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SCIPE: A Hybrid Framework for Measuring the Quality of Life in Low-Resource Countries Aligning with the Objectives of SDGs

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Research Article

Keywords: Quality of life, Composite Indicators, Non-traditional Data, SDGs, Data Governance

Posted Date: March 5th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-8982720/v1

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Additional Declarations: The authors declare no competing interests.

SCIPE: A Hybrid Framework for Measuring the Quality of Life in Low-Resource Countries Aligning with the Objectives of SDGs

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Abstract

The effective realization of the United Nations' 2030 Agenda relies on precise, timely monitoring; yet, for many low-resource nations, the lack of consistent data remains a critical barrier. In these contexts, traditional household surveys are often infrequent, resource-intensive, and prone to organizational gaps, hindering the granular assessment of Sustainable Development Goals (SDGs). To bridge this gap, this paper proposes the **Sustainable Composite Indicator for Policy Enforcement (SCIPE)**, a robust hybrid framework designed to quantify quality of life by integrating traditional statistical sources with high-frequency non-traditional data (NTD), including satellite imagery and nighttime lights. Designed explicitly for data-scarce environments, we demonstrate the efficacy of SCIPE through a representative case study in **Bangladesh**, organizing the analysis at a granular, district-level resolution. This manuscript provides a policy-aligned conceptual mapping that connects specific quality of life domains to relevant SDGs and alike targets. We consider the SDGs as a standardized benchmark for categorising domains to specify necessary determinants for a holistic measurement. The methodological blueprint articulates rigorous protocols for normalization, participatory weighting, and validation, while explicitly incorporating governance measures to mitigate privacy risks and representational bias. We lay out a complete path to establish a system supporting timely and spatially resolved insights to support initiatives such as Five-Year Plans and Voluntary National Reviews in the context of Bangladesh or a country with a similar socio-economic category. Ultimately, the study demonstrates that while the hybrid SCIPE index offers superior responsiveness and spatial resolution, its responsible deployment requires prudent implementation, strong data governance, and continuous fairness audits to ensure equitable policy enforcement.

Keywords

Quality of life; composite indicators; non-traditional data; SDGs; data governance.

1. Introduction

Since the 1930s, Gross Domestic Product (GDP) has served as the dominant metric for national progress (Bordo, 1993). However, the limitations of GDP in capturing multidimensional well-being have become increasingly evident, prompting a global paradigm shift toward composite measures that account for health, education, environmental sustainability, and social equity (OECD, 2008). It is now widely recognized that economic growth does not automatically translate into societal advancement; profit-driven models often neglect social maturation and environmental protection (Hariram et al., 2023). True sustainability requires a delicate balance between economic, social, and environmental goals. To operationalize this balance, Composite Indicators (CIs) have emerged as essential tools. By condensing multidimensional information into communicable scores, CIs address the asymmetry between

economic growth and human well-being. However, they require transparent methodological choices regarding normalization, weighting, and aggregation to ensure validity (OECD, 2008).

In the context of Bangladesh, national planning has been rigorously aligned with the United Nations' Sustainable Development Goals (SDGs)[1]. While agencies such as the General Economics Division (GED) produce periodic progress reports, official documentation repeatedly cites critical constraints, demonstrating gaps in data availability, lack of timeliness, and insufficient granularity (GED, 2022; GED, 2025). For example, SDG 1 (No Poverty) monitoring is mainly reliant on the Household Income and Expenditure Survey. However, the significant six-year gap between the 2016 and 2022 survey cycles caused a key data vacuum. As a result, during the COVID-19 pandemic, relief administrators were compelled to develop relief efforts in the absence of current poverty information, instead relying on dated 2016 estimates that failed to identify the crisis's additional and new poor population (BBS, 2023).

Districts serve as the primary administrative units for resource allocation and intervention in Bangladesh; yet, without high-frequency detailed data, policymakers struggle to identify lagging regions and materialize the strategy of leaving no one behind principle effectively. Similarly, achieving the 17 diverse goals of the SDG is a complex challenge that cannot be monitored by infrequent surveys. To bridge this information gap while preserving statistical rigor, there is a compelling opportunity to complement Traditional Data (TD) sources, such as censuses, with high-frequency Non-Traditional Data (NTD), such as satellite images, etc. While conventional sources are reliable but resource-intensive and slow, NTDs offer rapid, fine-grained insights essential for monitoring fast-changing development scenarios (Albanna et al., 2022). By treating TD as an exemplary benchmark, analysts can calibrate and validate NTDs to correct for inherent biases and noise. The result is a vigorous hybrid system that captures the richness of a data source while maintaining the statistical integrity of established methods.

This paper proposes the **Sustainable Composite Indicator for Policy Enforcement (SCIPE)**, a conceptual blueprint for constructing a hybrid composite indicator designed for low-resource countries where data scarcity is the utmost concern. As the case study to understand the capability of SCIPE, Bangladesh has been brought into consideration in our manuscript. SCIPE integrates both traditional and non-traditional data sources to provide a robust, timely, and granular measure of quality of life. Within the context of Bangladesh, by functioning at the district level, this framework aims to inform SDG-aligned policymaking (Rahman et al., 2021), allowing for the precise identification of regional disparities and the targeted allocation of resources for the future well-being of the nation.

The remainder of this manuscript is organized as follows:

- **Section 2** reviews the relevant literature and prevailing computational techniques in welfare measurement.
- **Section 3** outlines the computational framework for aligning composite indicators with the SDGs.
- **Section 4** provides a critical discussion on data sources, evaluating the qualities required for integrating heterogeneous data into a computational model.
- **Section 5** details the proposed methodology for constructing the SCIPE in the context of Bangladesh.
- **Sections 6 and 7** present a rigorous analysis of the results, offering insights from the composite indicator at district-level granularity.
- **Section 8** addresses the practical implementation of these insights for policy formulation.
- **Section 9** discusses current limitations and outlines a pipeline for future extensions, followed by concluding remarks in **Section 10**.

2. Literature Review

This section highlights key peer-reviewed contributions relevant to data definition, composite indicators, and SCIPE within those literatures.

2.1. Traditional Data Sources to Measure Quality of Life and Limitations

[1] https://sdgs.un.org/goals

Traditional data sources refer to the long-established, formal mechanisms through which governments, academic institutions, and statistical agencies collect information about populations and social conditions. The most common examples include censuses, household surveys, and administrative records. They are generally structured, systematically collected, and often produced by official institutions. Economic indicators such as GDP, unemployment, and trade statistics provide standardized benchmarks for societal and economic conditions, and they rely on these sources.

However, each of these sources carries important limitations, especially when used to understand society in modern contexts. For example, many traditional data sources operate at relatively low temporal frequency. Censuses typically occur only every 5–10 years. It is difficult to include rapidly unfolding changes (e.g., sudden economic shocks, pandemic impacts, etc.). It also cannot capture data happening in real-time. Moreover, surveys now face declining participation rates and increasingly high costs, which compromise their representativeness and suffer from timeliness (Holtom, 2022). This results in sampling bias, coverage error, and threats to external validity of survey-based estimates (Chen et al., 2021). Lastly, administrative data are large and longitudinal, and most were not created for research purposes, which means they often lack important variables, face linkage problems, and represent only those who use certain services. (Foote et al., 2022).

TD often shows only big, national-level patterns, not detailed information about specific neighbourhoods or people. This hides important differences within communities. Surveys can also be unreliable because people may forget things, answer in ways they think look good, or respond differently depending on how the questionnaire is asked (Morrison et al., 2015). Additionally, TD is often slow to release and inconsistent across sources, making it challenging to use promptly or compare over time and across places.

Despite these, they do still remain essential because of providing high-quality, systematically collected, and nationally representative information. Unlike many new digital data streams, the censuses and well-designed surveys are built on rigorous sampling frames and methodological standards that support validity, reliability, and comparability over time if done accurately (De Leeuw et al., 2008). These sources also enable cross-national comparisons because they adhere to internationally recognized standards and measurement frameworks, which strengthens their usefulness for long-term analysis (Smith, 2019).

2.2. Non-Traditional Data Sources to Measure Quality of Life and Limitations

Non-traditional data (NTD), also termed as alternative or unconventional data, are data sources that are digitally captured, mediated, or observed outside classical methods of surveys. For example, mobile phone records, social-media posts, GPS traces, satellite imagery, transaction logs, sensor and wearable outputs, web-scraped feeds, and other passively or operationally collected digital traces, etc. can be categorized as non-traditional data sources (Bolt et al., 2024).

Researchers typically classify NTDs into several broad categories. One major category is digital trace data, which includes call detail records, mobile app usage, web-browsing metadata, and GPS mobility logs. Furthermore, remote sensing data, particularly high-resolution satellite or aerial imagery, are datasets that can be transformed into indicators, for example, night-time lights, building density, vegetation indices, infrastructure presence, and land-use classifications, etc. All of these can support socioeconomic and environmental research goals (Hall et al., 2023).

A growing body of methodological work evaluates the limitations of NTD and algorithmic models. Wesolowski et al. (2013) quantified ownership bias in mobile phone data and its implications for mobility estimates; Blumenstock (2015) and others highlighted the risk that algorithmic proxies amplify existing inequalities if underrepresented groups are missing from training data. Surveys and fairness audits are needed to identify representational gaps and mitigate bias (Mehrabi et al., 2019). Therefore, emphasis on the necessity of calibrating non-traditional indicators against reliable ground truth, such as survey data or administrative records, has been made. (Hall et al., 2023). SCIPE incorporates these findings in its recommended fairness audits, representativeness checks, and a governance architecture requiring independent oversight.

2.3. Composite Indicators and Their Effectiveness

Composite indicators (CI) synthesize diverse individual metrics into a unified index, allowing for the quantification of latent, multidimensional phenomena (Greco et al., 2019). It aggregates several indicators, such as education, income, health, etc., within a mathematical model to generate interpretable scores. Construction of CI is a mature field with well-established methodological prescriptions. The OECD Handbook on constructing CIs is the foundational reference of such rigorous work. The handbook details the best practices for theoretical framework design, indicator selection, missing data treatment, normalization, weighting methods, etc. It also discusses the techniques of aggregation, sensitivity analysis, and transparent reporting (OECD, 2008).

2.4. Techniques to Develop CI

To construct a robust CI, one must follow a logical narrative arc: transforming raw, incomparable data into a unified metric, assigning relative importance to that data, synthesizing it into a single score, and finally stress-testing the result for reliability. Raw indicators often possess distinct units of measurement, such as measuring GDP in dollars but life expectancy in years, which makes any sort of calculations impossible. To fix this, it is required to mathematically normalize these diverse indicators into a standardized range (often between 0 and 1 or similar), creating a common scale that allows different variables to be accurately compared and combined (OECD, 2008).

In the following sections, we discuss various mathematical techniques addressed in the literature and associated with the formulation of a CI.

2.4.1. Normalization Techniques

The narrative of index construction begins with the standardization of data. Raw indicators often possess distinct units of measurement and varying ranges, rendering them mathematically incompatible. Normalization resolves this by bringing all indicators onto a common scale. The most prevalent method is Min-Max Normalization, which rescales indicators to a range of [0, 1]. This technique transforms the data based on the range of observed values, preserving the relative distribution of the dataset. The equation is defined as:

$$I_{qc} = \frac{x_{qc} - min_c(x_q)}{max_c(x_q) - min_c(x_q)}$$

Where x_{qc} is the value of indicator q for unit c. $min_c(x_q)$ and $max_c(x_q)$, denote the minimum and maximum value observed, respectively, within the indicator values. I_{qc} denotes the normalized score.

Alternatively, Z-score Standardization converts indicators based on the average behavior of the dataset. It calculates how many standard deviations a data point is away from the mean, centering the distribution at 0 with a variance of 1. This is particularly useful when the objective is to reward exceptional performance relative to the group average, defined as:

$$I_{qc} = \frac{x_{qc} - \mu_q}{\boldsymbol{\sigma}_q}$$

Where μ_q is the mean and $\boldsymbol{\sigma}_q$ is the standard deviation of the indicator q for unit c. While statistically sound, this method can introduce negative values, which may complicate subsequent aggregation steps (Freudenberg, 2003).

2.4.2. Weighing Technique

Once the data is standardized, the narrative shifts to determining value. This stage, known as weighting, decides how much influence each specific indicator has on the final score. It creates a central tension between relying on human expertise (subjective) versus letting the data speak for itself (objective).

Subjective weighting trusts expert opinion to decide what matters most.

- Introduced by Saaty (1980) introduced Analytic Hierarchy Process (AHP) breaks complex decisions down into a structured hierarchy. Instead of guessing weights, experts perform pairwise comparisons between indicators to determine the most important one. This ensures that the human judgment applied to the index remains consistent and logical.

Objective weighting removes human bias, deriving importance strictly from the mathematical patterns within the data.

- Shannon Entropy: Based on Shannon (1948), this method assumes that data with high variability holds more useful information. Therefore, indicators that differentiate more between cases are given higher weights.
- CRITIC Method: Proposed by Diakoulaki et al. (1995), this approach looks at two factors: *how spread out the numbers are* and *how much an indicator disagrees with others*. It assigns higher weights to indicators that provide unique and strong information.
- Principal Component Analysis (PCA): As described by OECD (2008) and Jolliffe et al. (2016), PCA is a technique for efficiency. It groups highly similar indicators to avoid redundancy, calculating weights that capture the maximum amount of information (variance) from the original dataset.

Because weights embody value judgments, participatory methods for weight elicitation have been proposed to increase legitimacy. Participatory weighting refers to the importance of each indicator being decided by human judgment of the experts and policymakers rather than by a mathematical formulation (OECD, 2008). Saaty's AHP is widely used to derive weights from structured stakeholder comparisons and includes consistency checks to detect incoherent judgments. Recent composite index work often combines AHP with statistical weighting to achieve both buy-in and empirical defensibility (Libório et al., 2024).

SCIPE adopts a similar blended approach. participatory weights as raw data, supported by PCA for transparency and robustness checks, alongside enforcing higher weights to the indicators as per their capability to hold discriminating information (Zhang et al., 2011).

2.4.3. Aggregation Techniques

With normalized values and assigned weights, the next phase involves mathematically synthesizing these components. The choice of aggregation method dictates the compensability of the index, to an extent, to which a high score in one can offset a deficit in another.

Linear Aggregation is the most common approach, useful when indicators are considered mutually independent and fully compensable. It is calculated as the weighted sum of normalized indicators:

$$CI_c = \sum_{q=1}^{Q} w_q \, I_{qc}$$

Where CI_c is the composite indicator for unit c, and w_q is the weight of indicator q. While simple, this implies that a total lack of performance in one area (e.g., low quality of environment) can be perfectly compensated by high performance in another (e.g., high infrastructural development) (Munda, 2008).

To restrict this compensability, Geometric Aggregation is often preferred. This method rewards balance across dimensions, as low scores in any single indicator significantly penalize the total score. The equation is defined as:

$$CI_c = \prod_{q=1}^{Q} (I_{qc})^{w_q}$$

In contexts requiring strict ranking, Multi-Criteria Decision Making (MCDM) methods like TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) are employed. TOPSIS ranks units based on their geometric distance to an ideal solution, as opposed to an anti-ideal solution (Hwang et al., 1981).

2.4.4. Robustness and Sensitivity Analysis

The index generation framework's last step centers on validation. Because the production of CI involves various subjective methodological choices, which range from the selection of normalization procedures to the determination of weighting schemes. This stage checks if the final rankings represent true underlying phenomena or are just the product of certain methodological assumptions. However, this analysis largely depends on the comparison with properly scored or ranked data. In the absence of such data, this kind of analysis becomes challenging.

2.5 Previous Works on CI Representing Quality of Life

Researchers have adhered to the building of an index to quantify the Quality of Life (QoL). Some of the earliest work was done by Morris (1978), through introducing a QoL measure named the Physical Quality of Life Index (PQLI). Three key indicators - literacy, infant mortality, and life expectancy at age one were accounted as participatory weights here. The indicators were standardized on a scale between [1, 100] and then averaged to produce PQLI.

The United Nations Development Programme (UNDP) introduced a Human Development Index (HDI) in the Human Development Report, 1990. The index was formulated considering a country's shortfall in three dimensions: Life expectancy (X_1), Education (X_2), and Adjusted income (X_3). Deprivation indicator (I_{ij}) with respect to the indicator i for the country j (X_{ij}) is defined as:

$$I_{ij} = \frac{max_k\,(X_{ik}) - X_{ij}}{max_k\,(X_{ik}) - min_k\,(X_{ik})}$$

Here, the max and min operator denotes the maximum and minimum value observed across all k countries for the i^{th} indicator. The average deprivation index for a country j is defined as:

$$I_j = \frac{1}{3}\sum_{i=1}^{3} I_{ij}$$

Thus, the HDI for the country j is $H_j = 1 - I_j$.

Diener (1995) introduced a value-based index for measuring national QoL using Schwartz's theory of basic human values as a foundation. Two QoL indexes, Basic QoL and Advanced QoL, were constructed. Construction of Basic QoL involves purchasing power, homicide rate, fulfillment of basic physical needs, suicide rate, literacy rate, gross human rights violations, and deforestation. Advanced QoL involves physicians per capita, savings rate, per capita income, subjective well-being, percent attending college, income equality, and environmental treaties signed. Combining these two indices, he also constructed a reliable measure of QoL. The author standardized the factors and calculated the mean considering equal weight to measure the QoL index.

The Multidimensional Poverty Index (MPI), developed by Alkire and Santos (2010) with the UNDP, measures QoL beyond income. It uses indicators across health, education, and living standards like nutrition, child mortality, schooling, sanitation, water, electricity, and assets. The Alkire-Foster method identifies deprivations for each household. Those with deprivation scores above 0.33 are classified as multidimensionally poor. The MPI is then obtained by multiplying these two components:

$$MPI = H \times A.$$

Where H refers to the Headcount Ratio, i.e., the proportion of people identified as multidimensionally poor, and A refers to the Intensity of Poverty, i.e., the average deprivation score among the poor.

Numbeo, an organization based in Serbia. publishes a QoL index. Dimensions used in this index are cost of living and purchasing power, affordability of housing, crime rates, health system quality, traffic, and pollution, including air, water, etc. A separate index is constructed for each dimension, and the indices are aggregated by weighted means to construct the final index (Numbeo, 2024).

These are some of the prior QoL indexes. But they mainly use Traditional data sources; to the best of our knowledge, usage of NTD sources is not common. The goal of this paper is to make a high-impact and interpretable CI that can derive quality and explainable results in a timely fashion.

2.6. Current Progress in the Literature on Forming a CI

Recent studies on CIs show steady progress in how these measures are designed and used.

The study by Sebestyén et al. (2024) develops a GIS-based Objective Well-being Level (OWL) indicator to assess the quality of life in cities using spatial data. The OWL index integrates six different categories of urban well-being, such as walkability, environment, health, society, climate change, and safety. These Categories were based on 24 underlying models. The authors apply multilevel PCA to weight these dimensions and aggregate them into a composite well-being score, enabling spatial mapping of intra-urban disparities and supporting sustainable urban planning.

Rijpma et al. (2025) examine multidimensional composite well-being indicators and how their design affects long-run assessments of well-being. Their composite indicators typically combine dimensions such as health, education, material living conditions, environmental quality, and work-life balance or social conditions, reflecting the multidimensional nature of well-being beyond GDP. By applying these indicators to long-term historical data, they show that different choices in indicator selection, normalization, and aggregation (e.g., additive vs hierarchical) significantly influence conclusions about trends and the relationship between economic growth and well-being.

In 2025, the Institute of Macroeconomic Analysis and Development of the Republic of Slovenia in, employed a CI framework to assess national well-being across multiple dimensions. Their QoL framework encompasses domains such as material well-being (income, wealth, inequality), health (life years, unmet care needs), skills, spatial quality, social cohesion, and institutional quality. By normalizing and aggregating these domain-specific indicators, the report facilitates longitudinal comparisons against EU benchmarks, effectively highlighting both national strengths and persistent structural challenges.

The recent progress in CI research has made these tools far more dependable and meaningful. Improved methods, clearer frameworks, and stronger validation practices now help reduce confusion and bias. These developments make CI better suited for understanding complex social and economic realities.

2.7. Previous Work and Literature Relevant to Bangladesh

There are substantive case studies of hybrid indices and NTD integration in LMIC (Low and Middle-Income Countries) settings that offer lessons applicable to Bangladesh.

Empirical research increasingly demonstrates the analytical value of integrating traditional survey data with remotely sensed and digital behavioral indicators to improve socioeconomic measurement. A substantial literature demonstrates that nighttime lights (NTL) provide a useful proxy for local economic activity and can complement survey-based GDP measures, especially where official statistics are sparse or outdated. Henderson et. al. (2012) developed a statistical framework to combine lights data with conventional measures to estimate economic growth, revealing that lights can materially alter growth estimates in data-sparse contexts. Subsequent studies have refined sensor choices (DMSP vs VIIRS), calibration techniques (e.g., correction for saturation, inter-sensor harmonization), and applications to subnational poverty mapping (Gibson et al., 2021; World Bank WPS on poverty from space). Nightlights produce especially valuable high-frequency spatial signals for urbanization and economic shocks (Gibson, 2021; World Bank, 2018).

One of the most influential and empirical demonstrations showed in Rwanda that mobile phone metadata can predict individual-level wealth, where features from call detail records (CDRs) and phone usage were strongly predictive of survey-measured wealth (Blumenstock et al., 2015). Steele et al. (2017) extended the approach to combine CDRs with satellite imagery and other public data, such as census, household survey data (e.g., DHS, LSMS), administrative boundaries, infrastructure data (roads, schools, health facilities), and climatic datasets to map poverty targeting low and middle-income countries. These studies underscore two important caveats. First one is, CDR-based models must

be validated against household surveys, and secondly, CDRs can be biased by unequal mobile ownership and usage patterns, requiring biased assessments and corrections.

Other studies have refined feature extraction, used open Sentinel imagery, and combined multi-sensor inputs to improve robustness (Pérez-Sindín et al., 2021; Gibson, 2021). These approaches provide a methodological template for SCIPE's integration of environmental and infrastructural proxies derived from remote sensing. Complementing these innovations, research on fairness and bias audits emphasizes the ethical and statistical dimensions of non-traditional data analytics.

2.8. Bangladesh-specific Monitoring and Addressing Data Gaps through BDQOL

Official surveys by Bangladesh's GED and Bureau of Statistics (BBS) are thorough, but they lack frequency and local specificity. BDQOL[2] addresses these deficits by employing hybrid data for timeliness and **S**mall Area Estimation (SAE) for granular mapping at the Upazila level. However, this web portal merely functions as a curated data repository rather than a robust framework as an indicator. Proposed framework, SCIPE offers agile, high-resolution insights for policy enforcement, relying on official survey data for essential ground-truth calibration with extension via NTD sources.

3. Conceptual Framework for SCIPE Index

The conceptual framework for the SCIPE index describes how social, economic, and environmental issues influence the overall quality of life. It combines classic well-being indicators with new, data-driven measurements to account for both individual experiences and structural factors. SCIPE works as a tool for understanding how different factors interact to impact people's everyday lives and long-term development. We present SCIPE for Bangladesh as a case study representative of low-resource countries.

3.1 Defining Quality of Life

Quality of Life is a multidimensional construct that transcends economic metrics to encompass general well-being. Modern assessment frameworks reflect this complexity by integrating quantitative service indicators with qualitative life satisfaction data, consistent with the WHO's holistic definition (WHO, 1997). To operationalize this concept for Bangladesh, we designed SCIPE based on six priority domains, explicitly calibrated to align national Five-Year Plan goals with the UN proposed SDGs. It will assist in achieving local operational leverers' prompt service delivery.

3.2 Mapping Domains to Indicators and SDG Targets

For ease, this paper sorts out the 17 SDGs into 6 categories. Each domain goes well with key SDG goals and indicators. An ideal index based on SDGs for granular-level evaluation is to be consistent and reflect all these domains.

1. Economic opportunities connect to SDGs 1, 5, 8, and 10 through measures like poverty reduction, employment, and income equality.
2. Health links to SDG 3 via indicators on maternal and child health, disease prevention, and access to essential services.
3. Education aligns with SDG 4 through indicators on school enrolment, learning outcomes, and skills development.
4. Environmental conditions relate to SDGs 6, 7, 11, 12, 13, and 15 by tracking water and sanitation access, clean energy, air quality, climate resilience, and ecosystem protection.
5. Social cohesion and safety correspond to SDGs 5 and 16 through indicators on violence reduction, gender equality, and community safety.
6. Effective governance is tied to SDGs 16 and 17 through measures of transparent institutions, reduced corruption, civic participation, and strong partnerships.

[2] https://bdqol.dndlab.org/

Combining these, SCIPE constructs the QoL index with both global development priorities and Bangladesh's national goals (United Nations Statistics Division, 2023). By integrating traditional statistics with high-frequency non-traditional data, this framework ensures timely monitoring, offering a comprehensive, spatially resolved assessment to enforce targeted interventions.

SCIPE employs an operational localization strategy targeting granular-level policy enforcement. It acts as an intermediate translation layer that aggregates specific, measurable indicators derived from traditional and non-traditional sources and maps them back to the broader SDG groups. While the measurement remains rooted in local data availability, the resulting insights directly inform progress toward specific targets of global standards.

4. Data Architecture and Pipeline Through BDQOL

The BDQOL web portal facilitates the visualization of QoL indicators across Bangladesh, allowing users to generate customized district rankings via adjustable weighting schemes, which can be useful for different stakeholders. While this flexibility supports granular socioeconomic analysis, the platform's development was constrained by the subjectivity of indicator selection and the challenges of combining data from diverse sources. Despite these limitations, BDQOL serves as a critical instrument for identifying regional inequalities supporting granular-level development planning while being the core data repository for SCIPE.

4.1 Hybrid Data Architecture

The SCIPE index pipeline has three layers:

1. Source layer: This layer collects data from different sources to be analyzed in a unified environment.
2. Processing layer: Standardizes and prepares the raw data through spatial and temporal harmonization, cleaning, and imputation.
3. Indexing layer: It transforms processed features into domain-specific subindices and computes the final index scores through normalization, weighting, and aggregation steps.

Strict data governance principles apply throughout the architecture. For NTDs, only pre-aggregated, anonymized metrics are ingested under formal Data Sharing Agreements (DSA), and raw personal data remains within providers' secure environments in line with international best practices.

4.2 Spatial & Temporal Resolution Choices

Designed for adaptability, SCIPE employs a dynamic resolution strategy. The spatial granularity of NTD-derived estimates is not static; rather, it is calibrated against validation performance and re-identification risk assessments to ensure an optimal balance between statistical utility and privacy compliance. In low-resource countries, for most socio-economic composite estimates, data are not updated in a timely manner. Official statistics rely on major national surveys like the Household Income and Expenditure Survey (HIES) or the Multiple Indicator Cluster Surveys (MICS), which are typically conducted only every 3 to 5 years. Consequently, SCIPE has to rely on data that is several years old. Due to this limitation, SCIPE has to consider data from different time periods.

4.3 Synthesis & Implications

The relevant literature establishes that while NTD offers superior timeliness and spatial granularity compared to censuses, it requires rigorous calibration against ground-truth surveys to mitigate bias (Rao et al., 2021). SCIPE index adheres to these principles but distinguishes itself methodologically in two ways. First, we utilize strictly statistical weighting rather than participatory approaches to eliminate subjective bias. Second, in the absence of labeled data, we validate findings through case-by-case interpretability analysis. Furthermore, we also conduct a sensitivity analysis to understand the reliability of the findings by comparing them against a well-known relevant indicator.

5. SCIPE Framework

This section discusses the steps regarding the construction process of SCIPE.

5.1 Categories of Data and Analysis of Unmapped Goals

SCIPE utilizes a hybrid framework of census statistics and remote-sensing data across five core domains, successfully capturing 12 of the 17 SDGs. Five goals were excluded due to the granularity and scope constraints: **SDG 5** (Gender Equality) and **SDG 10** (Reduced Inequalities) lack district-level disaggregated data; **SDG 12** (Responsible Consumption) falls outside our environmental focus on ambient quality; and **SDG 14** (Life Below Water) and **SDG 17** (Partnerships) are incompatible with universal, land-based granular analysis. Future iterations aim to incorporate these missing dimensions through heterogeneous data sources.

We synthesized the relevant SDG targets into five functional domains: *Health, Education, Infrastructure, Environment, and Living Conditions.* This grouping rationale is twofold. First, it reduces the high dimensionality of the global agenda into actionable administrative categories that align with the organizational structure of local governance (e.g., alignment with specific ministries). Second, it creates statistical coherence by clustering interdependent targets, such as Energy (SDG 7) and Transport (SDG 9), under single composite domains like *Infrastructure*, thereby minimizing redundancy.

5.2 Methodology

To construct a robust multidimensional indicator, we employed a rigorous multi-stage statistical framework. This study adopts a strictly data-driven methodology to ensure objective analysis, adhering to a distance from subjective bias. Leveraging curated, structured datasets from the BDQOL portal, we synthesized five core domains with their corresponding indicators to establish an index that is scientifically sound, devoid of user bias, and highly interpretable for policy assessment with regard to quantifying QoL. In Table 1, we highlight the chosen domains and the corresponding indicators with their data sources. We also provide the mapped SDGs, along with the targeted group SDGs mentioned in Section 3.2, to ensure the coverage.

Table 1: Mapping of SCIPE's considered domains and indicators aligning with the SDGs.

Source Domain	Indicator With Units	Data Source	SDG Number	Targeted SDG Cluster as per Section 3.2
Living Condition	Per Capita Income (BDT/Month)	Household Income and Expenditure Survey (HIES) 2016	8	Economic Opportunities
	Extreme Poverty Rate (%)		1.1	
	Access to Electricity (%)		7.1	Economic Opportunities and Environmental Conditions
	Households Using Tubewells as a Source of Drinking Water in the Rural Communities (%)		6.1	
	Households Using Sanitary Latrines (%)		6.2	
Health	Under-5 Mortality Rate (%)	Demographic and Health Surveys (DHS) 2014	3.2	Health
	Stunting Rate (Nutrition) (%)		2.2	
	Birth Registration (%)		16.9	Effective Governance
Education	Primary Completion Rate (%)	Bangladesh Bureau of Educational Information and Statistics (BANBEIS) 2015	4.1	Education

Infrastructure	Paved Roads (%)	Bangladesh Statistical Yearbook (2018)	9.1	Economic Opportunities
	Nighttime Luminosity	Wahed, M., et al., 2020	11.1	Environmental Conditions
Environment	Air Quality (PM2.5)	Energy Policy Institute, 2025	11.6	Environmental Conditions
	Multihazard Risk Score	Islam, M. M. (2017)	13.1	
	Reserve Forest Area (%)	Bangladesh Statistical Yearbook (2018)	15.1	

The construction of SCIPE follows four primary steps: Data Preprocessing, Normalization, Weighting via PCA, and Aggregation using the Mazziotta-Pareto Index**.**

5.3 Data Preprocessing

We have found a processed, structured, and easily accessible format for the data from the BDQOL portal for the majority of the indicators. However, prior to aggregation, the heterogeneous dataset underwent directional harmonization to ensure that higher values consistently reflect superior performance. While positive indicators (e.g., access to electricity) were retained in their original form, negative indicators (e.g., under-5 mortality) were inverted using a difference from maximum function ($X_{adjusted} = Max_{scale} - X_{observed}$). Subsequently, to resolve unit heterogeneity and prevent variables with large numerical ranges from skewing results, we have applied Z-score standardization for each indicator value under each domain.

5.4 Weighting Strategy: Principal Component Analysis

To avoid the subjectivity inherent in equal weighting or expert opinion, we utilize PCA to derive data-driven weights for the indicators (e.g., Per Capita Income) within each domain (e.g., Living Standard). We extracted the first principal component (PC1), which accounts for the largest possible variance in the data. The weight w_j for each indicator j under a domain was calculated based on the absolute values of the eigenvectors of PC1:

$$w_j = \frac{|e_j|}{\sum |e_k|}$$

Where $|e_j|$ represents the absolute contribution of the jth indicator to the first principal component. To compute the weight for each indicator, we normalize the absolute contributions by the total contributions of all the indicators. These weights are then used to linearly aggregate the indicators into intermediate domain scores for each district or the lowest

granularity. Then these scores were re-normalized using Min-Max scaling to the [0, 1] range to prepare for the final aggregation.

5.5 Final Aggregation: The Mazziotta-Pareto Index

To construct the final CI, we adopt a non-compensatory aggregation framework based on the Mazziotta-Pareto Index (MPI) (Mazziotta et al., 2013). Unlike linear averaging, which allows high performance in one sector to mask deficits in another, the MPI posits that fundamental domains (e.g., Health and Infrastructure, etc.) are non-substitutable. Consequently, MPI applies a penalty for horizontal variability by subtracting the standard deviation from the mean of the domain scores (Mazziott et al., 2013). This explicitly rewards districts with balanced development while penalizing those with extreme inequalities between sectors. Adhering to the principle of statistical parsimony, we employ a unitary penalty coefficient R, assuming that internal instability is equally detrimental to QoL as average performance is beneficial. The final composite scores, representing a balanced performance corrected for disparity, were then normalized within [0,1], where values approaching 1 signify a superior, equilibrium-status of well-being. The final formulation of SCIPE to quantify the QoL score in district-level granularity can be stated as below:

SCIPE Index: $CI_D = \boldsymbol{\mu}_D - R \times \boldsymbol{\sigma}_D$ ..... (1)

Where:

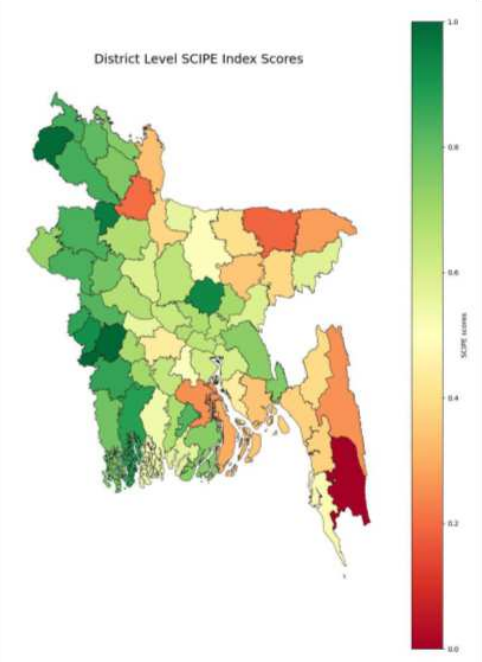
- $\boldsymbol{\mu}_D$ and $\boldsymbol{\sigma}_D$ denote the mean and standard deviation of the domain scores for district d.
- **R** denotes the scaling factor to penalize. As the scaling factor, we have used the value of 1 as per the base literature proposing MPI as a measure to develop a CI.

6. Interpretation of the Results and Explanation

For the purpose of understanding how getting a general grasp of Bangladesh's quality at the district level granularity might be helpful, we look at the extracted findings from SCIPE in this section.

6.1 Performance of SCIPE and Order of the Districts

Figure 1 displays the spatial distribution of our proposed SCIPE index's values across Bangladesh. District identifiers are left out for clarity, but the image shows the clear geographic difference between high-performing and low-performing areas. As a means to give context for the spectrum of progress, the top five-ranked and worst five-ranked districts are highlighted. In Figure 2, we illustrate the frequency distribution of the composite scores.



Rank	District	Score from SCIPE
1	Jhenaidah	1
2	Thakurgaon	0.99
3	Joypurhat	0.96
4	Gazipur	0.93
5	Chuadanga	0.91

Top-5 districts according to the score

Rank	District	Score from SCIPE
60	Rangamati	0.26
61	Barisal	0.25
62	Gaibandha	0.20
63	Sunamganj	0.19
64	Bandarban	0

Bottom-5 districts according to the score

Figure 1: Spatial distribution of SCIPE values across 64 districts in Bangladesh. The map illustrates the CI scores, utilizing a diverging color scale: green shades denote higher QoL performance, while red shades indicate districts with lower aggregate scores or higher vulnerability. We also show the Top-5 and Bottom-5 districts as per the generated score.

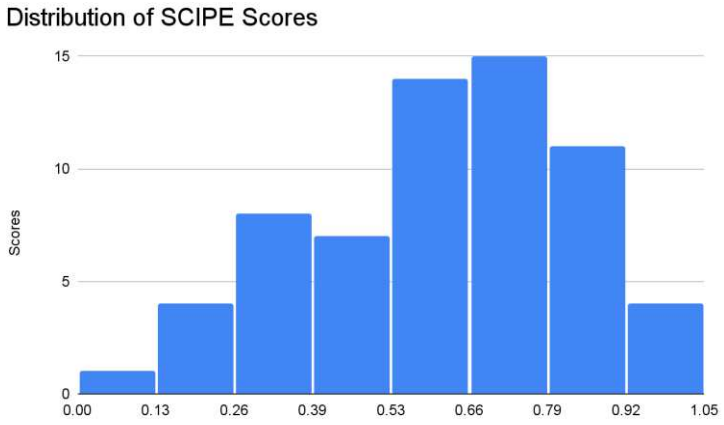
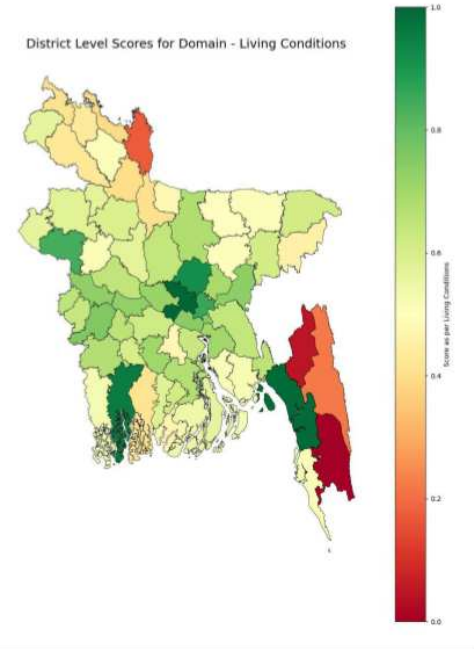


Figure 2: Distribution of the composite indicator scores for each district.

The composite analysis from SCIPE's formulation reveals a distinct geographical dichotomy. Top-performing districts are primarily emerging secondary cities in the western region (e.g., Jhenaidah 1.00, Thakurgaon 0.99), which benefit from a favorable synergy between economic stability and environmental quality. This contrasts with the industrial outlier Gazipur (0.93), where infrastructure compensates for environmental degradation. Conversely, the lowest rankings are strictly defined by topographical isolation in the Hill Tracts (Bandarban 0.00) and Haor basins (Sunamganj 0.19). Statistically, the distribution (0.61 ± 0.22) exhibits negative skew, identifying a persistent tail of underdevelopment (20.3% lagging districts). Spatially, the results align with Tobler's First Law (1970); the distinct clustering of the high-performing *western belt* versus the heterogeneous Dhaka-Chattogram corridor confirms that the index successfully captures regional spillover effects and the organic continuity of socioeconomic development.

6.2.1 Analysis of Living Condition Domain



Rank	District	Domain Scores
1	Dhaka	1.00
2	Chattogram	0.99
3	Khulna	0.96
4	Gazipur	0.92
5	Narayanganj	0.86

Top-5 districts according to the score

Rank	District	Domain Score
60	Lalmonirhat	0.39
61	Rangamati	0.22
62	Kurigram	0.18
63	Khagrachhari	0.04
64	Bandarban	0.00

Bottom-5 districts according to the score

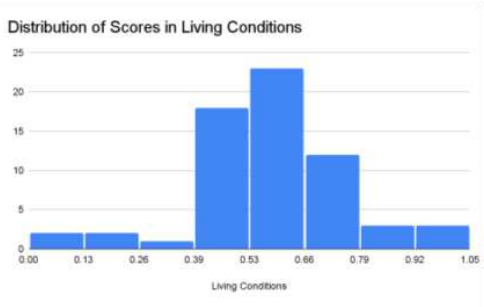
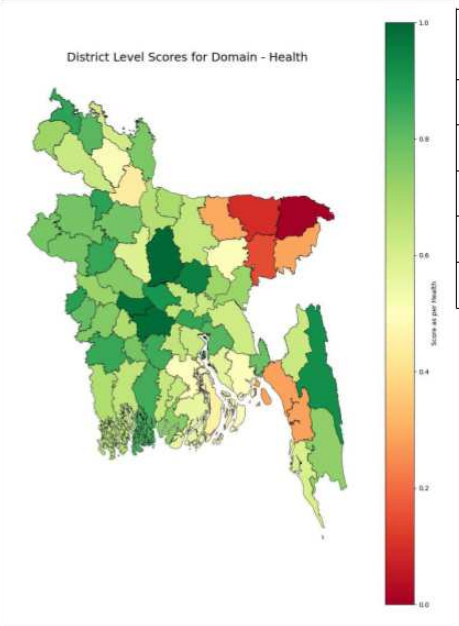


Figure 3: Spatial Distribution and Statistical Profile of the Living Condition Scores.

The living condition dimension, shown in Figure 3, (0.58 ± 0.19) reveals a structural inequality driven by the impact of urbanization. Unlike the composite index, which balances a harmony among multiple domains, this specific dimension is dominated by the industrial metropolises: Dhaka (1.00), Chattogram (0.99), and Khulna (0.96), confirming a strong positive correlation between urbanization and access to modern amenities (housing, electricity, internet, etc.). While these urban centers suffer from environmental degradation, their superior utility infrastructure secures their top rankings. Conversely, the bottom rankings illustrate a severe penalty associated to geographic placement, the Chattogram Hill Tracts (Bandarban 0.00) and flood-prone northern districts (Kurigram 0.18) lag significantly, as challenging topography and isolation impede the logistical delivery of essential services.

6.2.2 Analysis of the Health Domain



Rank	District	Domain Scores
1	Tangail	1.00
2	Faridpur	0.99
3	Rajbari	0.98
4	Gazipur	0.95
5	Rangamati	0.92

Top-5 districts according to the score

Rank	District	Domain Score
60	Moulvibazar	0.29
61	Chattogram	0.28
62	Habiganj	0.14
63	Sunamganj	0.10
64	Sylhet	0.00

Bottom-5 districts according to the score

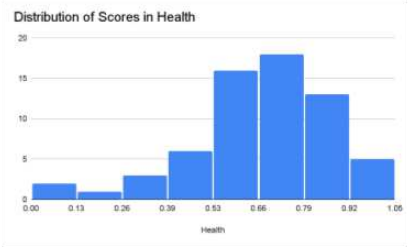
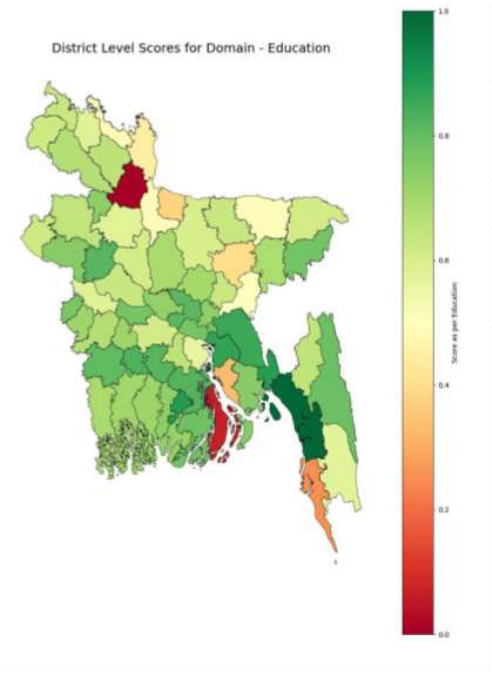


Figure 4: Spatial Distribution and Statistical Profile of the Health Domain Scores.

As demonstrated in Figure 4, the health dimension exhibits a negative skew (0.67 ± 0.21), indicating generally robust national performance punctuated by a striking pattern of disconnection between wealth and health. The affluent Sylhet Division creates a distinct northeastern red zone of underperformance (Sylhet 0.00, Sunamganj 0.10), suggesting that economic wealth does not guarantee health outcomes due to persistent socio-cultural or structural barriers. This decoupling is further evidenced by Chattogram (0.28), where industrial density likely exerts a penalty associated with environmental quality degradation due to uncontrolled urbanization. In sharp contrast, Rangamati (0.92) illustrates an inverse trade-off; despite ranking the lowest in infrastructure, it achieves top-tier health scores, suggesting that superior environmental quality and community-based interventions in the Hill Tracts compensate for the lack of physical amenities. However, recognizing the temporal lag in available datasets, these anomalies underscore the necessity of integrating real-time data streams in future iterations to accurately capture the impact of recent policy interventions.

6.2.3 Analysis of the Education Domain



Rank	District	Domain Scores
1	Chattogram	1.00
2	Jhalokati	0.89
3	Feni	0.88
4	Chandpur	0.86
5	Comilla	0.85

Top-5 districts according to the score

Rank	District	Domain Score
60	Sherpur	0.38
61	Lakshmipur	0.33
62	Cox's bazar	0.26
63	Bhola	0.70
64	Gaibandha	0.00

Bottom-5 districts according to the score

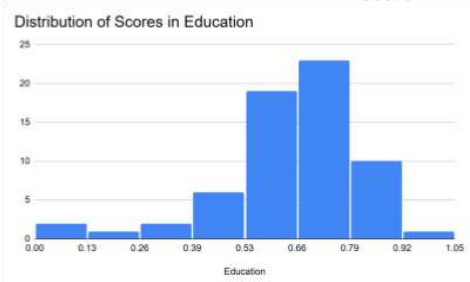
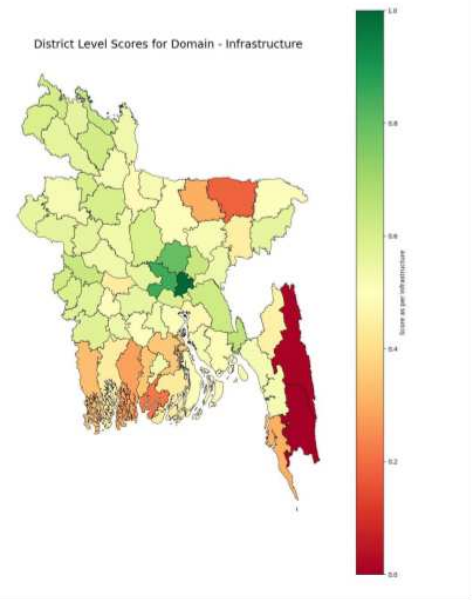


Figure 5: Spatial Distribution and Statistical Profile of the Domain Scores in Education.

The Education dimension, illustrated in Figure 5, exhibits the highest degree of national homogeneity (0.65 ± 0.18), with 81.3% of districts clustering within the average range, suggesting a successful universalization of baseline infrastructure. The regional analysis highlights a distinctive literacy belt in southern regions, comprising Chattogram (1.00), Jhalokati (0.89), and Feni (0.88), where performance is driven by a historical cultural prioritization of education rather than recent urbanization. In contrast, the lowest rankings reveal a severe penalty surrounding riverine regions; districts prone to hydro-geological instability, such as Gaibandha (0.00) and Bhola (0.07), face persistent barriers to infrastructure retention. However, we acknowledge that these insights are currently derived from a single available indicator, necessitating future expansion to include multi-metric indicator data relevant to education.

6.2.4 Analysis of the Infrastructure Domain



Rank	District	Domain Scores
1	Narayanganj	1.00
2	Dhaka	0.85
3	Gazipur	0.79
4	Feni	0.64
5	Narsingdi	0.63

Top-5 districts according to the score

Rank	District	Domain Score
60	Bagerhat	0.28
61	Barguna	0.22
62	Sunamganj	0.19
63	Rangamati	0.01
64	Bandarban	0.00

Bottom-5 districts according to the score

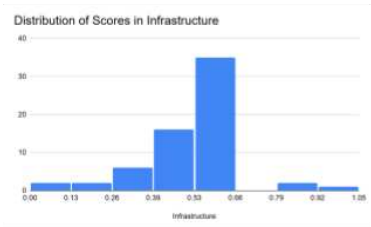


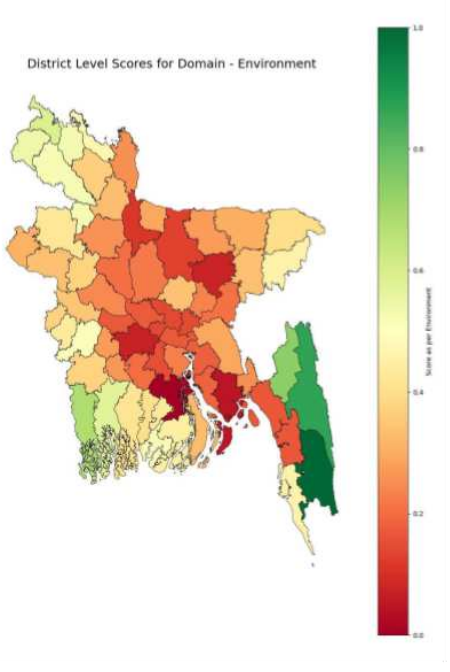
Figure 6: Spatial Distribution and Statistical Profile of the Domain Scores associated with Infrastructure.

The Infrastructure dimension, illustrated in Figure 6, reveals a hyper-centralized development pattern (0.51 ± 0.16), where excellence is confined to a small number of industrially developed regions. Only three districts, Narayanganj (1.00), Dhaka (0.85), and Gazipur (0.79), break the statistical ceiling, though Narayanganj's top rank highlights an inherent bias in Night Time Light (NTL) data toward compact manufacturing zones. While intermediate districts like Feni (0.64) benefit from a logistic corridor effect along national highways, the bottom rankings illustrate that regions that are ecologically blessed are falling behind in terms of industrial development. Geographically constrained regions, including the mountainous Hill Tracts (Bandarban 0.00) and the wetland basins (Sunamganj 0.19), remain structurally isolated due to the prohibitive economic costs of expanding grid infrastructure in rugged or aquatic terrain.

6.2.5 Analysis of the Environment Domain

In Figure 7, we present the scores extracted from analysing the environment domain.

The Environment dimension reveals a generalized national crisis, recording the lowest mean score among all domains (0.34 ± 0.19). With 75% of districts clustering in the low-performing range, high scores are restricted to topographically blessed regions: the Hill Tracts (Bandarban 1.00, Rangamati 0.87) and mangrove-buffered zones (Satkhira 0.68). Conversely, densely populated deltaic districts like Barisal (0.00) exhibit severe ecological deficits. Most significantly, this domain demonstrates a near-perfect inverse correlation with infrastructure. The industrial hubs that dominate physical development are notably absent from the environmental top tier, while geographically isolated districts rank the highest. This quantifies a stark development trade-off**,** indicating that current urbanization models in Bangladesh achieve economic density at the direct expense of ecological integrity.



Rank	District	Domain Scores
1	Bandarban	1.00
2	Rangamati	0.87
3	Khagrachhari	0.74
4	Satkhira	0.68
5	Panchagarh	0.59

Top-5 districts according to the score

Rank	District	Domain Score
60	Jamalpur	0.11
61	Kishoreganj	0.08
62	Faridpur	0.07
63	Noakhali	0.04
64	Barisal	0.00

Bottom-5 districts according to the score

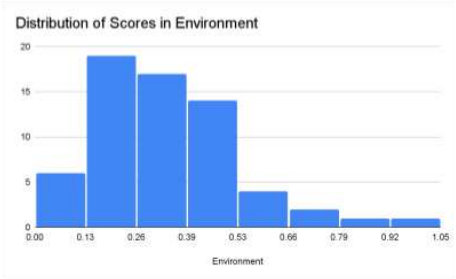


Figure 7: Spatial Distribution and Statistical Profile of the Domain Scores associated with Environment.

6.2.6 Sensitivity Analysis

To evaluate the external validity of the SCIPE index, we benchmarked our composite scores against the 2023 District-level Human Development Index (HDI) (Biggeri et al., 2018). The analysis yields a moderate positive correlation (Pearson r = 0.527, Spearman s = 0.547), establishing convergent validity. The statistical results provide two distinct insights into the index's performance. First, the Pearson correlation (r = 0.527) confirms a linear consistency in magnitude: as the standard of living (HDI) increases, the SCIPE scores generally follow a similar upward trajectory. Complementing this, the Spearman rank correlation (s = 0.547) validates the hierarchical consistency. By ignoring raw values and focusing solely on rank order, the Spearman coefficient confirms that the relative positioning of districts, from best to worst, remains robust across both methodologies. Together, these metrics demonstrate that our hybrid framework, despite leveraging heterogeneous non-traditional data, successfully captures the fundamental signal regarding QoL.

Crucially, the correlation is distinct from unity ($r << 1.0$). This statistical divergence is both expected and desirable, as it quantifies the novel information provided by SCIPE. While the overlap ($r^2 \approx 0.28$) reflects the shared focus on basic welfare, the coefficient of non-determination ($1 - r^2 \approx 72\%$) is of particular significance. This value represents the unexplained variance, the 72% of the SCIPE score that cannot be predicted by the traditional HDI alone (Biggeri et al., 2018). This substantial portion captures the unique socio-environmental dimensions introduced by our framework, specifically because of the integration of the information extracted from different types, including non-traditional data sources. Thus, the SCIPE index does not merely replicate existing economic metrics; it expands the definition of quality of life to include critical spatial and ecological factors that traditional indicators often overlook.

7. Synergies and Trade-offs in District-Level Development

In this section, we offer a correlation study between the individual domains and the composite indicator scores. This analysis is carried out to demonstrate the genuine potential of developing a CI to comprehend the overall status of the country. It is particularly useful for synthesizing how policies concentrating on one domain influence others.

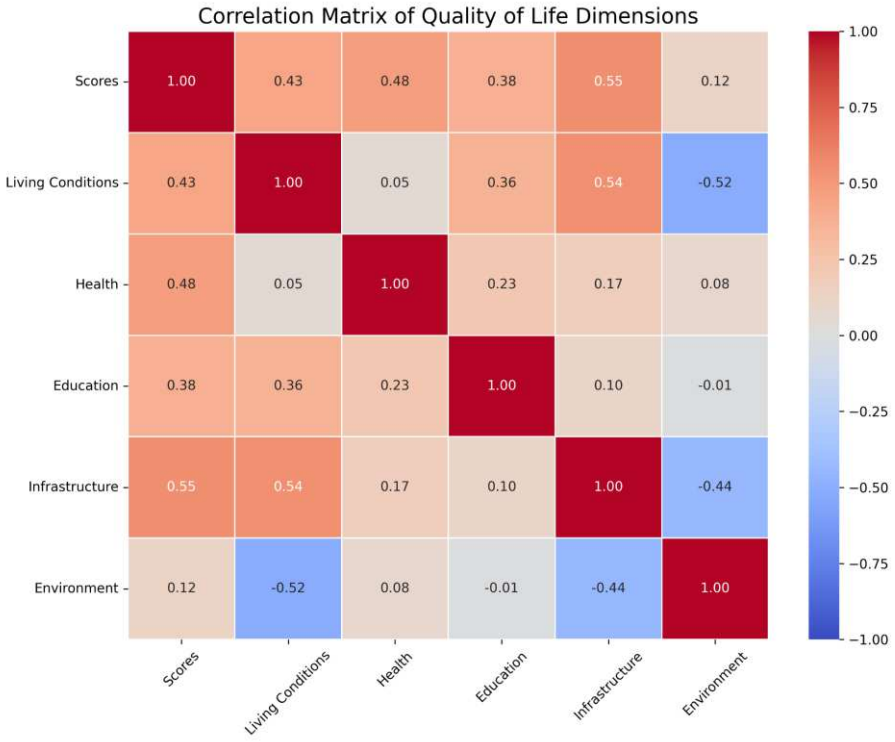


Figure 8: Pearson Correlation Coefficient analysis among the domain variables and SCIPE.

As stated, to elucidate systemic policy interactions, we conducted a Pearson correlation analysis (Figure 8). The results statistically verify a stark development trade-off: the environment dimension correlates negatively with both living conditions ($r = -0.52$) and infrastructure ($r = -0.44$), indicating that current urbanization models achieve high living standards at the direct cost of ecological integrity. Conversely, a strong industrial synergy exists between infrastructure and living conditions ($r = 0.54$), defining industrial hubs like Narayanganj and Dhaka, with infrastructure emerging as the primary driver of the overall composite score ($r = 0.55$). Notably, the health domain operates independently, exhibiting negligible correlation with living conditions ($r = 0.05$) or infrastructure ($r = 0.17$). This disconnection is exemplified by the underperformance of affluent districts like Sylhet, which suggests that health outcomes are driven by non-economic determinants. While we acknowledge that data biases may influence these specific points, warranting future investigation, the overall quantitative patterns align closely with Bangladesh's socioeconomic beliefs, reinforcing the SCIPE's capacity to transform anecdotal beliefs into rigorous evidence.

8. Implementation Roadmap and Institutional Integration for SCIPE

The formulation of SCIPE follows a robust approach with the ease of integrating more domains and corresponding indicators. Our strategy is completely data-driven, avoid of subjective bias. However, it has the feasibility to control weights by varying the penalizing parameter R in Equation (1) or updating the PCA formulation. This section highlights a guideline on the practical implementation of SCIPE within Bangladesh.

8.1 Institutional Roles

The national adoption of SCIPE relies on a robust institutional framework. The GED, as the custodian of national planning, is best positioned to integrate the index into Five-Year Plans and Voluntary National Reviews (VNRs), ensuring political legitimacy (Ravallion, 2012). Simultaneously, the National Statistical Office (NSO) must safeguard statistical integrity by validating sampling frames and arbitrating DSAs with commercial providers. This coordinated governance ensures SCIPE expands its spatial resolution securely (Hickmann et al., 2024) while being fully embedded within Bangladesh's SDG reporting system.

8.2 Forecasted Phased deployment

To ensure operational sustainability, we propose a three-stage deployment roadmap. First, a multi-sector steering committee comprising GED, BBS, and academia should be established to oversee governance. Second, a pilot phase in 2-4 districts is recommended to verify data quality and contextual relevance prior to national scaling (Saisana et al., 2005). Finally, a three-year operationalization phase will formally integrate SCIPE into routine GED planning cycles, cementing its role in long-term evidence-based policy formulation (Lepenies, 2023).

8.3 Validation and Representation

In this section, we present some guidance on the validation, fairness, and governance protocols for a successful implementation of the SCIPE.

Validation step will employ a triangulation strategy: first, internal consistency is verified using directionality tests to ensure logical variable alignment (OECD, 2008), and then external validity is established by forming the results of composite estimates combining curated survey data from the BBS and HIES. The result is further strengthened by sensitivity analysis and case-by-case normative assessments. To achieve fairness and reduce the representational bias inherent in NTD, SCIPE will combine digital footprints with representative survey data (Blumenstock, 2018). Finally, Governance is enforced through a privacy-first architecture involving strict DSAs with providers (World Economic Forum, 2021; OECD, 2024). The BDQOL portal releases only aggregated data, employing techniques like differential privacy to mathematically guarantee citizen anonymity while retaining policy utility.

9. Limitations and Considerations

While the SCIPE offers granular insights, it inherits specific limitations inherent to hybrid indices that require prudent management. The limitations are presented in the context of Bangladesh, which aligns with the limitations existing in other low-resource countries as well. First, the scarcity of synchronized sub-national data necessitated the integration of sources with temporal heterogeneity; although strict normalization protocols minimize statistical distortion, the index remains a locally adapted measure rather than a mirror of all global SDG targets. Second, the reliance on NTD introduces risks of representational bias, particularly where the digital divide may skew signals against marginalized demographics. To counteract this, the methodology prioritizes survey-based calibration and continuous fairness audits to prevent the reinforcement of structural inequities. Finally, the long-term sustainability of the framework hinges on securing stable data pipelines against private provider volatility with a responsible deployment dictating that policymakers must utilize sub-indices and sensitivity diagnostics rather than relying solely on aggregate rankings to avoid reductionist interpretations of well-being.

10. Conclusion

SCIPE represents a paradigm shift for development monitoring in Bangladesh, offering a robust, data-driven alternative to traditional GDP-centric metrics, emphasizing its applicability for low-resource countries. By synthesizing the statistical reliability of official census data with the high-frequency temporal resolution of non-traditional data, the proposed framework successfully operationalizes a multidimensional assessment of QoL. This hybrid approach bridges the critical data gaps identified in national SDG monitoring, demonstrating that granular, responsive measurement is achievable even within the constraints of a low-resource setting.

Beyond methodological innovation, the analysis underscores the framework's practical utility in uncovering spatial disparities. By disaggregating development outcomes to the district level, SCIPE exposes regional inequalities that

are frequently masked by national averages. The resulting indicator translates complex multidimensional data into intuitive, actionable intelligence, making the insights accessible to a broad spectrum of stakeholders, from central planners in the capital to field-level administrators in remote districts. This capability is crucial for identifying lagging regions and ensuring that development interventions are geographically targeted.

SCIPE is designed with inherent transferability for other LMICs facing similar data situations (Jerven, 2013). For instance, Pakistan shares Bangladesh's hydro-geological vulnerabilities and a history of census irregularity, which has a notable 19-year gap between 1998 and 2017, and could utilize SCIPE to monitor flood-prone districts in real-time (Goujon & Wazir, 2020). Similarly, Nigeria, grappling with rapid urbanization amidst a decades-long census gap since 2006, can use SCIPE (World Bank, 2022) to track both the progressing and failing domains.

To ensure long-term viability, this study outlines a clear implementation roadmap moving beyond the theoretical model. We propose a structured pipeline for piloting, refining, and eventually institutionalizing the index within the GED and the BBS. Central to this deployment, there also lies a commitment to strong data governance, transparency, and continuous fairness audits, which are essential for maintaining public trust and statistical integrity. Ultimately, SCIPE is positioned to become a vital instrument for evidence-based governance. By aligning with national priorities, the framework offers a scalable mechanism to guide Five-Year Plans, strengthen VNRs, and accelerate Bangladesh's journey toward inclusive, equitable, and sustainable well-being for all citizens.

11. Statements and Declarations

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. All the data sources used in this manuscript has been addressed with proper citations in respective sections.

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