

7 **Regional growth, convergence, and spatial spillovers in**
8 **India: A view from outer space**
9 **Replication and extension using spatial Durbin models**

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12 **Abstract.** Using satellite nighttime light data as proxy for economic activity, Chanda
13 and Kabiraj (2020, World Development) studied regional growth and convergence across
14 520 districts in India. This article builds on their work by confirming and extending their
15 main findings in three fronts. First, we illustrate regional convergence patterns using
16 an interactive web-based tool for satellite image visualization. Second, we assess the
17 degree of spatial dependence in their main econometric specification. Third, we employ a
18 spatial Durbin model to measure the role of spatial spillovers in the convergence process.
19 Our results indicate that spatial spillovers significantly increase the speed of regional
20 convergence. Overall, the results emphasize the role of spatial dependence in regional
21 convergence through the lens of satellite imagery, interactive visualizations, and spillover
22 modeling.

23 **1 Introduction**

24 Regional economic growth and convergence are key concerns in developing countries,
25 particularly in large federal states like India where spatial inequalities can threaten
26 social cohesion and political stability. However, studying regional convergence patterns
27 in developing countries has been historically challenging due to limited availability of
28 consistent economic data at subnational administrative levels. The emergence of satellite
29 nighttime light data as a proxy for economic activity has created new opportunities to
30 analyze regional growth dynamics at granular geographic scales.

31 In an important contribution, Chanda, Kabiraj (2020) leveraged nighttime light data
32 to document evidence of regional convergence across 520 districts in India between 1996
33 and 2010. Their analysis showed that poorer districts grew faster than richer ones
34 during this period, suggesting a gradual reduction in spatial inequalities. However, their
35 econometric approach did not account for potential spatial spillovers in the convergence
36 process—the possibility that a district's growth trajectory might be influenced not only
37 by its own initial conditions but also by those of its neighbors.

38 In this context, this paper confirms and extends the study of Chanda, Kabiraj (2020)
39 in three key methodological directions. First, we develop an interactive web-based
40 visualization tool that allows researchers to dynamically explore spatial and temporal
41 patterns in the nighttime light data. This tool facilitates the identification of converging
42 regions and growth hotspots that may be difficult to detect in static representations.
43 Second, we formally test for spatial dependence in both the dependent and independent
44 variables of the convergence equations, highlighting that spatial autocorrelation is an
45 inherent feature of satellite data and the regional convergence process. Third, we employ

1 a spatial Durbin model that explicitly accounts for spatial spillovers, quantifying how
2 neighborhood effects influence the speed of regional convergence.

3 Our results yield three main findings that advance our understanding of regional
4 convergence in India. First, interactive visualization tools reveal clear spatial patterns
5 in both the initial distribution and subsequent growth of nighttime lights. Second,
6 formal tests of spatial dependence indicate that district-level economic trajectories are
7 not independent of their neighbors. Third, accounting for spatial spillovers through the
8 spatial Durbin model shows that the total convergence effect is substantially larger than
9 previous non-spatial estimates would suggest. Specifically, spatial spillovers appear to
10 accelerate the convergence process by creating additional channels through which lagging
11 regions can catch up.

12 These findings have important implications for both research methodology and policy
13 design. Methodologically, they demonstrate that conventional non-spatial approaches
14 may significantly underestimate the speed of regional convergence by failing to account
15 for inter-district spillovers. From a policy perspective, they suggest that the benefits of
16 place-based development interventions may extend beyond target districts through spatial
17 multiplier effects, potentially increasing their cost-effectiveness. The results also highlight
18 the value of new data sources and methodological tools in advancing our understanding
19 of regional economic dynamics in developing countries.

20 The rest of this article is organized as follows. Section 2 provides an overview
21 of the data and methods, describing our use of nighttime light data as a proxy for
22 economic activity and introducing the spatial Durbin model that forms the basis of our
23 empirical strategy. We also detail our methodological extensions related to interactive
24 visualizations, spatial dependence testing, and spillover modeling. Section 3 presents
25 our empirical results, beginning with an interactive exploration of regional convergence
26 patterns, followed by formal tests of spatial dependence, and concluding with estimates
27 of direct and indirect convergence effects from the spatial Durbin model. Finally, Section
28 4 offers some concluding remarks.

29 **2 Data, model specification, and extensions**

30 **2.1 Data: Nightlights as a proxy for economic activity**

31 One of the key challenges in studying economic growth in developing countries like India
32 is the limited availability and reliability of data on aggregate economic activity at finer
33 administrative levels beyond the state level. To address this issue, a growing body of
34 literature, pioneered by [Henderson et al. \(2012\)](#), has utilized satellite nighttime light data
35 as a proxy for economic activity at sub-national levels.

36 Nightlight data has been widely used to investigate economic growth and convergence
37 across national and sub-national regions in various countries. For instance, [Adhikari,](#)
[Dhital \(2021\)](#) examine the impact of decentralization on regional convergence using
38 nightlight data, while [Pinkovskiy, Sala-i Martin \(2016\)](#) argue that nightlight data better
39 captures aggregate economic activity compared to household surveys. Similarly, [Lessmann,](#)
[Seidel \(2017\)](#) leverage nightlight data to estimate GDP per capita and income inequality
40 globally, and [Gennaioli et al. \(2014\)](#) study regional convergence through the lens of light
41 data.

42 Nightlight data has been widely utilized in India across various contexts. For example,
43 [Asher, Novosad \(2016\)](#) and [Cook, Shah \(2022\)](#) use nightlight data to analyze the impact
44 of road infrastructure and public welfare programs, respectively. Similarly, [Jha, Talathi](#)
[\(2023\)](#) examine the effects of colonization, while [Chanda, Cook \(2022\)](#) investigate the
45 impact of demonetization using nightlight data. [Beyer et al. \(2021\)](#) employ it to study
46 the effects of COVID-19. In the context of convergence studies, [Chakravarty, Dehejia](#)
[\(2017\)](#) finds state-level divergence in India using nightlight data, while ([Chanda, Kabiraj](#)
50 [2020\)](#) highlights district-level convergence using the same.

51 Our study draws inspiration from ([Chanda, Kabiraj 2020](#)). Following their approach,
52 we use the per capita growth in nightlights as the dependent variable and the initial
53 nightlights per capita as the primary variable of interest. These variables are derived from
54 nightlight data released by the National Geophysical Data Center (NGDC), based on

1 observations from the DMSP/OLS satellites spanning the period from 1996 to 2010. To
 2 mitigate the issue of top-coding in light data, the NGDC released “radiance-calibrated”
 3 nighttime lights for eight specific years within this period. This dataset employs high
 4 magnification settings for low-light regions and low magnification settings for brightly lit
 5 areas. For this study, we utilize the “radiance-calibrated” nighttime lights data.¹

6 *2.2 Modeling regional convergence*

7 In neoclassical growth models, such as the Solow model, it is argued that the per capita
 8 growth rate should be negatively correlated with a region’s initial endowment primarily
 9 due to diminishing returns to capital. Specifically, poorer regions, assuming similar
 10 technology and preferences, are expected to experience higher growth rates compared
 11 to their wealthier counterparts. Consequently, over the long run, regions with similar
 12 characteristics should converge to a common steady state. We would like to explore such
 13 convergence (denoted by **β -convergence**) employing a Barro-style growth regressions
 14 framework. Equation (1) analyzes absolute convergence.

$$g_t = \beta_1 x_{t-1} + \varepsilon_t \quad (1)$$

15 where g_t represents an N -by-1 vector of observations on NTL growth for each of the N
 16 regions over the period t and x_{t-1} represents an N -by-1 vector of observations on the initial
 17 (log) level of NTL. The scalar β_1 is a regression coefficient that indicates the direction
 18 and strength of regional convergence. Finally, ε_t represents a vector of idiosyncratic error
 19 terms.

20 While absolute convergence implies that districts converge to a common steady state,
 21 regions may differ in various aspects such as geography, socio-economic conditions, and
 22 policy implementation. To account for these differences, we include state dummies in
 23 our analysis to examine whether heterogeneity in state-specific institutions and policies
 24 influences the rate of convergence. Additionally, we control for the initial share of unlit
 25 pixels in districts to address any potential under-coding in nightlights data.

26 To further explore the determinants of district-level growth rates, we incorporate a
 27 range of geo-climatic controls alongside initial district-specific conditions related to demo-
 28 graphics, human capital, and infrastructure. Equation 1 explores conditional convergence.

$$g_t = \beta_1 x_{t-1} + X_t \alpha + \varepsilon_t \quad (2)$$

29 Here, the matrix X_t is a N -by- k collection of observations on control variables for each
 30 region. The vector α , with dimensions $k \times 1$, captures the regression coefficients for these
 31 variables. The control variables are listed in Table A.1 in Chanda, Kabiraj (2020).

32 *2.3 Extensions: Interactive visualizations, spatial dependence testing, and spillover
 33 modeling*

34 *2.3.1 Interactive spatial visualizations*

35 Interactive visualizations of nighttime lights imagery offer distinct methodological ad-
 36 vantages over static representations, particularly when analyzing temporal and spatial
 37 heterogeneity in economic activity. The dynamic nature of these visualizations enables
 38 researchers to simultaneously examine multiple dimensions of the data, including tem-
 39 poral variations in light intensity, the spatial distribution of economic activity, and the
 40 relationship between nighttime lights and other georeferenced variables. This interactivity
 41 is especially valuable when investigating economic phenomena that exhibit significant
 42 spatial and temporal variation, such as urbanization patterns, economic shocks, or regional
 43 development disparities. The ability to dynamically adjust visualization parameters, such

¹Following Chanda, Kabiraj (2020), our sample consists of 520 districts (out of a possible 593). There were 593 districts in 2001, which rose to 640 districts in the 2011 census. To match the districts among two census files, we summed up the curved-out districts with their origin districts in the 2011 census files. Eight districts among 47 new districts were created by curving out some areas from multiple districts. Those new districts along with their multiple-origin districts were dropped from our sample. We dropped all the districts in the state of Assam where more than 50% of districts were created in that manner.

1 as temporal ranges, spatial scales, and light intensity thresholds, allows for more nuanced
 2 exploration of economic patterns that might be obscured in static representations.

3 Google Earth Engine (GEE) substantially reduces the computational and technical
 4 barriers to creating such interactive visualizations, offering a particularly advantageous
 5 platform for economic research utilizing nighttime lights data. The platform's browser-
 6 based integrated development environment facilitates the creation of interactive web
 7 applications without requiring extensive infrastructure or specialized software installation.
 8 This capability is especially valuable for reproducible research, as it enables the devel-
 9 opment of web applications that can be shared with other researchers or stakeholders,
 10 allowing them to interact with the data and verify findings independently. The platform's
 11 ability to handle large-scale geospatial computations server-side, combined with its ex-
 12 tensive catalog of pre-processed nighttime lights datasets, including the DMSP-OLS and
 13 VIIRS collections, significantly streamlines the workflow from raw data to interactive
 14 visualization. This computational efficiency is particularly beneficial when analyzing long
 15 time series or large geographic areas, which would be computationally intensive using
 16 traditional desktop-based approaches.

17 Interactive visualizations of nighttime lights data are particularly instrumental in
 18 identifying and analyzing patterns of regional convergence in luminosity, providing visual
 19 insights into economic convergence processes. Through dynamic visualization tools,
 20 researchers can track the evolution of light intensity across regions over time, effectively
 21 identifying areas that exhibit catch-up growth patterns - where initially dim regions
 22 progressively converge toward the luminosity levels of their brighter counterparts.

23 2.3.2 Spatial dependence testing

24 The analysis of regional convergence using nighttime light data requires explicit consider-
 25 ation of spatial dependence patterns across Indian districts. To formally test and account
 26 for such spatial relationships, we employ the global Moran's I test and applied to the
 27 main variables of the convergence Equation 2 . The Moran's I test quantifies the degree
 28 of spatial autocorrelation among geographic units and can be expressed as:

$$I = \frac{\sum_i \sum_j w_{ij} z_i \cdot z_j / \sum_i \sum_j w_{ij}}{\sum_i z_i^2 / n}$$

29 where z_i represents the deviation of observation i from the mean, and w_{ij} denotes the
 30 spatial weight between units i and j . The Moran statistic can range from -1 to +1,
 31 with positive values indicating spatial clustering and negative values suggesting spatial
 32 dispersion.

33 The specification of the spatial weights matrix \mathbf{W} is crucial for capturing the underlying
 34 spatial structure. We primarily employ a Queen contiguity matrix defined as:

$$\mathbf{W} = \begin{bmatrix} w_{11} & w_{12} & w_{13} & \cdots & w_{1n} \\ w_{21} & w_{22} & w_{23} & \cdots & w_{2n} \\ \vdots & \vdots & \vdots & & \vdots \\ w_{n1} & w_{n2} & w_{n3} & \cdots & w_{nn} \end{bmatrix}$$

35 where $w_{ij} = 1$ for districts sharing either a border or vertex and 0 otherwise. Following
 36 standard practice, we row-normalize the weights matrix.

37 The detection of significant spatial dependence would justify the use of spatial econo-
 38 metric techniques. In particular, [Ertur, Koch \(2007\)](#) and [Fischer \(2011\)](#) argue that
 39 the spatial Durbin model can properly account for spatial spillovers in the convergence
 40 process. This methodological choice allows us to distinguish between direct effects of
 41 district characteristics and indirect effects operating through spatial channels.

42 2.3.3 Spatial spillover modeling

43 Our spatial spillover modeling builds upon the spatial Solow growth model developed by
 44 [Ertur, Koch \(2007\)](#) and [Fischer \(2011\)](#), which extends the traditional Solow framework
 45 to account for technological interdependence across regions. The model considers an

- 1 economy of N subnational regions, each characterized by a Cobb-Douglas production
 2 function with constant returns to scale:

$$Y_{it} = A_{it} K_{it}^{\alpha_K} H_{it}^{\alpha_H} L_{it}^{1-\alpha_K-\alpha_H} \quad (3)$$

3 where Y_{it} represents output, K_{it} physical capital, H_{it} human capital, L_{it} labor force,
 4 and A_{it} the level of technological knowledge for region i at time t . The parameters α_K and
 5 α_H denote the output elasticities with respect to physical and human capital, respectively.
 6 A key innovation of this framework is the modeling of technological knowledge, which
 7 incorporates both internal and external factors:

$$A_{it} = \Omega_t k_{it}^\theta h_{it}^\phi \prod_{j \neq i}^N A_{jt}^{\rho W_{ij}} \quad (4)$$

8 This specification captures three distinct components of technological progress:

- 9 • An exogenous component (Ω_t) representing the common stock of knowledge across
 regions
- 10 • An embodied component ($k_{it}^\theta h_{it}^\phi$) reflecting technology embedded in physical and
 human capital per worker
- 11 • A spatial component ($\prod_{j \neq i}^N A_{jt}^{\rho W_{ij}}$) capturing technological interdependence between
 regions

12 Based on this theoretical framework, Ertur, Koch (2007) derived a spatial panel
 13 Durbin model that for regional spillovers across economies. Their model can be compactly
 14 written in matrix notation as:

$$g_t = \beta_1 x_{t-1} + X_t \alpha + \beta_2 Wx_{t-1} + WX_t \gamma + \lambda Wg_t + \varepsilon_t \quad (5)$$

15 In this model, g_t represents an N -by-1 vector of observations on NTL growth for each
 16 of the N regions over the period t and x_{t-1} represents an N -by-1 vector of observations
 17 on the initial (log) level of NTL. The scalar β_1 is a regression coefficient that indicates
 18 the direction and strength of regional convergence. The matrix X_t is a N -by- k collection
 19 of observations on control variables for each region. The vector α , with dimensions $k \times 1$,
 20 captures the regression coefficients for these variables. Additionally, WX_t denotes a $N \times k$
 21 matrix of spatially lagged observations, composed of a linear combination of neighboring
 22 values for the variables of interest in each region. The vector γ represents the regression
 23 coefficients associated with these spatial lags. The terms Wx_{t-1} and Wg_t refer to N -by-1
 24 vectors capturing the spatial lags of initial (log) level of NTL, and the NTL growth,
 25 respectively. Finally, ε_t represents a vector of idiosyncratic error terms.

29 3 Results: Replication and extensions

30 3.1 Regional convergence: An interactive exploration from outer space

31 Before presenting the regression results, we conducted three exercises to visually illustrate
 32 the concepts of growth and convergence in nightlights. Firstly, we created an interactive
 33 map of India displaying regional luminosity levels for 1996 and 2010.² Secondly, we
 34 examine absolute convergence by constructing a scatterplot that depicts the relationship
 35 between per capita growth rates in nightlights (1996–2010) and the initial per capita
 36 nightlight levels (1996) at the district level. Finally, we used case studies to emphasize
 37 the nightlight growth that occurred during our study period. Focusing on some of the
 38 poorest regions in the country, we demonstrate an increase in nighttime lights that aligns
 39 with our convergence hypothesis.

40 Figure 1 presents static maps (captured from our interactive maps) of luminosity for
 41 our boundary years (1996 and 2010), using the same index scale for comparison. The
 42 maps show a noticeable increase in brightness across most parts of the country in 2010.
 43 Since nightlights serve as a proxy for economic activity, this increase in luminosity reflects
 44 economic growth over the period. Figure 2 illustrates the relationship between per capita

²The Interactive web application is available at <https://bit.ly/india-rc-ntl>.

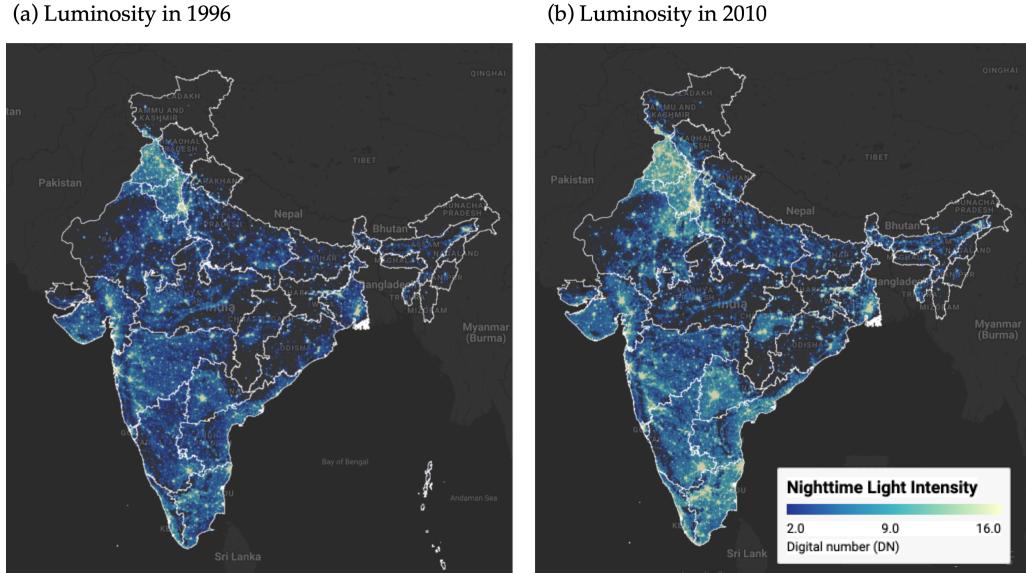


Figure 1: Regional luminosity in India: 1996 vs 2010 Notes: The unit of measurement for Nighttime Light (NTL) luminosity TBA. Interactive web application available at <https://bit.ly/india-rc-ntl>. Source: Pre-processed luminosity images are from the Earth Observation Group TBA.

¹ growth in nightlights and initial per capita nightlight levels. The scatter plot reveals a
² clear inverse relationship, indicating a β -convergence rate of 2% consistent with Barro's
³ "Iron Law" of convergence.

⁴ Next, we examine case studies of three economically disadvantaged states in India
⁵ to illustrate their growth patterns over the study period. Among these, Bihar is the
⁶ poorest, with a per capita income at 39.2% of the national average, while Uttar Pradesh
⁷ and Chhattisgarh have per capita incomes of 43.8% and 52.3% of the national average,
⁸ respectively.³ Figure 3 displays the change in luminosity in these three states during our
⁹ study period. Although these states remain among the poorest, there is a noticeable
¹⁰ increase in luminosity over the course of the study.

³The data is taken from a report by the Economic Advisory Council to the Prime Minister (EAC-PM), released on September 18, 2024.

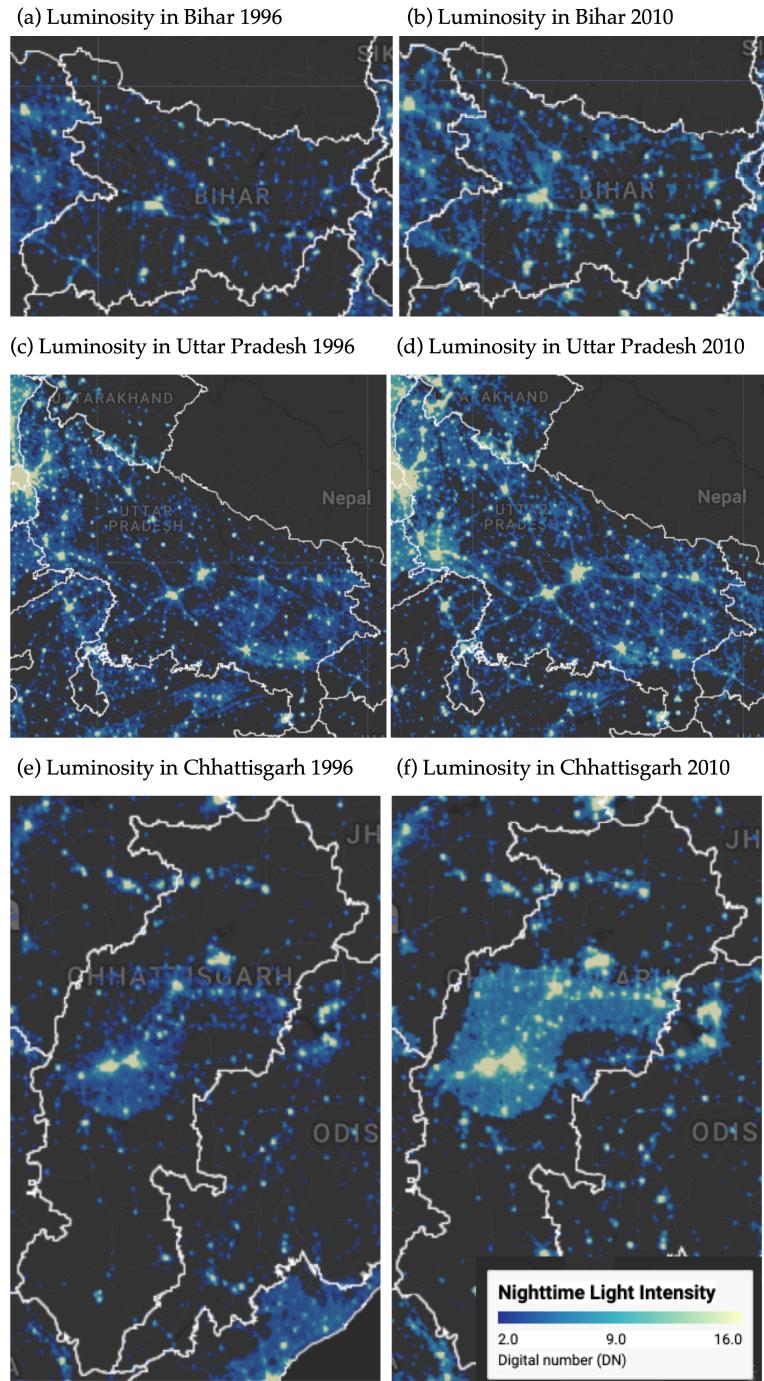


Figure 2: Some illustrative examples of regional convergence Notes: The unit of measurement for Nighttime Light (NTL) luminosity TBA. Interactive web application available at <https://bit.ly/india-rc-ntl>. Source: Pre-processed luminosity images are from the Earth Observation Group TBA.

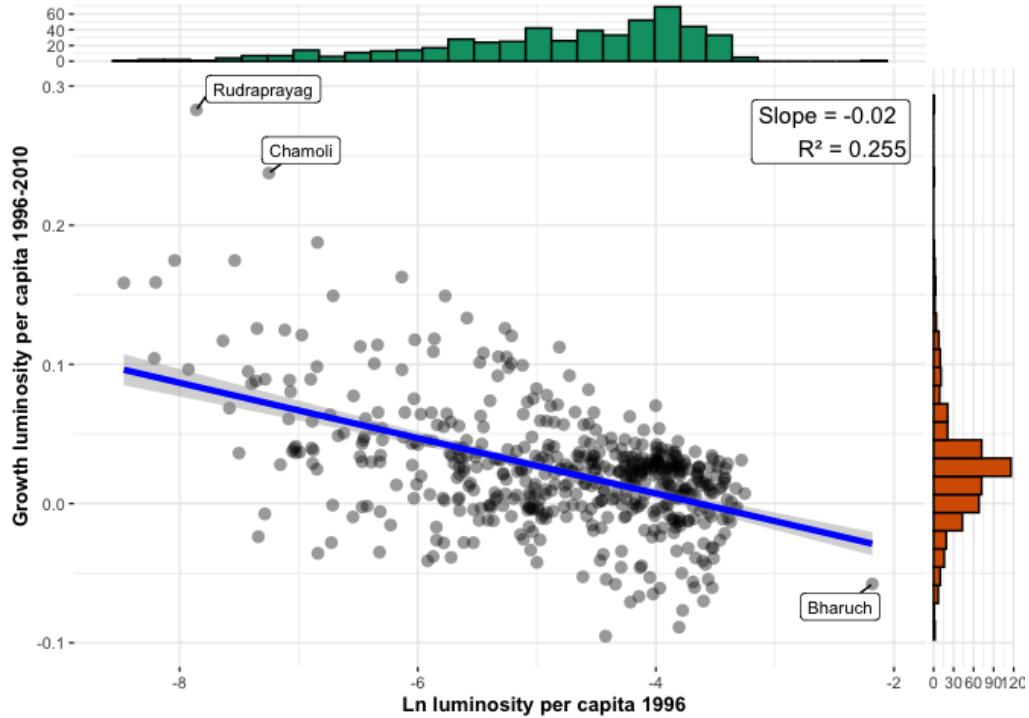


Figure 3: Regional luminosity convergence across districts in India

¹ Source: [Scatterplots for Regional Convergence Analysis](#)

² 3.2 Spatial dependence is a feature of the convergence process

- ³ In this study, the spatial lag terms of luminosity per capita growth and initial luminosity
- ⁴ per capita are computed by applying the Queen contiguity weight matrix. FigureX
- ⁵ visually presents the relationship between local luminosity per capita growth rate and
- ⁶ initial luminosity per capita and its spatial lag term, respectively. The strong positive
- ⁷ spatial correlations observed between the variables and their neighboring regions suggest
- ⁸ that regional convergence is not an isolated phenomenon, but rather a process intrinsically
- ⁹ shaped by the influence of adjacent regions. The Moran's I values of 0.644 and 0.739 for
- ¹⁰ the variables, coupled with a statistically significant spatial autocorrelation in the error
- ¹¹ term, underscore the critical importance of spatial dependence in convergence research.
- ¹² These findings demonstrate that spatial interactions profoundly influence the convergence
- ¹³ process, rendering it imperative to incorporate spatial effects in empirical analyses.

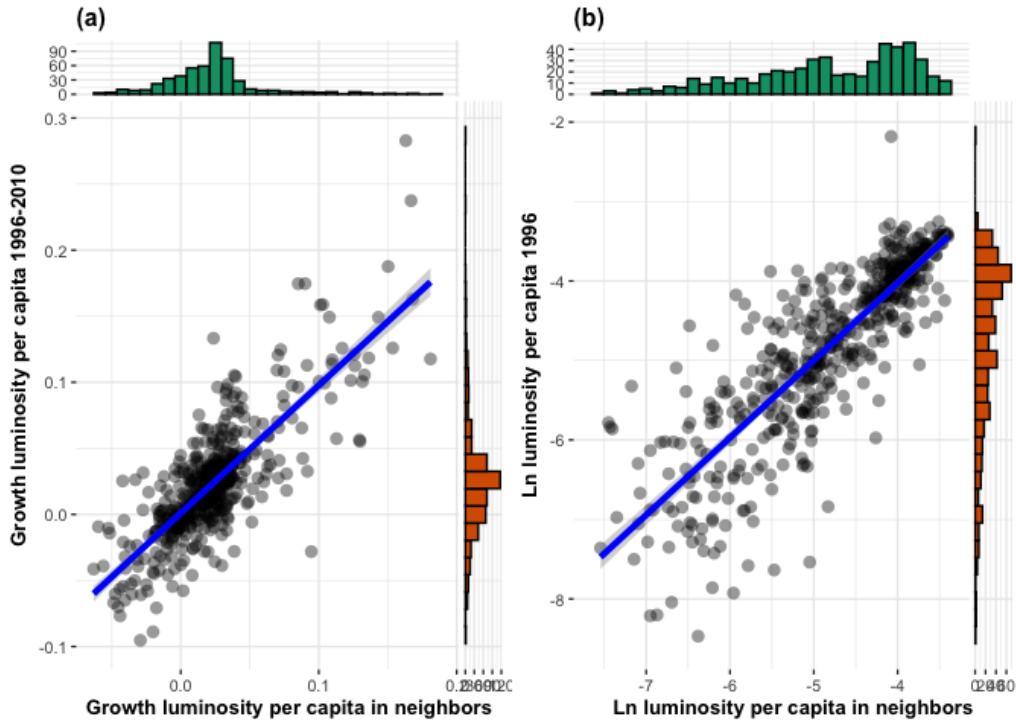


Figure 4: Spatial dependence in the growth rate and initial level of luminosity

¹ Source: [Spatial dependence](#)

² 3.3 Spatial spillovers accelerate regional convergence

³ The regression results of TableX provide evidence of both unconditional and conditional
⁴ convergence across districts in India, with both conventional OLS and spatial econometric
⁵ approaches indicating significant negative relationships between initial luminosity levels
⁶ and subsequent growth rates. The direct effects, representing within-district convergence,
⁷ remain remarkably stable across specifications, ranging from -0.020 to -0.026. This
⁸ consistency across different model specifications and estimation methods provides evidence
⁹ that poorer districts are indeed catching up to their wealthier counterparts, even after
¹⁰ controlling for various district characteristics and state-level fixed effects.

Table 1: Unconditional and conditional convergence across districts

	Model 1		Model 2		Model 3		Model 4	
Direct	OLS	SDM	OLS	SDM	OLS	SDM	OLS	SDM
	-	-	-	-	-	-	-	-
	0.020*** (0.002)	0.020*** (0.002)	0.022*** (0.003)	0.021*** (0.002)	0.025*** (0.003)	0.026*** (0.002)	0.025*** (0.003)	0.025*** (0.002)
Indirect	-	-	-0.002 (0.004)	-	-0.008 (0.006)	-	-0.008 (0.006)	-
Total	-	-	-	-	-	-	-	-
	0.020*** (0.002)	0.022*** (0.005)	0.022*** (0.003)	0.029*** (0.007)	0.025*** (0.003)	0.034*** (0.007)	0.025*** (0.003)	0.034*** (0.005)
Controls	No	No	No	No	Yes	Yes	Yes	Yes
State	No	No	Yes	Yes	No	No	Yes	Yes
FE								
AIC	-1945	-2278	-2413	-2457	-2211	-2345	-2469	-2462

¹¹ Importantly, the spatial Durbin model uncovers significant spatial spillover effects

1 that are masked in traditional OLS estimations. These indirect effects, which capture the
 2 influence of neighboring districts' initial conditions on a district's growth rate, become
 3 increasingly prominent and statistically significant as we add controls and state fixed
 4 effects to our specifications. In our most comprehensive model, we find a significant
 5 indirect effect of -0.009, suggesting that a district's growth trajectory is meaningfully
 6 influenced by the initial economic conditions of its neighbors. This finding highlights the
 7 importance of geographical proximity and spatial interactions in the convergence process.

8 The total impact of initial conditions on growth, combining both direct and spillover
 9 effects, is substantially larger when we account for spatial dependence. In our fully
 10 specified model, the total convergence effect in the spatial Durbin model (-0.034) is
 11 approximately 36% larger than the OLS estimate (-0.025). This difference, supported
 12 by better model fit statistics, indicates that conventional non-spatial approaches may
 13 significantly underestimate the speed of regional convergence by failing to capture the
 14 additional convergence channels created through spatial spillovers. These results emphasize
 15 that regional convergence in India operates not only through district-specific factors but
 16 also through significant spatial interactions between neighboring districts.

17 4 Concluding remarks

18 This article examines regional convergence patterns across Indian districts using satellite
 19 nighttime light data, interactive visualizations, and spatial econometric modeling. Ex-
 20 panding on the work of Chanda, Kabiraj (2020), we developed an interactive web-based
 21 visualization tool that illustrates spatial and convergence patterns across Indian districts.
 22 Spatial autocorrelation tests confirm that spatial dependence is a fundamental character-
 23 istic of satellite data and the regional convergence process in India. Estimates from our
 24 spatial Durbin model indicate that incorporating spatial spillovers significantly increases
 25 the estimated speed of regional convergence. The total convergence effect in our fully
 26 specified model is approximately 36% larger than conventional non-spatial estimates of
 27 Chanda, Kabiraj (2020). This finding implies that non-spatial convergence models may
 28 considerably underestimate the speed of regional convergence. Additionally, it suggests
 29 that place-based development interventions may have broader impacts, as their benefits
 30 can extend to neighboring districts through spatial spillover effects.

31 These results have important implications for both research methodology and policy
 32 design in developing countries. From a methodological perspective, they highlight the
 33 value of combining new data sources, interactive geospatial visualization tools, and spatial
 34 econometric methods to better understand regional economic dynamics. From a policy
 35 standpoint, they suggest that regional convergence operates not just through district-
 36 specific factors, but through complex spatial interactions that create additional channels
 37 for catch-up growth. This spatial perspective is crucial for the analysis and design of
 38 policies aimed at reducing regional inequalities in developing countries.

39 References

- 40 Adhikari B, Dhital S (2021) Decentralization and regional convergence: Evidence from
 41 night-time lights data. *Economic Inquiry* 59: 1066–1088. [CrossRef](#)
- 42 Asher S, Novosad P (2016) Market access and structural transformation: Evidence from
 43 rural roads in India. *Job Market Paper January* 11: 2016
- 44 Beyer RC, Franco-Bedoya S, Galdo V (2021) Examining the economic impact of covid-19
 45 in india through daily electricity consumption and nighttime light intensity. *World
 46 Development* 140: 105287
- 47 Chakravarty P, Dehejia V (2017) Will gst exacerbate regional divergence. *Economic and
 48 Political Weekly* 52: 97–101
- 49 Chanda A, Cook CJ (2022, September) Was India's demonetization redistributive? insights
 50 from satellites and surveys. *Journal of Macroeconomics* 73: 103438. [CrossRef](#)

- ¹ Chanda A, Kabiraj S (2020) Shedding light on regional growth and convergence in india.
² *World Development* 133: 104961
- ³ Cook CJ, Shah M (2022, July) Aggregate effects from public works: Evidence from India.
⁴ *The Review of Economics and Statistics* 104: 797–806. [CrossRef](#)
- ⁵ Ertur C, Koch W (2007) Growth, technological interdependence and spatial externalities:
⁶ theory and evidence. *Journal of applied econometrics* 22: 1033–1062
- ⁷ Fischer MM (2011) A spatial mankiw–romer–weil model: theory and evidence. *The
⁸ Annals of Regional Science* 47: 419–436
- ⁹ Gennaioli N, La Porta R, De Silanes FL, Shleifer A (2014) Growth in regions. *Journal of
¹⁰ Economic growth* 19: 259–309
- ¹¹ Henderson JV, Storeygard A, Weil DN (2012) Measuring economic growth from outer
¹² space. *American Economic Review* 102: 994–1028
- ¹³ Jha P, Talathi K (2023, March) Impact of colonial institutions on economic growth and
¹⁴ development in India: Evidence from night lights data. *Economic Development and
¹⁵ Cultural Change* 72: 1653–1708. [CrossRef](#)
- ¹⁶ Lessmann C, Seidel A (2017) Regional inequality, convergence, and its determinants—a
¹⁷ view from outer space. *European Economic Review* 92: 110–132
- ¹⁸ Pinkovskiy M, Sala-i Martin X (2016) Lights, camera ... income! illuminating the national
¹⁹ accounts-household surveys debate. *The Quarterly Journal of Economics* 131: 579–631.
²⁰ [CrossRef](#)



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