to 1.

As seen in Fig. 2 and Table 3, even when the ranges are the same, the distributions are not. Education has the greatest standard deviation at 0.274, transportation has the second greatest at 0.232, healthcare and electricity and gas have standard deviations between 0.19 and 0.20. Water has the smallest at 0.150. Electricity has a high average score but has minimal range, with a few outliers on the lower end. On the other hand, gas and water have scores concentrated around zero with only a few high outliers. For this reason, even with equal nominal weights, the actual influence of the variables on the rank is unequal (Becker et al., 2017; Paruolo et al., 2013).

When considering space, the maps presented in Fig. 3 clearly reflect these inequalities. Electricity has the highest values everywhere except in the southeastern hill regions. Gas and water both have their maximum values in the narrow central and southeastern corridor, particularly in Dhaka, Narayanganj, Gazipur, and Chattogram. Education and health have a sporadic distribution of high scores, including some of the

southern coastal districts. South-western districts like Bagerhat, Khulna and Satkhira have high scores in healthcare. The hill districts of Rangamati, Khagrachhari and Bandarban have low scores in both electricity and transportation. So, each domain has its own geography.

Following this geography, similar patterns are observed in the correlation coefficients as well. Table 4 and Fig. 4 provide the correlation between domains using the Pearson coefficient. Gas and water have a high positive correlation ($r = 0.81$). There is a strong positive correlation between education and healthcare ($r = 0.71$). There is a weak negative correlation between education and transportation ($r = -0.23$), and between healthcare and transportation ($r = -0.12$). Electricity is uncorrelated with education and healthcare. These are just descriptive correlations on skewed distributions. They do not establish any cause or validate the index. The next section explains how these domains come together to form the composite score.

Table 4
Pearson correlations among domain scores

Domain	Electricity	Gas	Water	Transport	Education	Health
Electricity	1.00	0.12	0.02	0.35	-0.03	-0.01
Gas	0.12	1.00	0.81	0.24	0.15	0.18
Water	0.02	0.81	1.00	0.15	0.31	0.38
Transport	0.35	0.24	0.15	1.00	-0.23	-0.12
Education	-0.03	0.15	0.31	-0.23	1.00	0.71
Health	-0.01	0.18	0.38	-0.12	0.71	1.00

3.2. Composite availability and regional variation

With the inclusion of the six domains, the index varies from 0.450693 to 5.598258. It has an average of 1.975368, a standard deviation of 0.704301 and a median value of 1.910708. The interquartile range for the index is from 1.596874 to 2.200500. As much as 39 districts score less than two, whereas there are only three districts scoring above three. Consequently, most districts find themselves towards the lower end of the zero to six range. This is not an indication of the fact that these districts do not have a consistent share of adequate services. The endpoints of the range have been drawn using the sample, but not from any specific service standard.

In this range, the center of the distribution has been very limited. As much as half of the districts, which number 32, are found in the range of 1.597 to 2.201. This means that there is only a difference of 0.6 points in the index for the range. The ranking therefore changes drastically on the basis of even a small difference in one domain.

Dhaka comes first, beating Chattogram and Bagerhat at a considerable distance (Table S1). Gazipur, Khulna, Narayanganj, Tangail, Natore, Rajshahi, and Manikganj come next to form the top ten. Dhaka excels through its strength in most of the dimensions. At the other end of the ranking, the last one is Rangamati,

followed by Khagrachhari, Bandarban, Jhalokati, Lakshmipur, and Habiganj. These districts are different from each other in terms of profiles. Rangamati has a value of zero in both electricity and transportation. Bandarban gets a value greater than zero in all the dimensions except for gas. The education dimension of Khagrachhari has a significantly higher value than that of transport, electricity, and water dimensions. Thus, weak dimensions weigh more than the ranking itself.

Upon closer analysis, Fig. 6 reveals the range of the ranking. The difference between Dhaka and Chattogram is 1.972 units. This is greater than the difference between Chattogram and Natore, which comes in eighth position. On the other hand, Rangamati and Khagrachhari fall way behind all other districts. The comparison of selected profile indicators is illustrated in Table 5. Bagerhat ranks third due to its highest health care and good education and electricity services with no reported gas services. Khulna ranks highly but does not have any gas services. The Narayanganj district has an almost similar rank with Khulna although it has very low education and healthcare indicators but higher gas and water indicators.

Table 5
Selected district profiles

District	Rank	E	H	T	El	G	W	PSAI
Dhaka	1	1.000	0.870	0.729	0.999	1.000	1.000	5.598
Chattogram	2	0.922	0.420	0.414	0.930	0.462	0.479	3.626
Bagerhat	3	0.704	1.000	0.401	0.965	0.000	0.055	3.125
Khulna	5	0.796	0.555	0.345	0.982	0.000	0.121	2.799
Narayanganj	6	0.056	0.000	0.378	0.999	0.909	0.442	2.785
Rajbari	13	0.277	0.048	1.000	0.987	0.000	0.023	2.334
Bhola	15	0.986	0.379	0.033	0.837	0.016	0.006	2.258
Bandarban	62	0.356	0.402	0.044	0.097	0.000	0.190	1.089
Khagrachhari	63	0.465	0.122	0.021	0.064	0.000	0.012	0.684
Rangamati	64	0.263	0.136	0.000	0.000	0.000	0.051	0.451

E education, H healthcare, T transportation, El electricity, G gas, W water. A zero marks the observed minimum.

Division summaries provide a regional picture beyond individual districts (Table 6). Dhaka division has the highest mean value, whereas Mymensingh and Khulna divisions come in second and third place. The division with the lowest mean value is Chattogram, but the district of Chattogram has the second-highest value in the country. This is because the division comprises three low-value hill districts. Thus, one cannot replace the distribution of the division with its label. Spread varies across divisions as well. Dhaka and Chattogram divisions have values of the standard deviation over 0.85. Mymensingh and Rangpur have very low spread values – 0.185 and 0.233, respectively. Divisional means do not reflect the population size

either. Chattogram division comprises 33.2 million people and has the lowest mean value, while Mymensingh has 12.2 million people and the second-highest mean value.

Table 6
PSAI by division

Division	Districts	Total population	Mean density (per km ²)	Mean PSAI	SD	Minimum	Maximum
Dhaka	13	44,215,759	2,401.52	2.504	1.015	1.555	5.598
Mymensingh	4	12,225,449	1,136.10	2.110	0.185	1.915	2.355
Khulna	10	17,415,924	890.08	2.054	0.526	1.491	3.125
Rajshahi	8	20,353,116	1,112.32	1.952	0.407	1.458	2.550
Barishal	6	9,100,104	769.69	1.759	0.422	1.163	2.258
Rangpur	8	17,610,955	1,084.96	1.734	0.233	1.498	2.190
Sylhet	4	11,034,952	890.05	1.711	0.389	1.366	2.269
Chattogram	11	33,202,357	1,181.14	1.637	0.857	0.451	3.626

Means are unweighted across districts. Divisions are ordered by mean PSAI.

3.3. Global and local spatial patterns

Spatial patterns are next, where Table 7 shows the findings for the world level. The Moran's I measure is 0.1371, while the value under the randomness assumption is -0.015873. The p-value using the analytical method is 0.0632. Using the permutation method, which uses 999 conditional permutations, the p-value is 0.027. Global clustering is thus insignificant under the analytical method but significant under the permutation method.

Table 7
Global Moran's I for PSAI

Run	Specification	I	Expected I	Variance	z	p-value	Inference at 5%
Queen contiguity	District polygon geometry, row-standardized, 999 conditional permutations	0.1371	-0.015873	n/a	n/a	0.063 (analytical); 0.027 (permutation)	Significant under permutation inference

Queen contiguity weights, row-standardized, 999 conditional permutations. The analytical p-value is two-tailed and the permutation p-value is one-tailed. n/a, not reported in the analysis output.

Next, Fig. 7 shows the Moran scatterplot. The fitted slope of 0.137 is shallow, and the points are widely spread. Dhaka appears as a high value whose neighbours are much less extreme. This borderline global result sets the scene for the local tests.

Locally, Table 8 provides the Local Moran Classes following the Benjamini-Hochberg adjustment. There are two districts that maintain a significant class at the 5% significance level while the rest of the 62 do not maintain any. The high-high class is one where the district and the neighbouring districts have scores that exceed the mean. High-Low class refers to a high scoring district being located in low scoring neighbours.

Table 8
Local Moran cluster classes
after Benjamini-Hochberg
adjustment

Cluster type	N districts
Not significant	62
High-Low	1
High-High	1

Queen contiguity weights, row-standardized, 999 conditional permutations. Classes are shown after Benjamini-Hochberg adjustment at the 5% level.

Of the two retained districts, one is high-high and lies in the central part of the country. The other is high-low and lies in the southeast. Figure 8 maps these two districts. No low-high or low-low class survives the adjustment.

This is due in part to the characteristics of the neighbour structure. There are more neighbours for central areas than peripheral areas. When a local statistic has few neighbours, it does not contain much information. But it is used for the adjustment just as effectively as other districts with more neighbours. So, these districts are the least robust. The retained high-high district is located within the well-connected central belt. Having more neighbours does not ensure robustness in itself. But in this case, it is the least affected by the problem of fragility of sparsely connected districts.

The overall conclusion from the spatial analysis is quite guarded. The global statistic is quite poor and significant only by the permutation test. At the local level, only two districts remain with a significant class after the adjustment. The global and local findings seem to corroborate each other. The availability is not evenly distributed across the districts, but it clusters around the districts surrounding the capital city. Still, there is no evidence for a nation-wide clustering in the data.

4. Discussion

Back to the research objectives, this chapter reads the results as one story. The research developed a reproducible six-domain index for Bangladesh. The study described sectoral and composite disparity among 64 districts, and it looked for spatial patterns. Such objectives are in response to an obvious gap.

There was no district-level framework in Bangladesh covering education, healthcare, transportation and utilities. Discussion goes from methodology to results, then data limitations, spatial results, contribution and planning application.

First, the construction criteria affect what the index says. The two-stage normalization is important for education and transportation, because these two domains are constructed using indicators of various units. Normalization of each indicator followed by the sum makes it comparable with the utility domain (Equations 3 and 4). Such methodology is recommended in published literature (Greco et al., 2019; OECD, European Union, & European Commission Joint Research Centre, 2008). Moreover, the index is formative and not reflective. The six domains are used to define availability, and they are not exchangeable markers of some latent construct (Bollen & Lennox, 1991; Diamantopoulos & Winklhofer, 2001). A weak correlation is therefore no reason to drop a domain.

For instance, transportation has a negative correlation with both education and healthcare (Table 4). In a reflective framework, this will be an alerting indicator. However, in the formative framework, this merely means that districts which have dense road and railway networks do not necessarily have many institutions per capita. The use of equal weighting requires one to be very cautious. While it treats all the domains equally on paper, it does not treat them equally in terms of their significance and weightage in statistics (Becker et al., 2017; Paruolo et al., 2013). Although additive form is easy to interpret, it is compensatory. Thus, this index should be interpreted along with its domain profile.

Second, it is quite evident from the results that electricity coverage is high in most districts, whereas gas and piped water availability is confined only to certain districts. One domain cannot represent the rest of the domains. Dhaka is ahead in the rank because it performs well in almost all the domains. While the districts at the bottom of the rank reach there because of their weakness in different domains. Bagerhat and Khulna rank high without any recorded gas. Narayanganj scores close to Khulna despite weak education and the lowest healthcare score. Rajbari ranks thirteenth mainly because of transportation (Table 5).

Thirdly, scale matters. Despite being ranked second in the nation, Chattogram Division comes last due to containing the three poorest hill districts (Table 6). A ranking label at one scale thus masks the pattern at another. Altogether, these findings demonstrate the ineffectiveness of a composite rank as a proxy for balanced provision. They reflect the inequality already established in the Greater Dhaka Region and Pabna (Hossain et al., 2021; Parvez, 2020), as well as support the claim that inequality in the provision of services can be masked by a single aggregate index (Sun et al., 2017).

Among all districts considered in the national context, the hill districts stand out. In terms of rankings, they occupy three of the lowest positions. They display the lowest coverage with electricity – about 50 percent of households – and low transportation indices, close to zero. The districts are known to be characterized by harsh terrain and dispersed settlements. This combination might affect the cost of network service provision; however, the cross-sectional analysis could not test such a hypothesis. Historical and administrative factors might play an important part.

Overall, these results have important implications for the use of composite service indices. The PSAI shares the multidimensionality of service provision with previous service indices. For example, there are the Uganda index of Muhanguzi et al. (2025) and the municipal indicator of D’Inverno and De Witte (2020). What the PSAI adds is two aspects. All domain scores remain visible along with the composite one, and spatial tests are done with explicit multiple-testing adjustment. The approach can be easily transferred to other developing countries with stable administrative units and comparable data. Some domains might require substitution. But scoring cannot be done across countries due to min-max normalization.

But these results should be interpreted considering the limitations of all these domains. The gas and water domains assess household types, which is not clean cooking fuel or water management (WHO & UNICEF, 2021). Healthcare includes only the ratio of hospitals, not beds, personnel or other care. Education includes institution rates, not enrolment or quality of teaching. Transportation includes selected roads, railways, and stations, not travel time or other transportation modes. All these limitations reflect the differentiation made by Penchansky and Thomas (1981) between availability and access.

Further, the underlying inventories provide an additional element of precaution. The missing Habiganj college inventory and the four discrepancies about railways indicate that data may not be complete even prior to normalization (Table S2). This conforms to the existing literature demonstrating the presence of OpenStreetMap incompleteness in relation to geography and object type (Barrington-Leigh & Millard-Ball, 2017; Haklay, 2010; Herfort et al., 2023). However, none of these pieces of research evaluates the completeness of schools or hospitals in Bangladesh. Hence, low scores in domain completeness have to be considered as an indication for the verification of the inventory rather than a portrayal of local conditions.

In addition, the results concerning the spatial dimension require caution, as their global significance will depend on the nature of the inference. Global Moran’s I value is significant according to the permutation but not analytical test (Table 7). At the local level, only two districts manage to preserve the significant category after adjustment (Anselin, 1995; Benjamini & Hochberg, 1995; Table 8). Local inference with 64 districts of an irregular form is sensitive to the neighbour structure. Local tests can also be dependent, so the adjustment is read with care (Caldas de Castro & Singer, 2006). The pattern is therefore neither random nor a confirmed national cluster. A small group of central districts shows the most consistent signal of higher availability.

There is also a practical aspect to this. Cluster maps at the local level are often included in planning documents as though they are established facts. In this case, the adjustment leaves only two districts with a stable class. Thus, planners need to view such cluster maps as starting points for further investigation. A substantial local cluster identifies itself as a validable cluster. By itself, however, it cannot be taken as sufficient reason for investment focus since there are well-known limitations in the facility data (Section 2.1). Central high-high and southeastern high-low clusters are the most obvious candidates for validation.

In this context, the key contribution of the paper is its methodological approach. This study provides a clear index based on a transparent and reproducible district index formula. The audit demonstrates that

the stored domain values give the index to an accuracy of 0.000001. Two-step normalization procedure is clearly described, while domain profile and the composite are presented side by side. Multiple testing of spatial outputs is performed, and the entire pipeline is reproducible through a single script. Thus, the values are a product of the methodology used. It does not confirm that the inventories capture the true state of services.

However, some limitations arise from this methodology. The model is based on cross-sectional information whose sources are from different time periods. The domains do not consider service quality, capacity, and effective access. The inventory includes a single omission and four discrepancies within the railways. Equal weighting in the additive formula was not validated by using other weighting options or other sensitivity analyses (Saisana et al., 2005). The findings could even be different when considering a new zoning scheme (Fotheringham & Wong, 1991; Openshaw, 1984) or a new spatial weight option.

This study suggests that future research should take into account some considerations. The field and administrative validation could be used to confirm the facility records, and the registry data might be used for validating the OpenStreetMap count. Measures related to capacity, quality, and travel-time should be considered. Some sensitivity analyses should be performed based on different weighting, normalization, and spatial weight specifications. An analysis based on upazilas would examine the same district pattern. They would let the index support subnational monitoring under the 2030 Agenda (United Nations, 2015; Huang et al., 2024).

For practical planning purposes, such limitations indicate the limited utility of the index. The index is effective not as a means for calculating public expenditure but as an initial screening method. A low index value, seen in Rangamati, Khagrachhari and Bandarban, serves as a pointer to those districts for which more study is needed. Nevertheless, each of these three districts arrives at such an index value by virtue of different weaknesses in the domains, hence they require different planning approaches. On the other hand, a high index value, as in the cases of Narayanganj and Bagerhat, may obscure a domain with a weak value that can be detected only with the domain profile.

5. Conclusion

In summary, this paper has developed and calculated a Public Service Availability Index in six equally weighted domains for 64 districts in Bangladesh. The spatial structure of the index was also investigated. In terms of the first objective, the index has incorporated both population and area rates and household utility percentages. Two-stage normalization is performed for the two domains (education and transportation), and six new domains were added to form an index. An audit verified the calculation up to 0.000001.

In terms of the second objective, it is found that there is much variation in terms of domains and districts. Dhaka is at the top with 5.598 and Rangamati is at the bottom with 0.451. Other districts are ranked in between but they have reached the rankings via different combinations of domains. There is no gas

recorded in both Bagerhat and Khulna while Narayanganj has good ranking despite poor education and healthcare services. Gas and water are highly correlated; so are education and healthcare.

Regarding the third goal, the evidence is spatially more elusive and unstable. Global Moran's I is small and positive. It is significant in the permutation test but not in the analytical test. After correction for multiple testing, only two districts maintain a significant local class, namely one high-high in the center and one high-low in the southeast. The formation of clusters of greater availability in the center districts appears to be the only consistently detected signal.

Other than that, the paper demonstrates that an index can be constructed in a developing country based on census and open geospatial data. Such index is defined through its algorithm and the spatial analysis is replicable from the provided code. Interpretation of the index as formative and compensatory explains the necessity of including domain profiles together with the composite index.

These contributions, however, have inherent limitations. The datasets are cross-sectional and not completely temporally synchronized. Quality, capacity, and access are excluded from the domains. There are omissions within the inventories and the weights have yet to be validated for sensitivity. In light of these limitations, it can be said that the PSAI provides a transparent foundation. It highlights areas that need further investigation regarding service availability.

Declarations

Author Contribution

S.M.J.N. contributed solely to the conceptualization of the study. S.M.J.N., A.K.P., V.P., S.H.C., and S.M.T.I. contributed to the development of the study. A.K.P. and S.M.J.N. conducted the data analysis. S.M.J.N. and A.K.P. prepared the manuscript. V.P., S.H.C., and S.M.T.I. contributed to the interpretation and revision of the manuscript. All authors reviewed and approved the final manuscript.

Data Availability

Yes. We used and generated research data in this study. The district-level analytical dataset, derived PSAI scores, spatial analysis outputs, and Python code used for the analysis are publicly available through the following repositories: PSAI Bangladesh GitHub repository (https://github.com/akprottay/PSAI_Bangladesh); PSAI Bangladesh dataset and code on Zenodo (<https://doi.org/10.5281/zenodo.22921177>) The underlying census data are from the Bangladesh Bureau of Statistics (BBS), and facility and network data are derived from OpenStreetMap.

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Figures

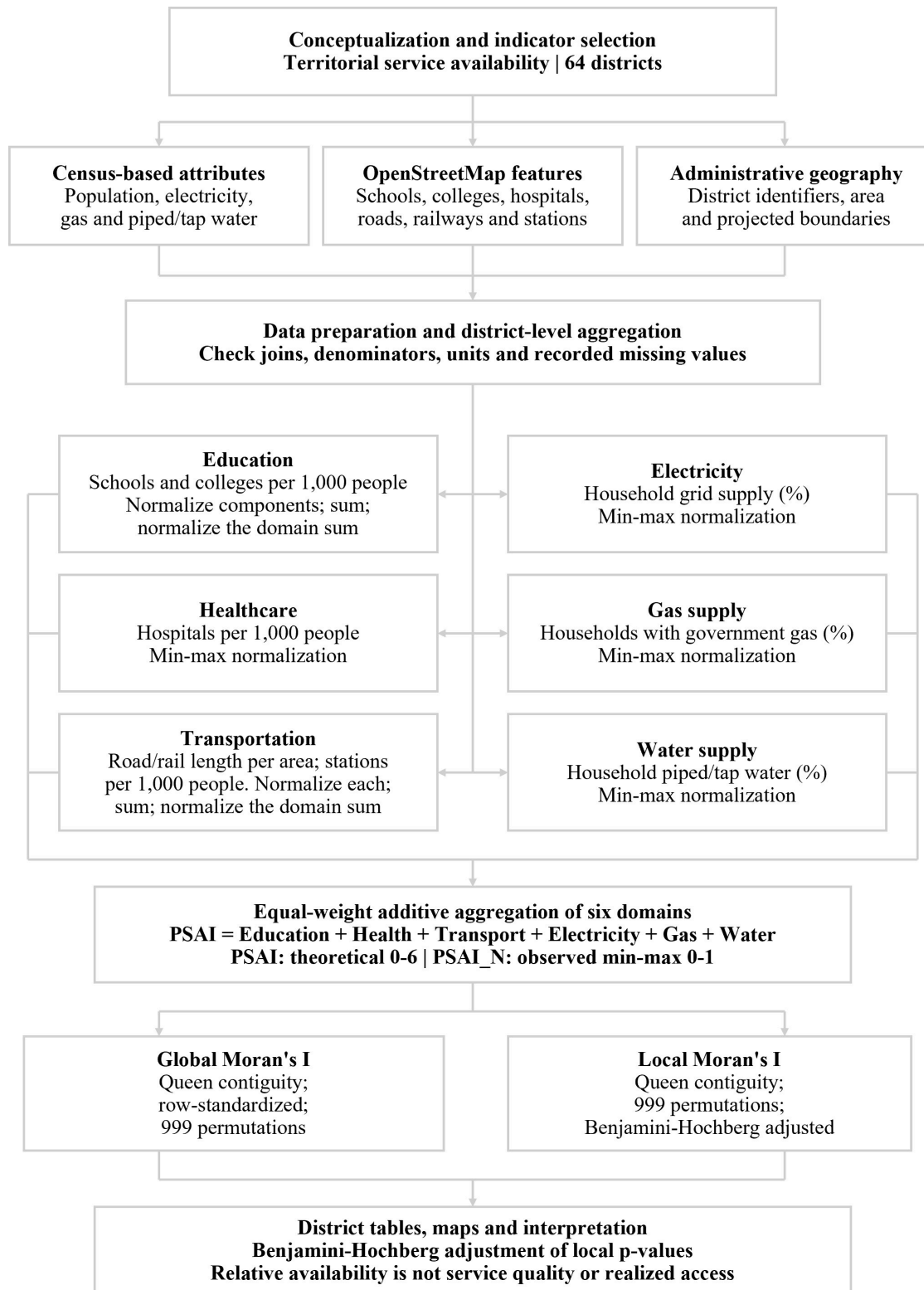


Figure 1

PSAI construction and analysis workflow

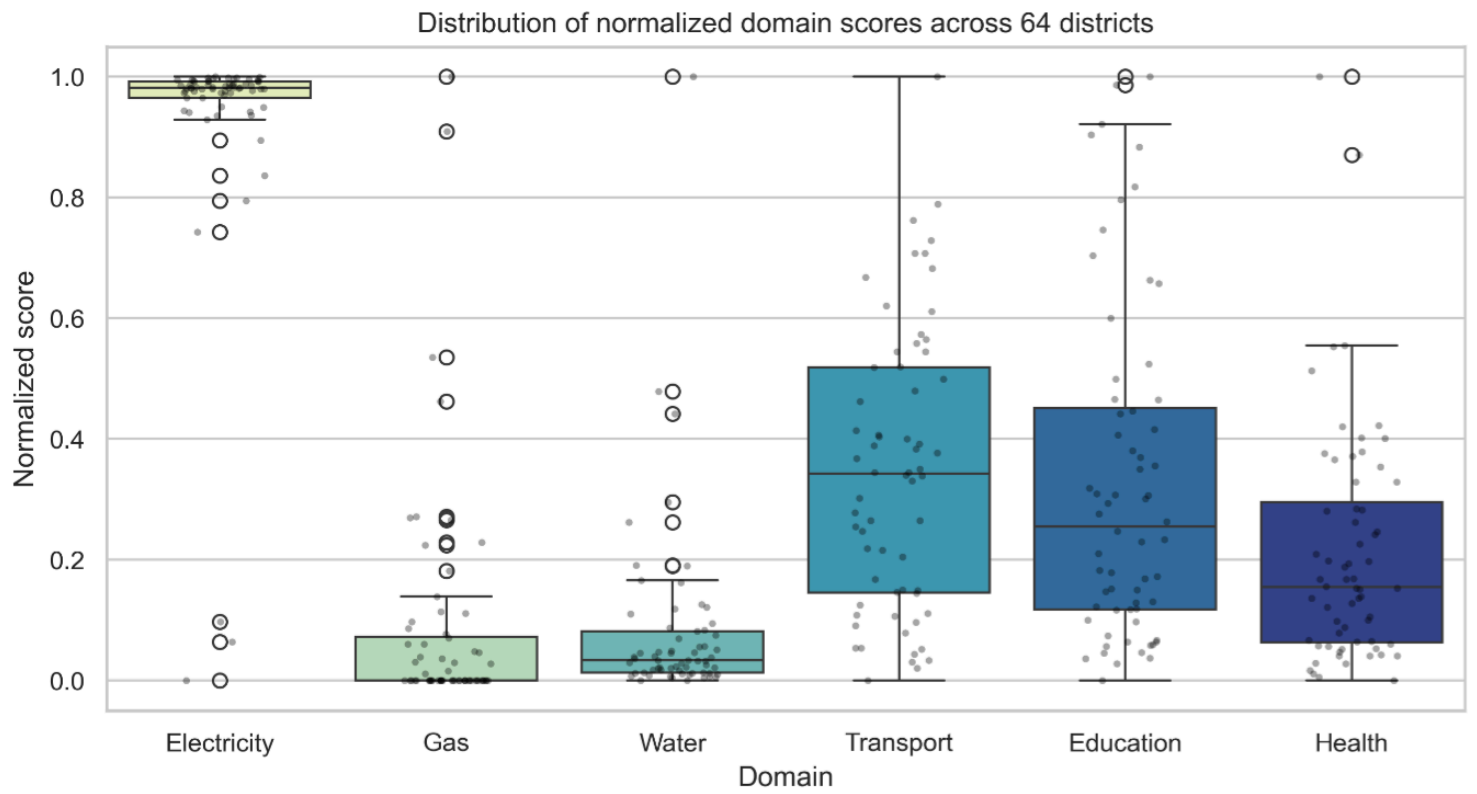


Figure 2

Distribution of normalized domain scores. Boxes show quartiles, circles show outliers and dots show districts

normalized domain scores by district

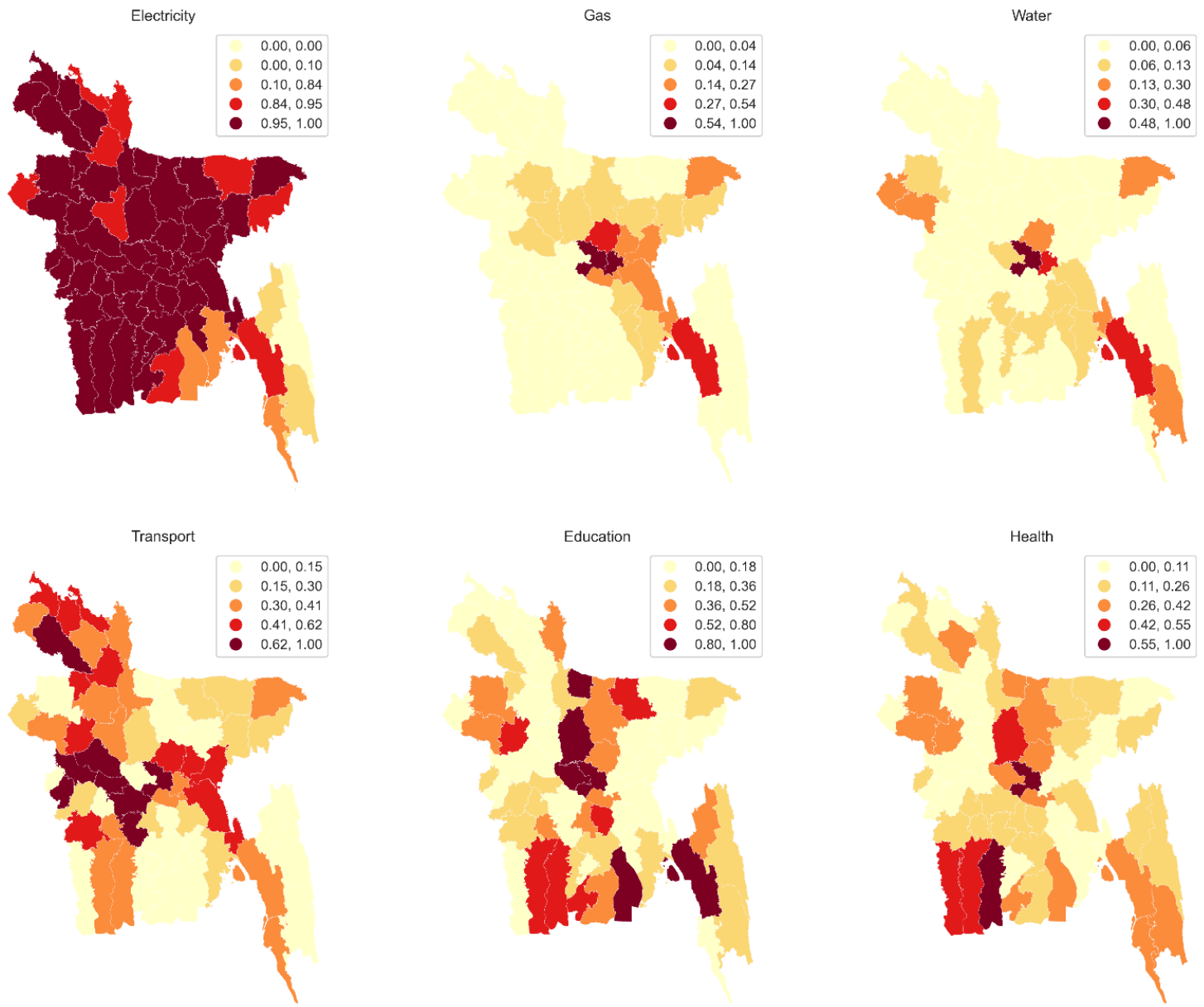


Figure 3

Normalized domain scores for (a) electricity, (b) gas, (c) water, (d) transport, (e) education and (f) health. Darker classes show higher scores

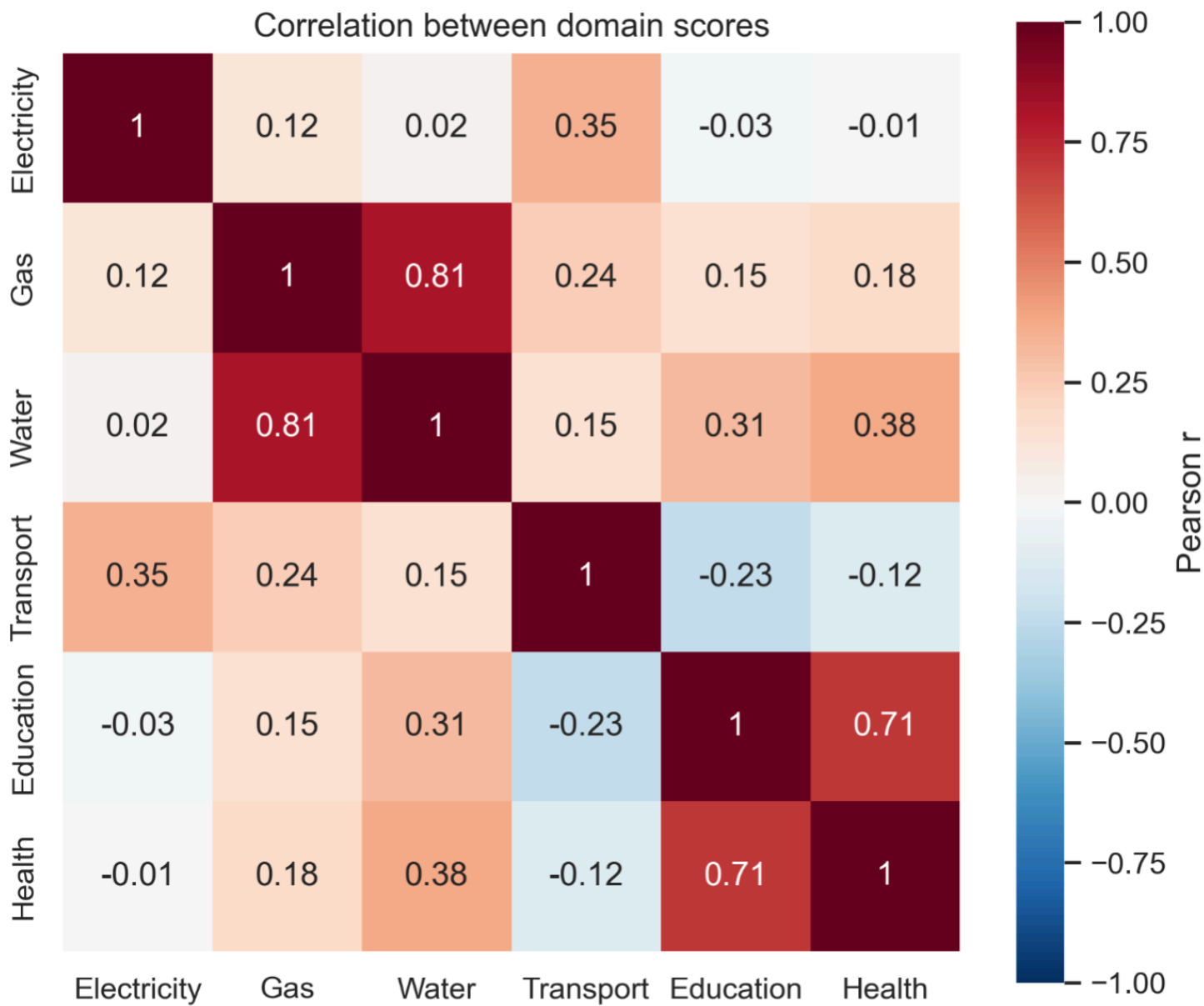


Figure 4

Pearson correlations between domain scores

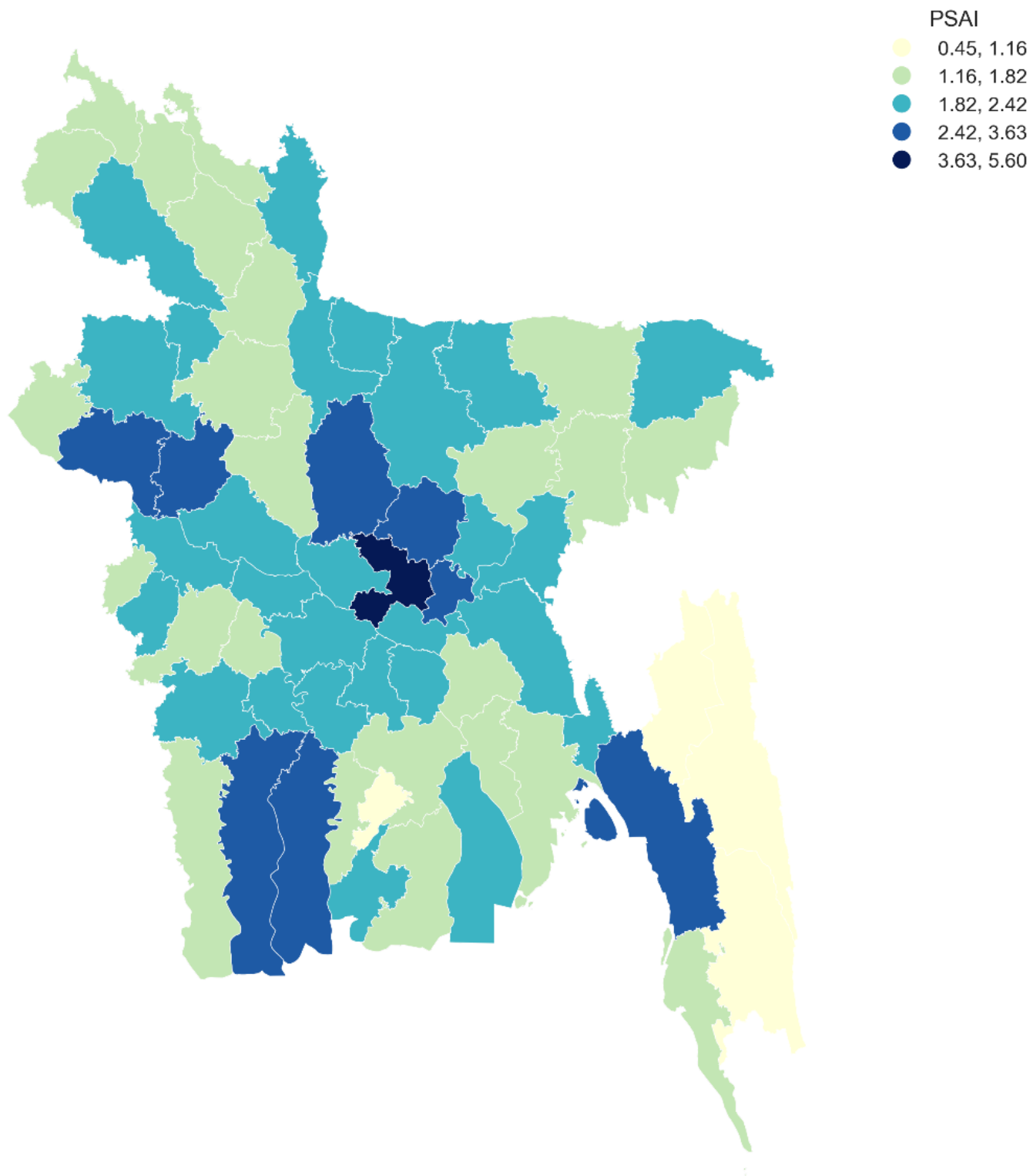


Figure 5

Composite PSAI by district. Darker classes show higher scores

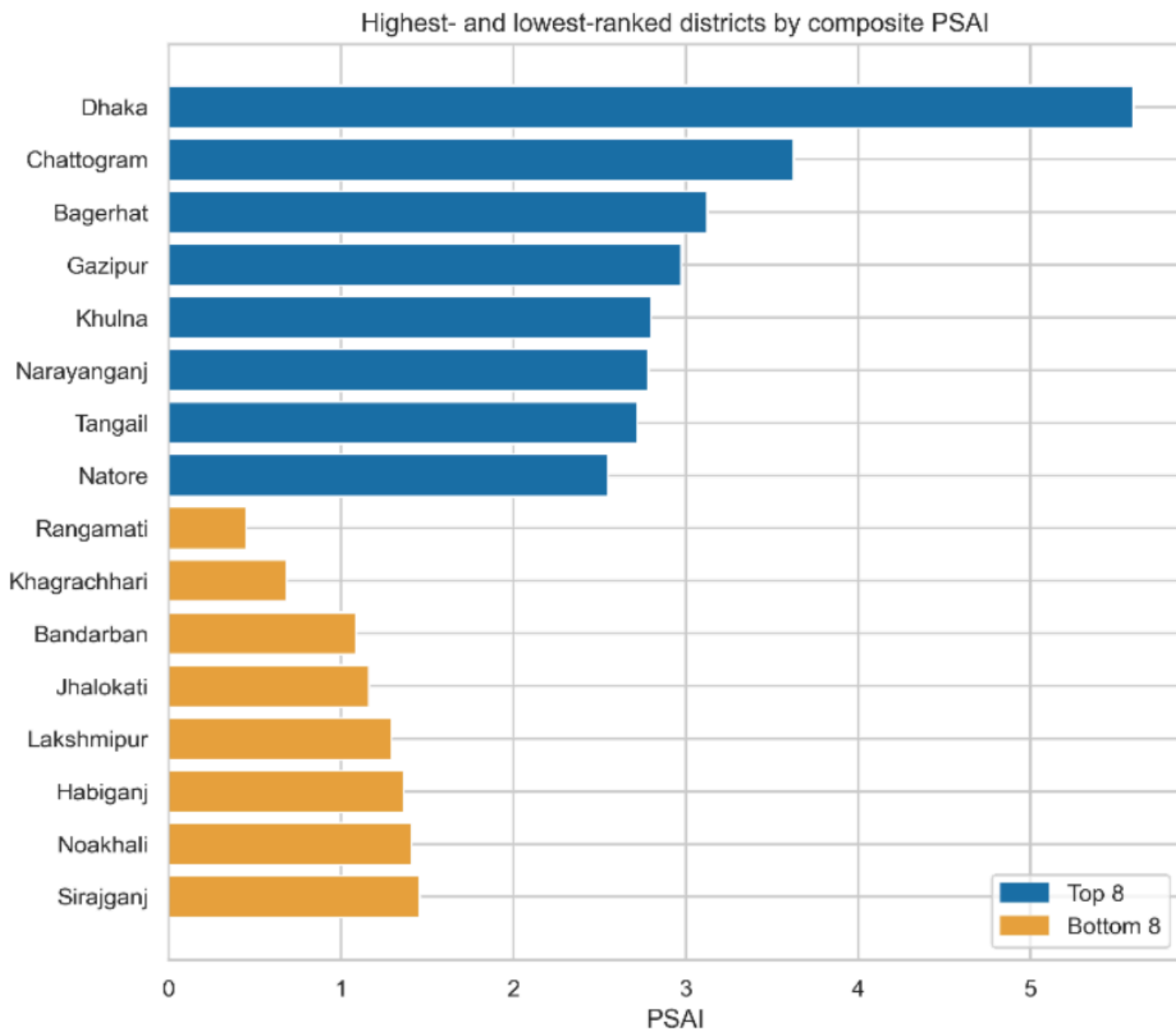


Figure 6

Highest- and lowest-ranked districts by composite PSAI

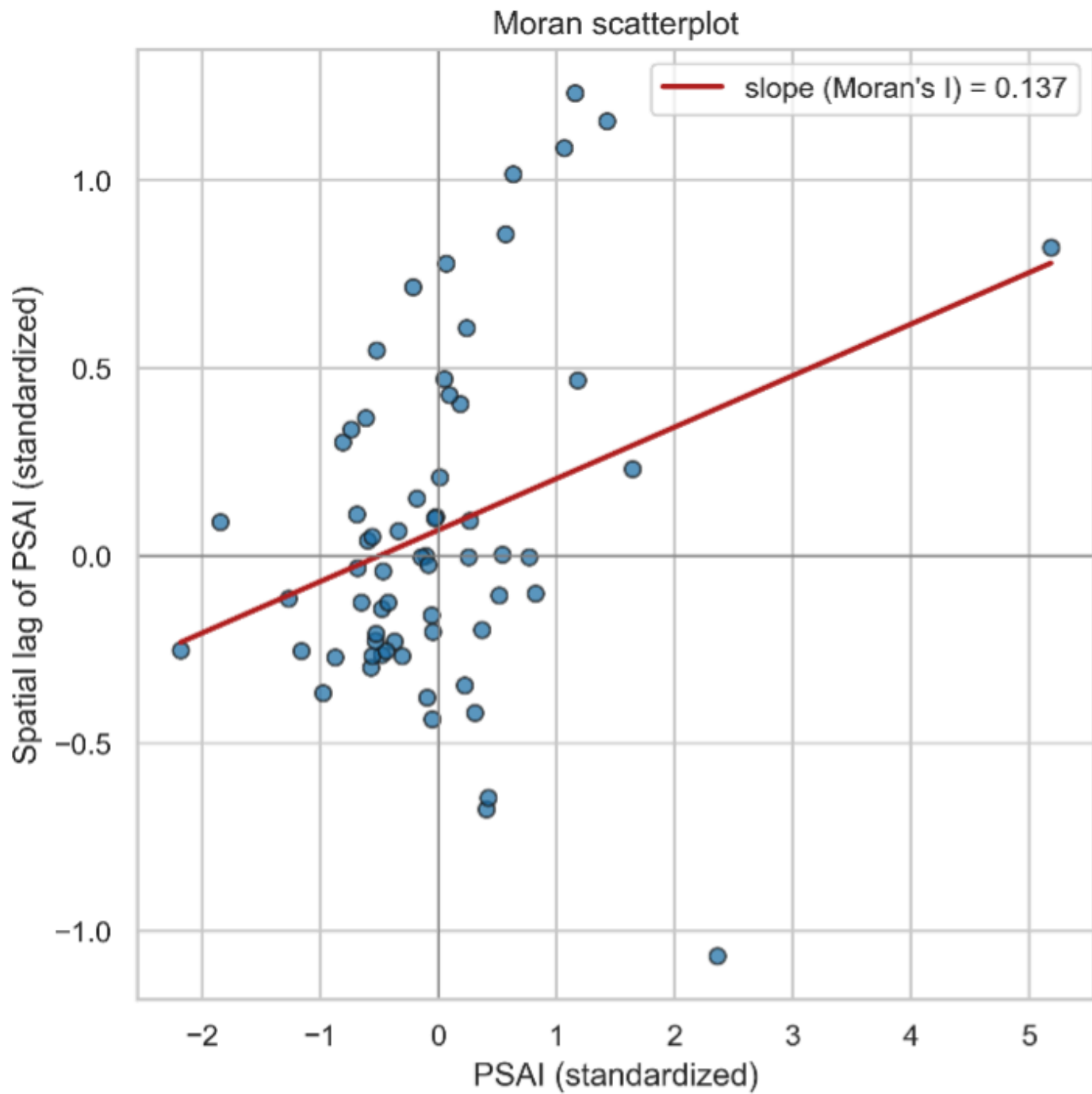


Figure 7

Moran scatterplot of PSAI with fitted slope

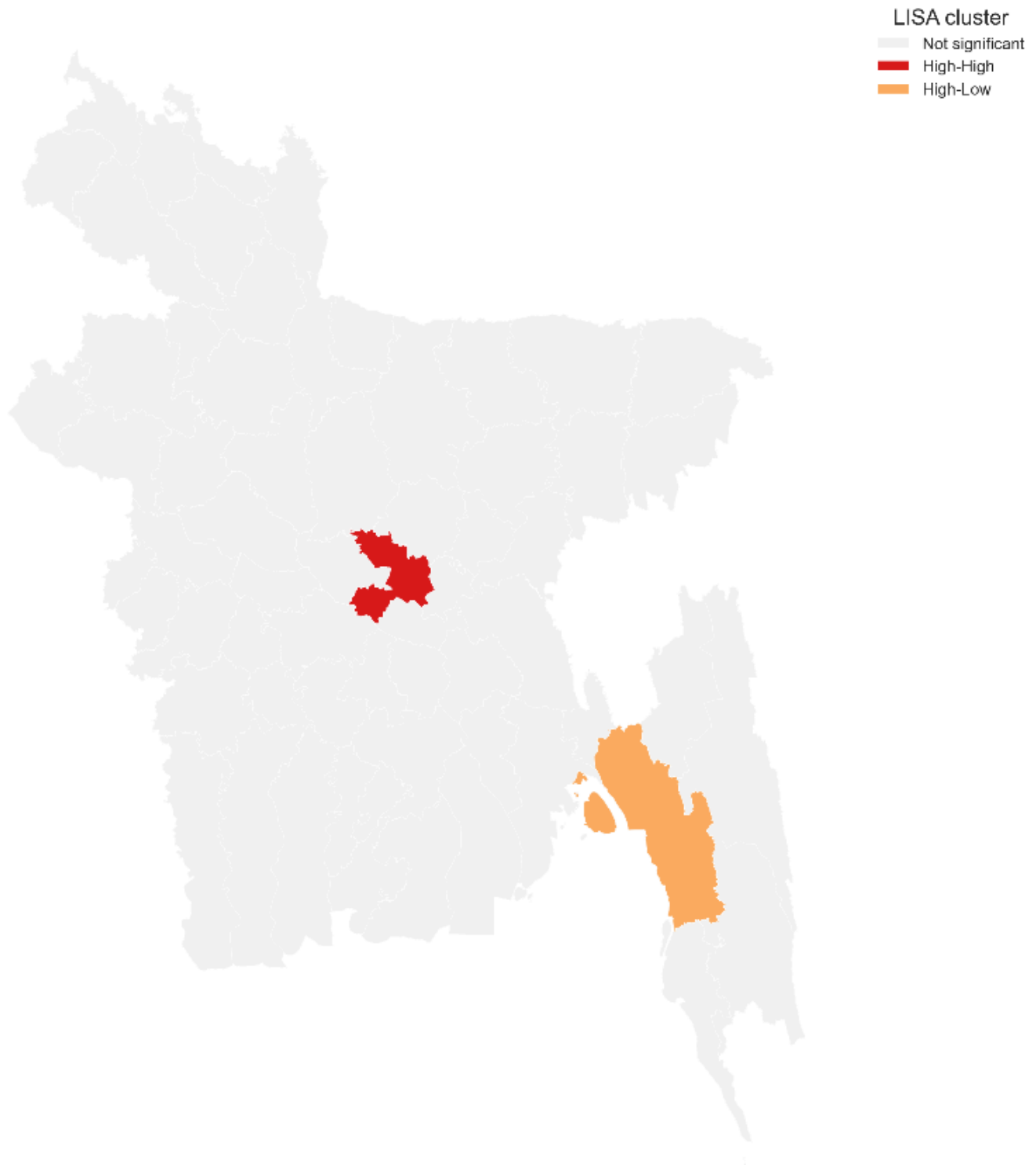


Figure 8

Local Moran clusters after Benjamini-Hochberg adjustment. Red marks the high-high district, orange the high-low district and grey the non-significant districts

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [PSAISupplementaryMaterialGeoJournal.docx](#)