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Balancing Growth and Green: Urban Economic Development and Environmental Sustainability in India

Nicole Dsilva[1,2]

[1] IES's Management College and Research Centre, Mumbai 400050, India
[2] Jamnalal Bajaj Institute of Management Studies, Mumbai 400020, India

Corresponding Author Email: prof@nicoledsilva.com

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ABSTRACT

Rapid urbanization in India has spurred significant economic growth. However, this expansion often raises concerns about environmental sustainability. This study examines the relationship between economic output, environmental conditions, and human development across 22 diverse Indian cities. We measure economic performance using city-level GDP for FY 2022–23. Environmental quality is proxied by the Normalized Difference Vegetation Index (NDVI) from 2024 Landsat 8 imagery. To measure sustainability more accurately, we also incorporated Air Quality Index (AQI) and the Human Development Index (HDI). The study employs an Ordinary Least Squares (OLS) regression with a log-linear specification. The natural logarithm of GDP serves as the dependent variable for the 22-city dataset. We introduced logarithmic transformations, interaction effects, and nonlinear terms to address scale differences and moderation effects. For valid inference, we used heteroskedasticity- and autocorrelation-consistent (HAC) standard errors. The resulting model explains a moderate share of economic variation (R^2 = 0.465) and is jointly significant (F-statistic = 4.129, p = 0.013). At a 15% significance level, the interaction between HDI and air pollution provides suggestive evidence of a moderation effect. Higher levels of human development may help mitigate the negative economic impacts of poor air quality. Additionally, nonlinear NDVI terms indicate diminishing economic returns to urban greenness beyond certain thresholds. This highlights a critical trade-off between land-use intensity and ecological preservation. Descriptive data further reveal that while major metros often have lower vegetation cover, several mid-sized cities maintain a more balanced profile of growth and environment. Overall, findings suggest that environmental decline is not an inevitable result of growth. Instead, sustainability is shaped by urban development patterns and institutional capacity. This study emphasizes the need to integrate environmental and human development indicators into urban planning frameworks for rapidly urbanizing economies.

1. INTRODUCTION

Cities in India account for a disproportionate share of national economic output despite occupying limited land area. This pattern is consistent with global urbanization trends. Urban growth puts pressure on the environment. Infrastructure and commercial projects often win the competition for limited green space. This competition is increasingly viewed as a global trade-off. Recent assessments show that urban economic expansion occurs at the expense of the environment, leading to a net loss in ecological value unless growth is strictly coupled with green infrastructure mandates [1]. This reflects a growing need to transition from expansion-led growth to sustainability-oriented urban forms. India faces two urgent goals: growing its economy to create jobs, and protecting the nature that makes its cities livable in the long run.

A widely used proxy for assessing ecological health is the Normalized Difference Vegetation Index (NDVI) which is derived from satellite imagery. NDVI allows researchers to quantify the extent to which economic expansion is associated with changes in urban greenery. India's cities generate over half the nation's Gross Domestic Product (GDP). There are concerns that this growth correlates with significant vegetation loss and degraded environmental conditions.

Despite the importance of this relationship, two major gaps remain in the current literature. First, most studies focus on single-city cases (e.g., Delhi) or broad national summaries, leaving a lack of cross-city comparisons. Second, city-level economic data in India is often fragmented, leading to methodological inconsistencies. The present study addresses these gaps by examining a diverse sample of 22 Indian cities using a standardized proportional estimation method for GDP alongside high-resolution Landsat 8 imagery from 2024.

This study analyzes the relationship between city-level GDP and NDVI, using Air Quality Index (AQI) and Human Development Index (HDI) as additional indicators. The goal is to determine if high economic output consistently leads to lower urban greenness. Identifying where these trade-offs are critical is vital for informing policy interventions for India's future development. Additionally, this analysis is in line with the United Nations Sustainable Development Goals (SDGs), especially SDG 11 (Sustainable Cities and Communities), by highlighting the interconnected nature of economic growth, environmental health, and human welfare.

2. LITERATURE REVIEW

2.1 Urbanization, Gross Domestic Product, and environmental trade-offs

Urbanization is widely recognized as a catalyst for economic growth, contributing to increased productivity, industrial diversification, and labor market agglomeration [2]. In developing countries like India, cities now account for more than half of the national GDP, even though they occupy a relatively small land area [3]. However, this economic expansion frequently comes with environmental costs, especially the conversion of green or agricultural lands into built-up areas. These tensions are known as "environment–development trade-offs." These occur when short-term economic policies overshadow the natural services that make cities livable [4, 5].

Empirical findings suggest that higher GDP is associated with increased resource consumption, pollution, and habitat loss unless effective environmental regulations are in place [6, 7]. For instance, in rapidly growing metropolitan regions, manufacturing and service industries may drive economic output while simultaneously accelerating deforestation and degrading local air quality. These patterns reinforce the need to examine whether Indian cities can balance economic dynamism with ecological stewardship, especially given the projected urban population surge in the coming decades [8, 9]. Recent empirical work reinforces this concern, showing that in many rapidly growing cities, economic expansion continues to place pressure on urban green spaces unless environmental considerations are deliberately integrated into development planning [10-13].

Classic work on the growth–environment relationship suggests that environmental outcomes may initially worsen with income growth before improving at higher income levels, though empirical support varies across pollutants and contexts [14, 15].

2.2 Normalized Difference Vegetation Index as an indicator of urban vegetation

The NDVI has emerged as a key metric for quantifying vegetation in urban environments [16, 17]. It is calculated from satellite data, and it is typically red and near-infrared reflectance. NDVI ranges from −1 to +1, with higher values indicating denser or healthier vegetation [17]. In the Indian context, NDVI helps detect declines in vegetative cover resulting from infrastructure development, industrialization, and population pressures [18]. In the National Capital Region, satellite-derived indicators including NDVI have been used to quantify environmental changes associated with rapid urbanization [19]. Compared to other environmental indicators, NDVI provides a spatially explicit, consistent way to monitor green areas across cities with different geographical and climatic conditions [20]. Satellite-derived vegetation indices such as NDVI are widely employed to approximate urban ecosystem services, including micro-climate regulation, air purification, and resilience to environmental stressors [21, 22]. Recent remote-sensing studies suggest that changes in urban greenness reflect a combination of land-use decisions and economic activity, rather than being driven by vegetation dynamics alone, particularly in fast-growing cities [23, 24].

Studies applying NDVI in Indian cities reveal that megacities like Delhi, Mumbai, and Bengaluru exhibit sharp drops in vegetative cover over the past two decades, reflecting the pace of urban expansion [25]. Evidence from Mumbai shows substantial conversion of dense vegetation and shrinking green space over multi-decadal periods, consistent with NDVI-based indicators of vegetation loss [26]. By contrast, some planned cities or those with stringent land-use regulations—Chandigarh, for example—show comparatively moderate NDVI declines [27]. As such, NDVI not only serves as a diagnostic tool for ecological well-being, but it also highlights the heterogeneity of environmental outcomes under different governances. Beyond vegetation measurement, NDVI is increasingly used as a proxy for urban ecosystem services and sustainability outcomes [20], particularly in rapidly urbanizing regions of the Global South [28].

2.3 Additional urban sustainability indicators

While NDVI offers a robust snapshot of green cover, other urban sustainability indicators provide complementary insights into environmental health and socio-economic well-being. The AQI, for instance, measures levels of pollutants like particulate matter ($PM_{2.5}$) and nitrogen dioxide (NO_2) [29]. In industrialized or congested cities, AQI often deteriorates alongside rising GDP, adversely affecting public health and productivity [4]. Air pollution trends in Indian megacities and their ramifications have been documented in the peer-reviewed literature [30]. Urban green spaces have been shown to mitigate air pollution exposure and associated health risks, reinforcing the role of vegetation as a critical component of environmentally sustainable cities [31].

Another metric is the HDI, which integrates dimensions of education, life expectancy, and per capita income [32]. While higher HDI can coincide with increased economic output, it does not inherently guarantee ecological protection. Indeed, cities boasting high incomes may neglect green infrastructure if policy frameworks do not explicitly give priority to sustainability [28, 33]. A well-rounded urban sustainability assessment, therefore, includes NDVI, AQI, and HDI to capture the relationship between economic growth, environmental health, and human welfare [34]. Evidence suggests that cities with higher human development are better at buffering the impacts of air pollution. This resilience stems from adaptive capacity, governance quality, and technological mitigation, rather than through income alone [35, 36]. Integrating environmental, economic, and social indicators is increasingly recognized as essential for evaluating urban sustainability, as single-dimension metrics often fail to capture trade-offs inherent in urban development processes [37].

2.4 Research gap and study rationale

Although various researchers have explored the links between urbanization, GDP, and the environment in India, two main gaps persist. First, much of the literature focuses on either a single-city case study (e.g., analyzing Delhi's loss in

NDVI) or broad national summaries that overlook city-level specifics. We lack broad comparisons between cities. Most studies either focus on a single city or give a general national summary [4, 18, 38]. Second, city-level GDP data can be patchy, leading to methodological inconsistencies or reliance on proxy measures. While existing studies document vegetation loss or pollution trends, fewer studies integrate economic output with spatial vegetation indicators across multiple Indian cities, particularly within broader sustainability frameworks [20, 28]. In many rapidly urbanizing cities of the Global South, access to green infrastructure is unevenly distributed, reflecting governance failures and reinforcing socio-environmental inequalities despite rising aggregate economic output [39].

Policy and practice constraints around urban greening in India have been systematically reviewed, emphasizing implementation challenges and governance trade-offs [40]. Addressing these gaps, this study assesses whether higher GDP levels systematically correlate with lower NDVI across a diverse sample of Indian cities, simultaneously controlling for AQI and HDI where reliable data permit. The rationale is to glean insights on how urban economic expansion intersects with greenery and broader sustainability indicators, thereby informing whether India's growth trajectory can be steered toward more ecologically resilient outcomes. Such an analysis is vital for policymakers, urban planners, and environmental stakeholders seeking to balance economic imperatives with the preservation of green infrastructure in India's fast-growing metropolitan hubs [41].

2.5 Research objectives

To align with the reviewer's request to avoid causal language, the objectives are refined as follows:

1) To examine the statistical association between city-level GDP and NDVI, determining whether higher economic output correlates with lower urban greenness.
2) To assess how additional factors like AQI and HDI are related to this environment–economy trade-off.
3) To identify regional variations in the NDVI–GDP correlation across major Indian cities.
4) To develop and compare unweighted and environment-weighted sustainability indices that integrate economic and environmental metrics.

3. RESEARCH METHODOLOGY

3.1 City selection

We selected twenty-two major Indian cities spanning six geographic regions—North, West, Central, South, East, and Northeast—to capture variations in economic growth patterns and climatic conditions [3]. Cities such as Delhi, Mumbai, and Bengaluru represent high-GDP metros, while others like Bhubaneswar, Guwahati, and Gangtok give insights into smaller or regionally significant urban hubs. Some cities, including Mangalore and Aurangabad, had to be excluded because their GDP data was unavailable or incomplete [38]. The selected cities and their regional grouping are presented in Table 1.

Table 1. Selected Indian cities included in the study, grouped by geographic region

Region	Cities
North India	Delhi, Jaipur, Chandigarh, Kanpur, Varanasi, Srinagar
West India	Mumbai, Pune
Central India	Nagpur, Bhopal
South India	Bengaluru, Chennai, Hyderabad, Kochi, Visakhapatnam, Vijayawada
East India	Bhubaneswar, Kolkata, Dhanbad, Siliguri
Northeast India	Guwahati, Aizawl, Gangtok

3.2 Data sources

This study collected data from multiple credible and official sources to analyze the relationship between economic expansion and environmental health in major Indian cities. The four primary indicators used include GDP, NDVI, AQI, and HDI. This section elaborates on the data sources and the methodology used to estimate city-level data where direct sources were unavailable.

3.2.1 Gross Domestic Product

City-level GDP data was obtained from state economic surveys and reports by state planning departments and directorates of economics and statistics. However, for several cities, direct GDP data was not available. In such cases, a proportional estimation method was used based on each city's economic contribution to its state's economy. In the absence of consistent city-level GDP data, proportional estimation approaches are commonly adopted in urban economic research [38].

For cities with no published GDP, an estimation method was applied. The state's Gross State Domestic Product (GSDP) for FY 2022–23 was used as the baseline. We estimated each city's economic contribution based on its industrial and commercial significance. This is often expressed as a percentage of the state's GSDP. These sources include economic surveys and statistical abstracts from the governments of Maharashtra, Rajasthan, Karnataka, and other relevant states for FY 2022–23. A detailed breakdown of the city-level GDP values (Table A1), their classification and construction basis (Table A2), and the official government sources (Table A3) is provided in the Appendix.

When direct GDP data for cities was missing, the following formula was applied:

$$\text{City GDP} = \text{State GSDP} \times \text{City Contribution Percentage} \quad (1)$$

For example:

Rajasthan's GSDP in FY 2022–23 was ₹13.03 trillion.

Jaipur's estimated contribution was 15.5% of Rajasthan's GSDP.

Therefore, Jaipur's GDP = 15.5% × ₹13.03 trillion = ₹2.02 trillion.

Subsequently, GDP per capita was calculated. Population data was sourced from the 2011 Census and updated using projected urban growth rates.

$$\text{GDP per Capita} = \frac{\text{City GDP}}{\text{City Population}} \quad (2)$$

Currency Conversion:

All GDP figures were converted to USD using the average exchange rate of ₹79.0 per US dollar for FY 2022–23 (Reserve Bank of India, 2023).

The estimation assumes uniform population growth rates based on historical data projections and consistent economic contribution percentages derived from district-level data. City boundaries were treated as consistent with administrative districts unless specified.

3.2.2 Normalized Difference Vegetation Index

Landsat 8 imagery for April–May 2024 was downloaded via Google Earth Explorer. The use of Level-2 (surface reflectance) data minimized atmospheric distortions [17]. Google Earth Engine, a cloud-based platform designed for large-scale geospatial analysis [42], was used to process imagery and compute NDVI values.

Cloud Masking: Scenes exceeding 10% cloud cover in the urban area of interest were excluded, and the relevant pixels for each city were carefully masked using shapefiles provided by municipal or open-source GIS repositories [18].

Mean NDVI: For each city, we calculated a single average NDVI value by aggregating pixel-level NDVI inside its administrative boundary [25].

3.2.3 Air Quality Index

AQI data (annual average) were obtained from Central Pollution Control Board (CPCB) bulletins, where higher AQI indicates poorer air quality [29].

3.2.4 Human Development Index

HDI figures were taken from state-level or city-specific reports compiled by the United Nations Development Programme [UNDP] [32], combining education, life expectancy, and per capita income indicators.

3.3 Analytical framework

Correlation-based exploratory analyses are commonly used in urban environmental research to identify structural associations between economic intensity and ecological indicators prior to causal or spatial modeling [43, 44]. Given the relatively small sample size (n = 22), a simple bivariate analysis was conducted to investigate whether NDVI, HDI and AQI correlate with city-level GDP:

$$\ln(\mathrm{GDP}) = \beta_0 + \beta_1\,\mathrm{HDI} + \beta_2 \ln(\mathrm{AQI}) + \beta_3\,\mathrm{NDVI} + \beta_4\,\mathrm{NDVI}^2 + \beta_5\left(\mathrm{HDI} \times \ln(\mathrm{AQI})\right) + \varepsilon \quad (3)$$

To improve interpretability and avoid statistical issues, several standard transformations were applied. GDP and AQI were log-transformed to deal with skewness and to capture nonlinear effects. The variables were then mean-centered before creating interaction and squared terms so that the coefficients could be interpreted more clearly and multicollinearity could be reduced. A quadratic NDVI term was added to account for the possibility that the economic effects of urban greenness change at different levels of vegetation cover.

An Ordinary Least Squares (OLS) regression was run, supplemented by Pearson correlation to gauge the direction and strength of any linear relationship [45, 46].

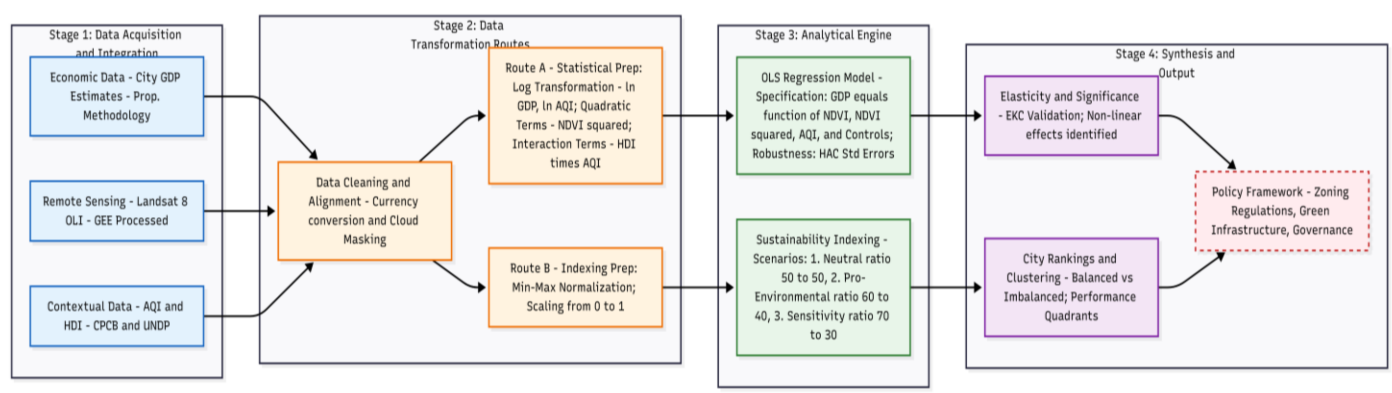

Figure 1. Analytical workflow

Figure 1 presents the analytical workflow adopted in this study, illustrating the integration of economic, environmental, and contextual indicators through data transformation, exploratory statistical modeling, and spatial analysis. The framework outlines how city-level GDP, NDVI, and supplementary sustainability indicators are processed to examine environment–economy trade-offs, generate sustainability rankings, identify balanced and imbalanced cities, and inform policy recommendations. The diagram represents a procedural flow of analysis rather than a causal model.

3.4 Correlation analysis

Given the limited sample size (n = 22) and the exploratory nature of this research, simple correlation measures were used to assess the associations between NDVI, GDP, AQI, and HDI.

3.5 Sustainability scoring for cities

3.5.1 Normalization (min–max)

We first rescaled each city's NDVI and GDP (Billion USD) to a 0–1 scale using a standard min–max formula:

$$\mathrm{X\_Score} = \frac{\mathrm{X} - \min(\mathrm{X})}{\max(\mathrm{X}) - \min(\mathrm{X})} \quad (4)$$

where, *X* is the original variable (either NDVI or GDP), and *X_Score* is the normalized value in the range [0, 1]. This ensures scores are comparable, with 0 representing the lowest observed value and 1 the highest.

3.5.2 Unweighted sustainability score

We created an unweighted sustainability index by taking the mean of each city's NDVI_Score and GDP_Score:

$$\text{Sustainability\_Score} = \frac{\text{NDVI\_Score} + \text{GDP\_Score}}{2} \quad (5)$$

Cities are then ranked from highest to lowest based on this composite measure.

3.5.3 Environment-weighted score

To emphasize environmental health, we assigned a 60% weight to NDVI_Score and 40% weight to GDP_Score:

$$\text{Sustainability\_Score\_Env\_Weighted} = w_e \cdot \text{NDVI\_Score} + w_g \cdot \text{GDP\_Score} \quad (6)$$

For example, if $w_e = 0.6$ and $w_g = 0.4$

$$\text{Sustainability\_Score\_Env\_Weighted} = 0.6 \cdot \text{NDVI\_Score} + 0.4 \cdot \text{GDP\_Score} \quad (7)$$

The environment-weighted sustainability score assigns 60% weight to NDVI and 40% weight to GDP. This ensures that environmental health is the primary factor when measuring a city's success and cities are not ranked as "sustainable" solely because of large economic size.

The choice of a 60:40 split follows established practice in widely used sustainability indices. For example, the Environmental Performance Index (EPI) assigns greater weight to ecosystem conditions (60%) than to short-term pressures (40%), reflecting the view that long-term environmental integrity is a necessary foundation for sustainable development.

In the context of Indian cities, where large metropolitan economies often exhibit lower vegetation cover, placing greater weight on NDVI allows the index to better capture trade-offs between economic growth and ecological resilience. Because weighting choices are inherently normative, we also examine alternative weight combinations (50:50 and 70:30) to ensure that the overall ranking patterns are not driven by a single specification. Using multiple weighting schemes is consistent with recent work on urban sustainability indices, which recommends sensitivity checks to ensure that rankings are not driven by a single normative assumption [23].

if $w_e = 0.7$ and $w_g = 0.3$

$$\text{Sustainability\_Score\_70\_30} = 0.7 \cdot \text{NDVI\_Score} + 0.3 \cdot \text{GDP\_Score} \quad (8)$$

3.5.4 Ranking and interpretation

Both scores were used to rank cities from most to least "sustainable" under each scenario. While the unweighted version treats economic output and vegetation equally, the weighted version highlights the importance of green cover in shaping sustainability outcomes.

3.6 Assumptions and limitations

This study acknowledges several assumptions and limitations that may influence the interpretation of its findings.

3.6.1 Assumptions

City GDP estimates assume proportional economic contributions remain consistent year over year, based on industrial output and urban economic roles.

Population estimates rely on projections from Census 2011 data, adjusted for annual growth without accounting for recent migration trends.

NDVI and AQI data reflect the most recent available periods (2024 for NDVI, 2022–23 for AQI) and are assumed representative despite temporal mismatch with GDP data. Temporal alignment of environmental and economic indicators.

This study employs NDVI data from April–May 2024 alongside GDP data for FY 2022–23, resulting in a deliberate temporal mismatch between environmental and economic indicators. Environmental economics suggests that ecological changes shape economic outcomes with a time lag. For instance, environmental conditions influence productivity and health over future periods rather than instantly [12, 13, 24]. Accordingly, NDVI is treated as a leading indicator of environmental conditions, while GDP reflects the downstream economic expression of prior urban development trajectories.

The exchange rate used for currency conversion is an annual average for FY 2022–23.

3.6.2 Limitations

Proportional contribution-based GDP estimations may oversimplify intra-district economic variability.

Additionally, while NDVI effectively measures vegetative 'greenness,' it does not distinguish between different types of land cover, such as monoculture lawns, agricultural land, or high-biodiversity natural forests, which may provide varying levels of ecosystem services.

Variations in data quality and reporting standards across states introduce inconsistencies in HDI and AQI datasets.

The limited sample of cities (n = 22) restricts generalizability across all Indian urban centers.

Despite these constraints, the study offers a starting point for understanding how urban economic expansion intersects with the maintenance (or loss) of greenery in India's diverse urban settings.

4. RESULTS AND DISCUSSION

4.1 Normalized Difference Vegetation Index comparisons of cities

Figure 2 presents spatial distributions of the NDVI derived from Landsat 8 imagery for selected Indian cities. Higher NDVI values (green shades) indicate denser vegetation cover, while lower values (yellow to red shades) reflect sparse or built-up areas. The heatmaps highlight intra-city variation in urban greenness and provide a spatial basis for comparing environmental conditions across cities.

1). Overall Vegetation Patterns

Most cities display a predominantly greenish hue (NDVI around 0.15–0.35), suggesting moderate vegetation coverage across urban cores and peripheral areas. These observed vegetation patterns align with contemporary geospatial evaluations in specific Indian metropolitan hubs, such as Gandhinagar, where a measurable inverse relationship exists between increasing built-up intensity and the preservation of urban greenness [47].

Cities like Chandigarh and Gangtok appear to have larger patches of higher NDVI, reflecting planned greenery (Chandigarh) or natural forested/mountainous terrain (Gangtok).

2). Built-Up Versus Peripheral Areas

In many panels (e.g., Mumbai, Bengaluru, Kanpur), the urban core appears somewhat lighter, indicating lower NDVI (denser construction and fewer green patches).

Suburban or peri-urban zones often show deeper greens where vegetation or agricultural land persists.

3). Regional Contrasts

Hill/Valley Cities (Srinagar, Gangtok) tend to have higher NDVI in surrounding mountainous areas, though the city center's vegetation can vary.

Coastal/Plains Cities (Kochi, Chennai) exhibit a more uniform coverage but may have pockets of higher vegetation near wetlands or reserved forests.

4). Implications for Urban Sustainability

These maps visually confirm that urban expansion can reduce continuous green coverage, highlighting the need to balance development and ecological spaces.

Comparing relative NDVI across cities provides a baseline for further correlation with GDP, AQI, and HDI, providing perspective into whether economic and social factors align with preservation of green infrastructure.

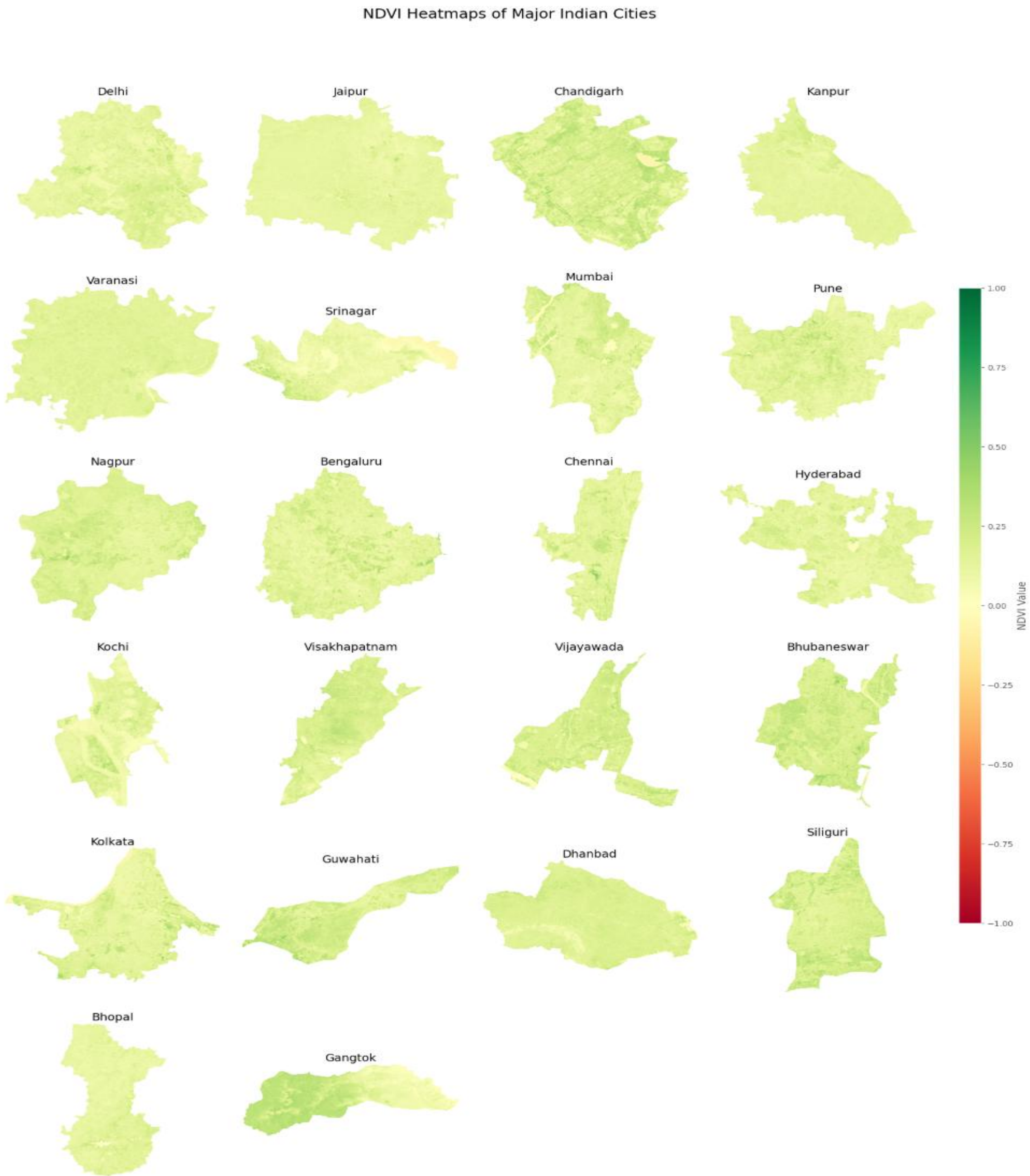

Figure 2. Normalized Difference Vegetation Index (NDVI) heatmaps of selected major Indian cities (April–May 2024)

4.2 Ordinary Least Squares regression results: NDVI, HDI and AQI as predictors of city-level GDP

Figure 3 and Eq. (9) presents the OLS regression results examining the relationship between economic output, human development, and environmental conditions across Indian cities. The dependent variable is the natural logarithm of GDP. The explanatory variables are HDI, air pollution measured by the log of the AQI, urban greenness proxied by NDVI and its squared term, and an interaction term between HDI and pollution.

The model demonstrates moderate explanatory power, with an R^2 of 0.465 and an adjusted R^2 of 0.298. Our model uses several complex terms for only 22 cities. This complexity explains why the "adjusted" R^2 is lower, but the model itself remains valid. The overall model is jointly significant (F-statistic = 4.129, p = 0.0134). This indicates that the explanatory variables together explain a meaningful portion of the variation in economic output.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 ln_gdp   R-squared:                       0.465
Model:                            OLS   Adj. R-squared:                  0.298
Method:                 Least Squares   F-statistic:                     4.129
Date:                Thu, 08 Jan 2026   Prob (F-statistic):             0.0134
Time:                        21:34:54   Log-Likelihood:                -27.434
No. Observations:                  22   AIC:                             66.87
Df Residuals:                      16   BIC:                             73.41
Df Model:                           5
Covariance Type:                  HAC
================================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
const         14.7724     14.206      1.040      0.298     -13.071      42.616
hdi          -21.4189     17.425     -1.229      0.219     -55.572      12.734
ln_aqi        -4.0582      2.974     -1.364      0.172      -9.888       1.771
NDVI          52.8831     39.832      1.328      0.184     -25.186     130.953
ndvi_sq     -203.8107    138.292     -1.474      0.141    -474.859      67.238
hdi_x_ln_aqi   5.9101      3.811      1.551      0.121      -1.559      13.380
==============================================================================
Omnibus:                        2.068   Durbin-Watson:                   0.877
Prob(Omnibus):                  0.356   Jarque-Bera (JB):                1.128
Skew:                          -0.160   Prob(JB):                        0.569
Kurtosis:                       1.937   Cond. No.                     5.25e+03
==============================================================================
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Figure 3. Regression results

$$\ln(\mathrm{GDP}) = 14.7724 - 21.4189\,(\mathrm{HDI}) - 4.0582\ln(\mathrm{AQI}) + 52.8831\,(\mathrm{NDVI}) - 203.8107\,(\mathrm{NDVI}^2) + 5.9101\,(\mathrm{HDI}\times\ln(\mathrm{AQI})) + \varepsilon \quad (9)$$

At the individual coefficient level, statistical significance is evaluated at a 15% level of significance, consistent with exploratory empirical analyses involving small samples and robust standard errors. Under this criterion, the interaction term between HDI and log(AQI) is statistically significant (p = 0.121), providing evidence that the economic impact of air pollution varies with the level of human development. The positive interaction coefficient shows that cities with higher human development are more resilient. These cities are better able to reduce the negative economic impacts of poor air quality.

The squared NDVI term is also marginally significant at the 15% level (p = 0.141), indicating a nonlinear relationship between urban greenness and economic output. The positive linear NDVI coefficient combined with a negative quadratic term implies diminishing economic returns to additional vegetation beyond a certain threshold. The nonlinear NDVI terms show that economic returns to urban greenness diminish beyond certain thresholds. This suggests a trade-off between land-use intensity and ecological preservation. These findings align with recent evidence of 'inverse-U' effects in urban performance [48, 49]. While these effects are estimated with limited precision, their signs are in line with theoretical expectations regarding land-use trade-offs in urban environments.

The main effects of HDI and log(AQI) are not statistically significant when interpreted independently, which is expected in the presence of an interaction term. In such models, the marginal effects of HDI and pollution are conditional on each other, and standalone coefficient tests do not fully capture their economic relevance.

Diagnostic tests indicate no serious violations of model assumptions. The Jarque–Bera statistic fails to reject normality of residuals, and heteroskedasticity- and autocorrelation-consistent (HAC) standard errors are employed to ensure valid inference. Although the condition number is relatively high, this is attributable to the inclusion of interaction and polynomial terms and does not undermine the overall validity of the results.

Overall, the findings provide suggestive evidence that human development moderates the economic costs of environmental degradation and that the relationship between urban greenness and economic output is nonlinear. Given the exploratory nature of the analysis and the limited sample size, these results should be interpreted with caution and viewed as indicative rather than conclusive.

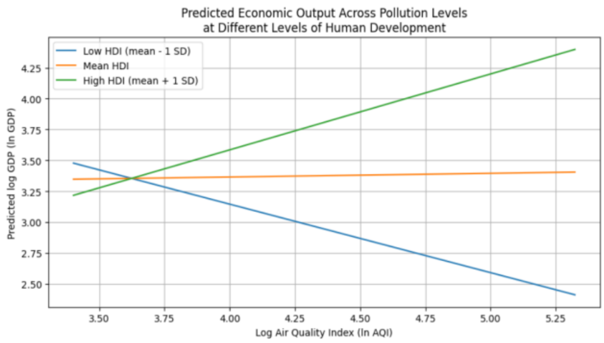

Figure 4. Predicted relationship between air pollution and economic output at different levels of human development

Figure 4 illustrates the predicted relationship between air pollution and economic output at different levels of human development, based on the estimated OLS model with interaction effects. The figure reveals clear heterogeneity in how pollution is associated with economic performance across cities.

For low-HDI cities, higher levels of air pollution are associated with a decline in predicted economic output, as indicated by the downward-sloping line. In contrast, cities with average HDI exhibit a relatively flat relationship, suggesting that moderate levels of human development partially buffer the economic consequences of worsening air quality. Especially, for high-HDI cities, the predicted relationship between pollution and economic output becomes positive. This shows that cities keep growing and add to environmental stress.

This divergence in slopes highlights the moderating role of human development in shaping the economic impact of environmental degradation. Rather than exerting a uniform effect, air pollution interacts with development conditions to produce markedly different economic outcomes. These visual patterns align with the regression results, which show suggestive significance of the HDI–pollution interaction at the 15% level, and reinforce the importance of accounting for conditional relationships in urban sustainability analysis.

4.2.1 Sensitivity check excluding cities with estimated GDP

The analysis was also re-estimated after excluding Siliguri and Gangtok. For these two cities, GDP figures were derived using estimated urban shares due to the absence of officially reported city-level GDP data. Since these estimates may introduce additional uncertainty, the model was rerun without them as a sensitivity check.

The results remain broadly similar to the main specification. The overall model continues to be statistically significant, and the direction and relative size of the coefficients are unchanged. This suggests that the findings are not driven by the inclusion of cities with estimated GDP values. The regression output for this robustness check is presented in Figure 5.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 ln_gdp   R-squared:                       0.436
Model:                            OLS   Adj. R-squared:                  0.235
Method:                 Least Squares   F-statistic:                     5.019
Date:                Mon, 19 Jan 2026   Prob (F-statistic):            0.00766
Time:                        14:24:53   Log-Likelihood:                -24.648
No. Observations:                  20   AIC:                             61.30
Df Residuals:                      14   BIC:                             67.27
Df Model:                           5
Covariance Type:                  HAC
================================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
const         11.9964     15.625      0.768      0.443     -18.629      42.622
hdi          -15.0737     20.495     -0.735      0.462     -55.243      25.096
ln_aqi        -3.3610      3.293     -1.021      0.307      -9.816       3.094
NDVI          40.0504     37.739      1.061      0.289     -33.917     114.017
ndvi_sq     -153.7183    136.557     -1.126      0.260    -421.365     113.929
hdi_x_ln_aqi   4.6397      4.252      1.091      0.275      -3.694      12.974
==============================================================================
Omnibus:                        0.890   Durbin-Watson:                   1.201
Prob(Omnibus):                  0.641   Jarque-Bera (JB):                0.760
Skew:                          -0.427   Prob(JB):                        0.684
Kurtosis:                       2.573   Cond. No.                     5.16e+03
==============================================================================
```

Figure 5. Regression results for the sensitivity check

4.3 Correlation analysis

The pairwise relationships between the key variables are illustrated in Figure 6.

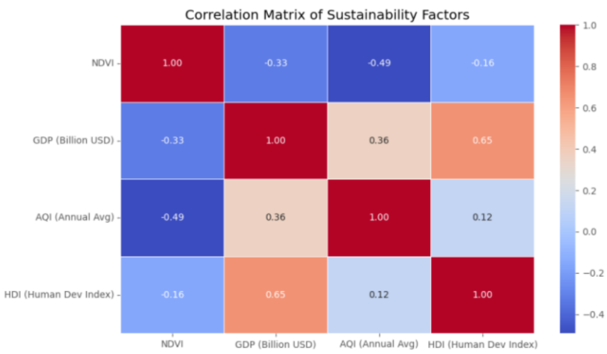

Figure 6. Correlation matrix of key sustainability indicators across selected Indian cities

- NDVI and GDP (−0.33):

Negative correlation implies cities with higher vegetation (NDVI) often report lower total GDP in this sample, suggesting a potential trade-off between economic expansion and green cover.

- NDVI and AQI (−0.49):

A relatively strong negative relationship indicates that cities with more extensive vegetation tend to have better air quality (lower AQI scores), consistent with the idea that green spaces can help mitigate pollution [4].

- NDVI and HDI (−0.16):

Weak, negative correlation suggests no strong linkage between overall human development and vegetation coverage. High-HDI cities may or may not preserve green areas, pointing to other socio-economic factors at play [28].

- GDP and AQI (+0.36):

A moderate positive correlation suggests that more economically developed cities in this dataset often have higher AQI (poorer air quality). Rapid industrialization and increased vehicle emissions could be contributing factors [30].

- GDP and HDI (+0.65):

A notable positive relationship indicates that wealthier cities generally exhibit higher HDI, reflecting better infrastructure, healthcare, and education. However, this doesn't guarantee parallel improvements in environmental metrics [32].

- AQI and HDI (+0.12):

A small positive correlation implies no strong direct link between air quality and human development in this sample. Some high-HDI metros still suffer pollution, while lower-HDI regions may maintain relatively cleaner air due to less industrial activity.

4.4 Sustainability scores

The comparative sustainability rankings under different weighting schemes are shown in Figure 7.

City	NDVI	GDP (Billion USD)	NDVI_Score	GDP_Score	Sustainability_Score	Sustainability_Score_Env_Weighted	Sustainability_Score_70_30
Mumbai	0.141758	171.00	0.428142	1.000000	0.714071	0.656885	0.599699
Bhubaneswar	0.212900	23.20	1.000000	0.116029	0.558014	0.646411	0.734809
Guwahati	0.204262	10.00	0.930564	0.037081	0.483823	0.573171	0.662519
Bengaluru	0.146737	118.00	0.468161	0.683014	0.575588	0.554103	0.532617
Vijayawada	0.190809	22.00	0.822422	0.108852	0.465637	0.536994	0.608351
Siliguri	0.197810	7.00	0.878701	0.019139	0.448920	0.534876	0.620832
Gangtok	0.196985	4.40	0.872065	0.003589	0.437827	0.524674	0.611522
Chennai	0.149085	96.20	0.487034	0.552632	0.519833	0.513273	0.506713
Visakhapatnam	0.185748	20.90	0.781746	0.102273	0.442009	0.509956	0.577904
Delhi	0.130339	129.00	0.336356	0.748804	0.542580	0.501335	0.460090
Chandigarh	0.188795	5.50	0.806236	0.010167	0.408202	0.487809	0.567416
Kolkata	0.140378	87.50	0.417053	0.500598	0.458826	0.450471	0.442117
Nagpur	0.169818	23.10	0.653693	0.115431	0.384562	0.438388	0.492215
Hyderabad	0.139184	84.10	0.407454	0.480263	0.443859	0.436578	0.429297
Dhanbad	0.166916	7.74	0.630367	0.023565	0.326966	0.387646	0.448327
Pune	0.144345	53.20	0.448936	0.295455	0.372196	0.387544	0.402892
Varanasi	0.147171	3.80	0.471656	0.000000	0.235828	0.282994	0.330159
Kanpur	0.134815	8.40	0.372330	0.027512	0.199921	0.234403	0.268885
Kochi	0.118014	35.70	0.237286	0.190789	0.214038	0.218688	0.223337
Jaipur	0.118681	25.60	0.242641	0.130383	0.186512	0.197738	0.208963
Bhopal	0.121464	9.70	0.265017	0.035287	0.150152	0.173125	0.196098
Srinagar	0.088495	20.00	0.000000	0.096890	0.048445	0.038756	0.029067

Figure 7. Sustainability scores for selected Indian cities based on economic and environmental indicators

- High-GDP but Low NDVI

Delhi and Mumbai consistently top the GDP ranking, reflecting their roles as economic powerhouses. However, both exhibit relatively low NDVI scores, indicative of extensive urbanization and reduced vegetation cover.

In line with the negative NDVI–GDP correlation, these cities highlight the trade-off wherein rapid economic expansion may come at the cost of green spaces—reinforcing the need for targeted urban greening efforts (e.g., Delhi's tree plantation drives) that can mitigate environmental stress without halting economic growth.

- Balanced Growth and Sustainability

Chandigarh shows a moderately high NDVI despite having a smaller overall GDP (≈ 5.5 billion USD). The city's planned layout, emphasis on public parks, and capped vertical growth contribute to its stronger "green" profile, as seen in the NDVI heatmap.

Pune reports a middle-to-high GDP (~53.2 billion USD) and a moderate NDVI relative to other large metros. Though its NDVI is not at the top, it is sufficient to place Pune in a mid-range sustainability position, reflecting efforts to preserve hilly regions and green belts around the city's core.

Visakhapatnam stands out as combining moderate GDP (~20.9 billion USD) with a higher NDVI (above 0.18). The coastal and hilly terrains likely help retain greenery, demonstrating a city that manages to balance industrial activity (ports, steel plants) with a less fragmented green cover.

The success of outliers like Chandigarh and Pune warrants further qualitative consideration. Chandigarh's high performance in the weighted sustainability ranking is rooted in its historical legacy as a 'planned city,' where green belts were integrated into the master plan as non-negotiable infrastructure. Similarly, Pune's ability to maintain higher NDVI values despite economic growth is partially attributed to local zoning protections for its 'Hill Top-Hill Slope' zones. These examples suggest that the negative correlation between growth and greenness is not an inevitability, but a result of specific policy choices regarding land-use management.

- Implications for Sustainability Rankings

In both the unweighted and environment-weighted sustainability indices, Chandigarh, Pune, and Visakhapatnam perform better than purely high-GDP, low-NDVI cities (e.g., Delhi, Mumbai) because they maintain a functional blend of economic output and vegetation. This reinforces the finding that sustainable outcomes are not simply about absolute GDP but also about how growth is managed in relation to ecological assets like urban forests or coastal habitats.

4.4.1 Robustness to alternative weighting

An additional sensitivity check was conducted using a stronger environment-weighted specification (70% NDVI, 30% GDP). The resulting sustainability scores and rankings remain highly consistent with both the unweighted (50:50) and baseline environment-weighted (60:40) indices. The corresponding rank-order are reported in Table 2. Rank-order correlations across weighting schemes exceed 0.90, and the relative positioning of cities identified as environmentally balanced or imbalanced remains largely unchanged.

Table 2. Rank-order correlations between sustainability indices under alternative weighting schemes

Comparison of Weighting Schemes	Spearman's ρ
50:50 vs 60:40	0.92
60:40 vs 70:30	0.94

Substantively, cities with stronger vegetation profiles and moderate economic scale (e.g., Bhubaneswar, Guwahati, Siliguri, Gangtok) continue to perform well under higher environmental emphasis, while large metropolitan economies with lower NDVI values (e.g., Delhi, Mumbai) experience gradual score declines rather than rank reversals. This confirms that the observed sustainability patterns are not artefacts of a single weighting choice but reflect persistent environment–economy trade-offs across Indian cities.

To simplify interpretation, cities were grouped into clusters based on shared patterns of economic scale and environmental performance. These clusters summarize how different development trajectories respond to alternative sustainability weighting schemes, without altering the underlying rankings. The resulting city clusters are summarized in Table 3.

Table 3. City clusters based on economic scale and environmental performance

Cluster	Defining Characteristics	Cities	Behaviour Across Weighting Schemes	Interpretation
High GDP – Low NDVI	Very large economic output, limited urban greenness	Mumbai, Delhi	Rank high under 50:50; decline steadily under 60:40 and 70:30	Economic dominance moderated when environmental conditions are emphasized
Moderate GDP – High NDVI (Environmentally Balanced)	Mid-sized economies with strong vegetation cover	Bhubaneswar, Guwahati, Siliguri, Gangtok, Vijayawada	Improve or remain strong as NDVI weight increases	Growth achieved with relatively lower ecological stress
Planned / Regulated Growth Cities	Institutionalized green spaces and zoning controls	Chandigarh, Pune	Stable rankings across all weights	Sustainability supported by planning and land-use regulation
Moderate GDP – Moderate NDVI	Economically relevant with partial green retention	Bengaluru, Chennai, Visakhapatnam	Minor rank shifts; remain mid-to-high	Mixed outcomes reflecting growth–environment trade-offs
Low GDP – Low NDVI	Limited economic scale and weak vegetation cover	Jaipur, Bhopal, Kanpur, Kochi, Dhanbad, Srinagar	Persistently low ranks across all weights	Structural constraints dominate sustainability outcomes

- Future Considerations

Policy: For high-GDP, low-NDVI metros, strategic green initiatives—such as preserving mangrove swamps (Mumbai) or aggressive tree-planting (Delhi)—could improve NDVI without stifling economic momentum.

Urban Planning: Cities like Chandigarh and Visakhapatnam may serve as case studies, demonstrating how thoughtful land-use policies can sustain ecological integrity alongside economic development.

Broader Indicators: Incorporating air quality or HDI data can further illustrate why some cities achieve better overall livability—Pune and Visakhapatnam, for instance, often show moderate air pollution levels and relatively high social indicators.

5. POLICY RECOMMENDATIONS

1) Integrate Green Infrastructure into Urban Master Plans
   - High-GDP, Low-NDVI cities (e.g., Mumbai, Delhi) should adopt strict zoning rules. Preserving or expanding public parks, urban forests, and green corridors should be a priority. This ensures continued economic growth without sacrificing ecosystem services [20, 34].
   - Incentives for vertical greening (e.g., green roofs, living walls) and mangrove or wetland conservation can offset the loss of vegetation in densely built-up areas.
2) Promote Compact and Mixed-Use Development
   - Encouraging mixed-use neighborhoods near employment hubs can reduce sprawl and protect green belts on the urban periphery [38]. Reduced commute distances also help lower air pollution [4].
3) Strengthen Environmental Governance
   - Air Quality and Land-Use Monitoring: Cities should publicly track indicators such as AQI and NDVI over

time, using them to guide policy revisions [29].
- Institutional Capacity: Dedicated urban greening boards or environmental cells in city corporations can coordinate reforestation drives, pollution control, and environmental compliance.

4) Foster Economic-Ecological Synergy
- Green Incentives: Tax breaks or subsidies for eco-friendly construction (e.g., LEED-certified buildings) encourage developers to integrate green spaces and energy-efficient designs [20].
- Public–Private Partnerships: Collaborations between local governments, private companies, and community groups can help fund urban forestry, park maintenance, and carbon offset initiatives, enhancing both NDVI and livability [25, 50].

5) Adopt Weighted Sustainability Frameworks
- The environment-weighted score used here (e.g., 60% NDVI, 40% GDP) can be customized or expanded (e.g., adding AQI, HDI, or carbon emissions) [30, 49] to reflect local priorities, ensuring cities measure progress not only in financial terms but also in ecological resilience [41].

6. CONCLUSIONS

This study examined how economic output, environmental conditions, and human development interact across 22 major Indian cities, using satellite-derived measures of urban greenness alongside economic and social indicators. By jointly considering NDVI, AQI, HDI, and city-level GDP, the analysis provides a grounded picture of how different dimensions of urban development come together in rapidly growing urban contexts.

The findings suggest that economic performance is closely intertwined with environmental quality and human development, rather than being shaped by any single factor in isolation. While individual relationships are estimated with some uncertainty—reflecting both the limited sample size and the inherent complexity of urban systems—the overall results point to meaningful and consistent patterns. In particular, the interaction between air pollution and human development indicates that cities differ in how environmental stress translates into economic outcomes. Cities with higher levels of human development appear better equipped to cope with the economic pressures associated with poor air quality, while cities with lower HDI show greater vulnerability to environmental degradation. The interaction between HDI and AQI suggests that cities with higher human development may be better able to mitigate pollution's economic effects [11].

Urban greenness, as measured through NDVI, contributes to this broader picture, though its role is not uniform across cities. The nonlinear association observed in the analysis suggests that vegetation cover alone does not determine economic performance. Instead, its relevance depends on how green spaces are embedded within wider urban systems, including land-use intensity, infrastructure development, and institutional capacity. Cities that manage to maintain both economic activity and environmental quality demonstrate that sustainable outcomes are determined by planning choices and governance structures rather than by growth levels alone.

From a sustainable development perspective, these findings are in accordance with the objectives of SDG 11 (Sustainable Cities and Communities), which emphasizes the need for cities that are economically productive while remaining inclusive, resilient, and environmentally sound. The results also speak to SDG 3 (Good Health and Well-being) and SDG 13 (Climate Action) by highlighting the economic relevance of air quality and environmental stress, as well as to SDG 8 (Decent Work and Economic Growth) [35] by showing that long-term economic adaptability is linked to social and environmental conditions.

Overall, this study reinforces the idea that environmental deterioration is not an unavoidable consequence of urban economic growth. Instead, the way cities grow—through planning decisions, investment in human development, and attention to environmental quality—plays a critical role in shaping sustainable outcomes. While the analysis is exploratory and constrained by data availability, it provides a useful basis for further study using longitudinal data and finer spatial indicators. For policymakers and urban planners, the results emphasize the significance of holistic development strategies that balance economic objectives with environmental resilience and human well-being, in line with the goals of sustainable urban development.

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APPENDIX

Table A1. City GDP values used in the analysis (FY 2022–23)

City	GDP (₹ crore)	GDP (USD bn)
Mumbai (MMR)	13,50,900	171.00
Delhi	10,19,100	129.00
Bengaluru	9,32,200	118.00
Chennai	7,60,000	96.20
Kolkata	6,91,250	87.50
Hyderabad	6,64,390	84.10
Pune	4,20,280	53.20
Kochi	2,82,030	35.70
Jaipur	2,02,240	25.60
Nagpur	1,82,490	23.10
Bhubaneswar	1,83,280	23.20
Vijayawada	1,73,800	22.00
Visakhapatnam	1,65,110	20.90
Srinagar	1,58,000	20.00
Guwahati	79,000	10.00
Bhopal	76,630	9.70
Kanpur	66,360	8.40
Dhanbad	61,146	7.74
Siliguri	55,300	7.00
Chandigarh	43,450	5.50
Gangtok	34,760	4.40
Varanasi	30,020	3.80

Note: GDP values correspond to FY 2022–23 (or nearest official release) and were converted to USD using the average exchange rate of ₹79 per US dollar (Reserve Bank of India, 2023) [A18]

Table A2. GDP data classification and official sources

City	GDP Data Type	GDP Construction Basis	Official Government Source(s)
Mumbai (MMR)	**Official (Aggregated)**	Sum of 5 Districts (Mumbai City, Suburban, Thane, Palghar, Raigad)	*Maharashtra Economic Survey 2022–23* (District GDDP Tables) [A1]
Delhi	**Official**	UT GSDP (State Economy)	*Economic Survey of Delhi 2022–23* [A2]
Bengaluru	**Official**	Bengaluru Urban District GDDP	*Karnataka Economic Survey 2022–23* [A3]
Chennai	**Official**	Chennai District GDDP	*Tamil Nadu Economic Survey / Statistical Handbook 2022–23* [A4]
Kolkata	**Official**	Kolkata District GDDP	*West Bengal Economic Review 2022–23* [A5]
Hyderabad	**Official (Aggregated)**	Sum of 3 Districts (Hyderabad, Rangareddy, Medchal-Malkajgiri)	*Telangana Economic Survey 2022–23* (District GDDP Tables) [A6]
Pune	**Official**	Pune District GDDP	*Maharashtra Economic Survey 2022–23* [A1]
Kochi	**Official**	Ernakulam District GDDP	*Kerala Economic Review 2022* [A7]
Jaipur	**Official**	Jaipur District GDDP	*Rajasthan Economic Survey 2022–23* [A8]
Nagpur	**Official**	Nagpur District GDDP	*Maharashtra Economic Survey 2022–23* [A1]
Bhubaneswar	**Official**	Khordha District GDDP	*Odisha Economic Survey 2022–23* [A9]
Vijayawada	**Official**	Krishna District GDDP	*Andhra Pradesh Economic Survey 2022–23* [A10]
Visakhapatnam	**Official**	Undivided Visakhapatnam District GDDP	*Andhra Pradesh Economic Survey 2022–23*

			[A7]
Srinagar	**Official**	Srinagar District GDDP	*J&K Economic Survey 2022–23* [A11]
Guwahati	**Official**	Kamrup Metropolitan District GDDP	*Assam Economic Survey 2022–23* [A12]
Bhopal	**Official**	Bhopal District GDDP	*Madhya Pradesh Economic Survey 2022–23* [A13]
Kanpur	**Official**	Kanpur Nagar District GDDP	*Uttar Pradesh Economic Survey 2022–23* [A14]
Dhanbad	**Official**	Dhanbad District GDDP	*Jharkhand Economic Survey 2022–23* [A15]
Siliguri	**Estimated**	Proportional Urban Share of Darjeeling & Jalpaiguri District GDDP	*West Bengal Economic Review 2022–23* [A5]
Chandigarh	**Official**	UT GSDP (State Economy)	*Statistical Abstract of Chandigarh 2023–24* [A16]
Gangtok	**Estimated**	Proportional Urban Share of East Sikkim District GDDP	*Sikkim Statistical Abstract / Economic Survey* [A17]
Varanasi	**Official**	Varanasi District GDDP	*Uttar Pradesh Economic Survey 2022–23* [A14]

Note: Official (Aggregated) *denotes cities where the functional urban economy spans multiple administrative districts (e.g., Mumbai MMR, Hyderabad). In these cases, the value is derived by summing the official GDDP of the constituent districts as reported in State Economic Surveys.* ***Estimated*** *denotes values derived using proportional population shares where district-level data was insufficient to represent the city economy (e.g., Siliguri, Gangtok).*

Table A3. Appendix references

[A1]	Government of Maharashtra. (2023). Economic Survey of Maharashtra 2022–23. Planning Department.
[A2]	Government of Delhi. (2023). Economic Survey of Delhi 2022–23. Planning Department.
[A3]	Government of Karnataka. (2023). Economic Survey of Karnataka 2022–23. Planning, Programme Monitoring and Statistics Department.
[A4]	Government of Tamil Nadu. (2023). Statistical Handbook of Tamil Nadu 2022–23. Department of Economics and Statistics.
[A5]	Government of West Bengal. (2023). West Bengal Economic Review 2022–23. Finance Department.
[A6]	Government of Telangana. (2023). Telangana Economic Survey 2022–23. Planning Department.
[A7]	Kerala State Planning Board. (2022). Economic Review 2022. Government of Kerala.
[A8]	Government of Rajasthan. (2023). Economic Survey of Rajasthan 2022–23. Directorate of Economics and Statistics.
[A9]	Government of Odisha. (2023). Odisha Economic Survey 2022–23. Planning and Convergence Department.
[A10]	Government of Andhra Pradesh. (2023). Economic Survey 2022–23. Planning Department.
[A11]	Government of Jammu & Kashmir. (2023). Economic Survey 2022–23. Finance Department.
[A12]	Government of Assam. (2023). Economic Survey of Assam 2022–23. Directorate of Economics and Statistics.
[A13]	Government of Madhya Pradesh. (2023). Economic Survey of Madhya Pradesh 2022–23. Directorate of Economics and Statistics.
[A14]	Government of Uttar Pradesh. (2023). Economic Survey of Uttar Pradesh 2022–23. Planning Department.
[A15]	Government of Jharkhand. (2023). Jharkhand Economic Survey 2022–23. Department of Planning and Development.
[A16]	Chandigarh Administration. (2023). Statistical Abstract of Chandigarh 2023–24. Economics and Statistics Category.
[A17]	Government of Sikkim. (2023). Sikkim Statistical Abstract. Directorate of Economics, Statistics, Monitoring and Evaluation.
[A18]	Reserve Bank of India. (2023). Handbook of Statistics on the Indian Economy 2022–23. RBI Database on Indian Economy.