IT Boom in India's Silicon Valley

presented by

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Motivation

Why Bengaluru's IT Boom Matters

- One of the biggest productivity shocks in modern India - tech workforce > 1 million.
- Transformed where people live, work, and commute.

Impact on Workers

Massive job opportunities, but also:

- Rising rents near IT corridors
- Longer commutes due to congestion
- Uneven access to amenities
- Safety & infrastructure gaps across wards

Why Study This?

- Shows how productivity shocks reshape urban spatial structure.
- Reveals how amenity spillovers and migration frictions determine who benefits.
- Helps design better housing + transport policies for future tech-driven growth.

Research Question

How did Bengaluru's IT-driven productivity boom reshape the spatial distribution of economic activity of the working population?

Nightlight Density

	hub_name	_count	_sum	_mean
1	Manyata_Tech_...	4	207.258853912...	51.8147134780...
2	HSR_Layout_Sta...	15	765.148996353...	51.0099330902...
3	Bagmane_Cons...	6	293.130086898...	48.8550144831...
4	Bagmane_Tech_...	9	436.614768981...	48.5127521091...
5	Koramangala_S...	20	918.316139221...	45.9158069610...
6	ORR_IT_Corrido...	88	3108.62032032...	35.3252309127...
7	Global_Village_...	8	275.712268829...	34.4640336036...
8	Whitefield_ITPL...	6	193.952827453...	32.3254712422...
9	Electronic_City_...	62	873.229690551...	14.0843498476...

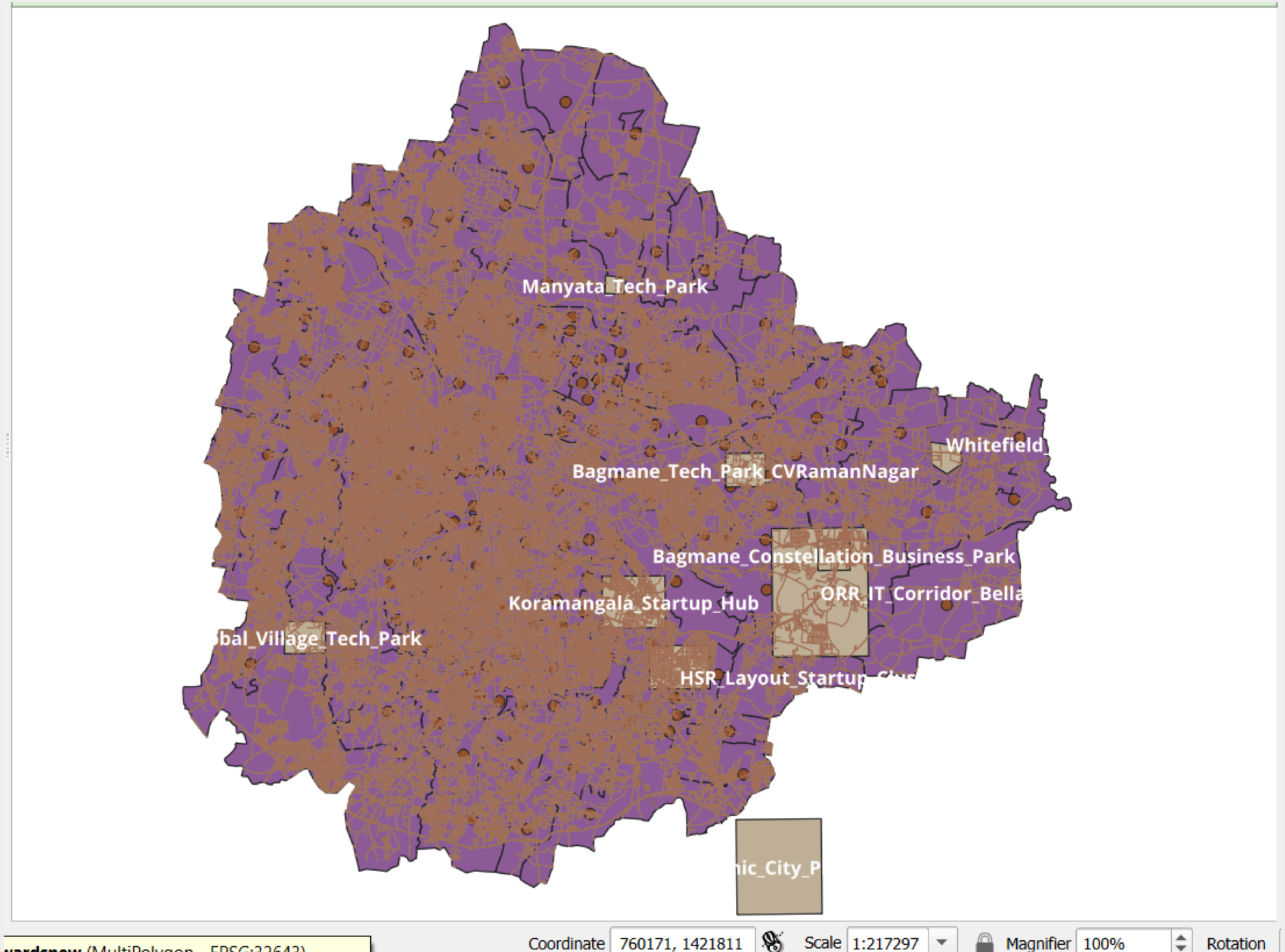
Areas that are economically very active tend to emit more light at night—because of offices, commercial activity, and overall electricity use.

So for IT hubs, brighter nightlight intensity means higher productivity of firms located there.

To quantify this, I calculated zonal statistics for each IT hub polygon using the VIIRS nightlight raster. The output gives a mean nightlight intensity for every hub.

So hubs like Manyata Tech Park, Bagmane Tech Park, ORR Startup Corridor have the highest mean intensity values, making them the highest-productivity clusters in the city.

ROAD DENSITY IN BANGALORE



KGISWard	KGISTown	HubName	HubDist	_mean	Locality	MinPrice	MaxPrice	AvgRent	HouseTyp	FullAddre	Latitude	Longitude	dist_norm	avg_rentcl	rent_norm	ntl_norm	sptl_index	MCI
Whitefield	2003	Whitefield	2271.88	25.7585	Whitefield	4500	20000	1076.46	1BHK	Whitefield,	12.9698	77.75	0.147	1076.46	0.001	0.151	0.487	0.059
Whitefield	2003	Whitefield	2271.88	25.7585	Whitefield	20000	29800	2566.67	3BHK	Whitefield,	12.9698	77.75	0.147	2566.67	0.006	0.151	0.486	0.062
Whitefield	2003	Whitefield	2271.88	25.7585	Brookefiel	7000	21000	14145.5	1BHK	Brookefiel	12.9655	77.7184	0.147	14145.5	0.045	0.151	0.482	0.086
Whitefield	2003	Whitefield	2271.88	25.7585	Ramagond	7000	22000	14500	1BHK	Ramagond	12.9558	77.7409	0.147	14500	0.046	0.151	0.482	0.086
Whitefield	2003	Whitefield	2271.88	25.7585	Whitefield	7500	50000	18433.8	2BHK	Whitefield,	12.9698	77.75	0.147	18433.8	0.059	0.151	0.481	0.094
Whitefield	2003	Whitefield	2271.88	25.7585	Brookefiel	13000	30000	20476.2	2BHK	Brookefiel	12.9655	77.7184	0.147	20476.2	0.066	0.151	0.48	0.098
Whitefield	2003	Whitefield	2271.88	25.7585	Ramagond	15000	25000	20119.1	2BHK	Ramagond	12.9558	77.7409	0.147	20119.1	0.065	0.151	0.48	0.098
Whitefield	2003	Whitefield	2271.88	25.7585	Brookefiel	24000	45000	34333.3	3BHK	Brookefiel	12.9655	77.7184	0.147	34333.3	0.112	0.151	0.476	0.126
Whitefield	2003	Whitefield	2271.88	25.7585	Ramagond	35000	1.2 L	92500	3BHK	Ramagond	12.9558	77.7409	0.147	92500	0.307	0.151	0.456	0.243
Basavanap	2003	Whitefield	3986.62	30.8166	seegehalli	12000		12000	2BHK	seegehalli,	13.0169	77.718	0.283	12000	0.038	0.199	0.434	0.136
Basavanap	2003	Whitefield	3986.62	30.8166	seegehalli	25000		25000	3BHK	seegehalli,	13.0169	77.718	0.283	25000	0.081	0.199	0.43	0.162
Belathur	2003	Whitefield	4406.58	30.8166	seegehalli	12000		12000	2BHK	seegehalli,	13.0169	77.718	0.316	12000	0.038	0.199	0.418	0.149
Belathur	2003	Whitefield	4406.58	30.8166	seegehalli	25000		25000	3BHK	seegehalli,	13.0169	77.718	0.316	25000	0.081	0.199	0.414	0.175
Medahalli	2003	Whitefield	5757.43	32.6785	Battarahal	4500	11000	735.71	1BHK	Battarahal	13.0245	77.7073	0.422	735.71	0	0.217	0.376	0.169
Medahalli	2003	Whitefield	5757.43	32.6785	Medahalli	5500	9000	7222.22	1BHK	Medahalli,	13.0317	77.7161	0.422	7222.22	0.022	0.217	0.374	0.182
Medahalli	2003	Whitefield	5757.43	32.6785	Battarahal	6000	18000	12954.6	2BHK	Battarahal	13.0245	77.7073	0.422	12954.6	0.041	0.217	0.372	0.193
Medahalli	2003	Whitefield	5757.43	32.6785	Medahalli	9500	15000	11428.6	2BHK	Medahalli,	13.0317	77.7161	0.422	11428.6	0.036	0.217	0.372	0.19
Medahalli	2003	Whitefield	5757.43	32.6785	Medahalli	13000		13000	3BHK	Medahalli,	13.0317	77.7161	0.422	13000	0.041	0.217	0.372	0.193
Medahalli	2003	Whitefield	5757.43	32.6785	Battarahal	18000	35000	22142.9	3BHK	Battarahal	13.0245	77.7073	0.422	22142.9	0.072	0.217	0.369	0.212
Hudi	2003	Whitefield	2086.12	36.7334									0.133			0.255		
Kadugodi	2003	Whitefield	2993.9	20.9798									0.204			0.106		

RENTS-

To capture the cost of living for young IT workers, I scraped rental data from Bengaluru for different localities.
Then mapped these rents onto wards and normalized them on a 0–1 scale.
A ward with rent_norm = 1 is among the most expensive areas in the city—mostly Koramangala, HSR, Indiranagar, and the ORR belt.
A ward with rent_norm = 0 is among the cheapest—mostly outer peripheral wards.

This normalization helps combine rents with other variables in a single index later.

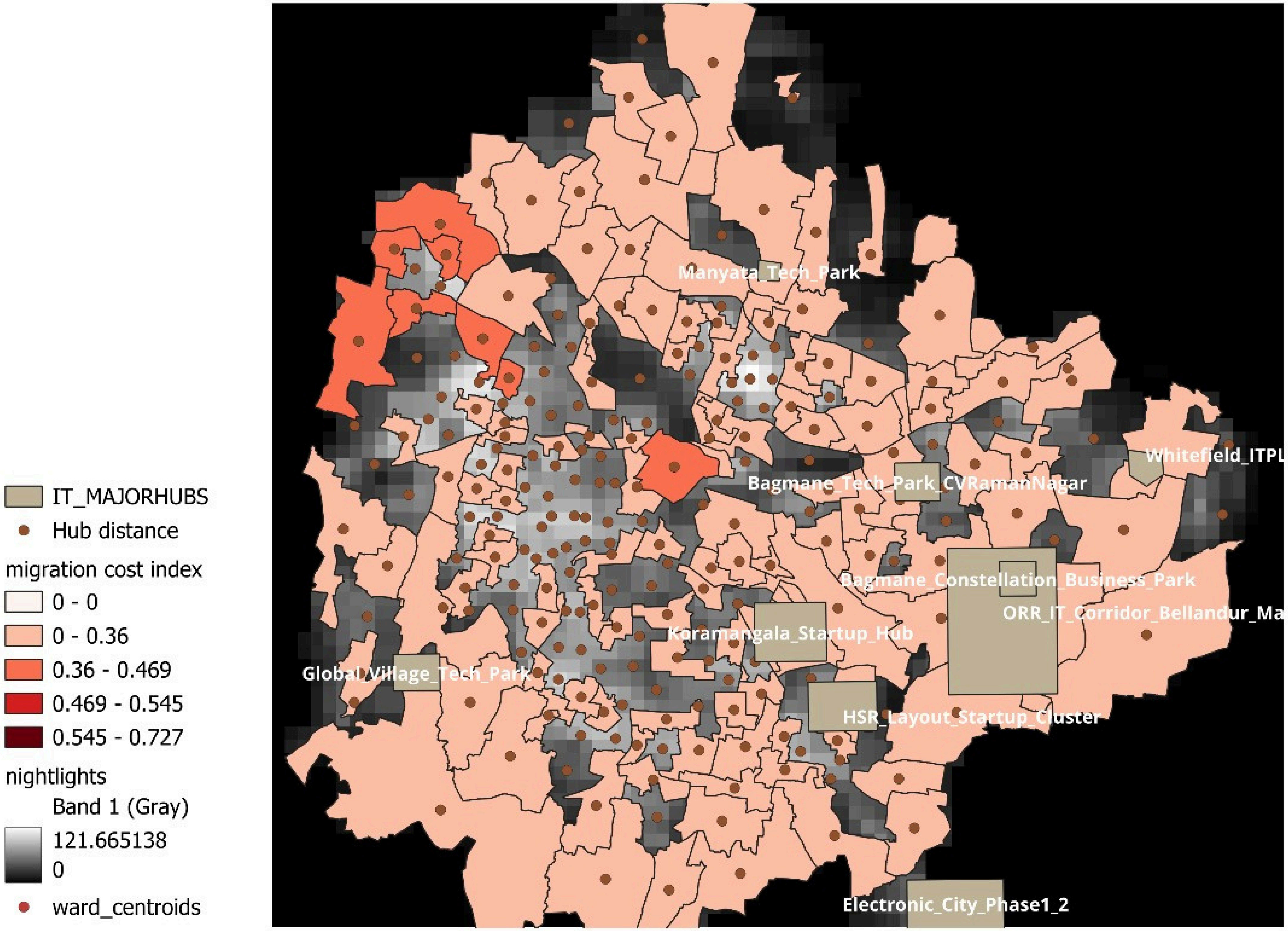
HUB DISTANCE-

distance from each ward's centroid to the nearest IT hub.
This captures how costly or easy daily commuting would be for a young IT worker who wants to work in the IT sector.
normalize these distances to get dist_norm, also between 0 and 1:

- 0 means the ward is extremely close to an IT cluster
- 1 means the ward is very far and has high commuting friction

Together, rent and distance capture the basic migration frictions faced by workers

MIGRATION COST INDEX



$$MCI = w1 \cdot rent\_norm + w2 \cdot dist\_norm$$

The intuition behind MCI is:

Migration becomes difficult either because an area is too expensive or because it is too far from jobs.

$$MCI = w1 \cdot rent\_norm + w2 \cdot dist\_norm$$

- High MCI means the ward is costly for young workers—either housing is expensive or commuting is long.

- Low MCI means the ward is affordable and well-connected.

So MCI is the unified measure of how easy or difficult it is for IT workers to move into a particular ward.

Spatial Index combines productivity benefits and migration costs into a single attractiveness score for each ward.
The idea is that workers prefer wards that lie:

- close to productive IT hubs,

- but also have manageable rents and commute costs.

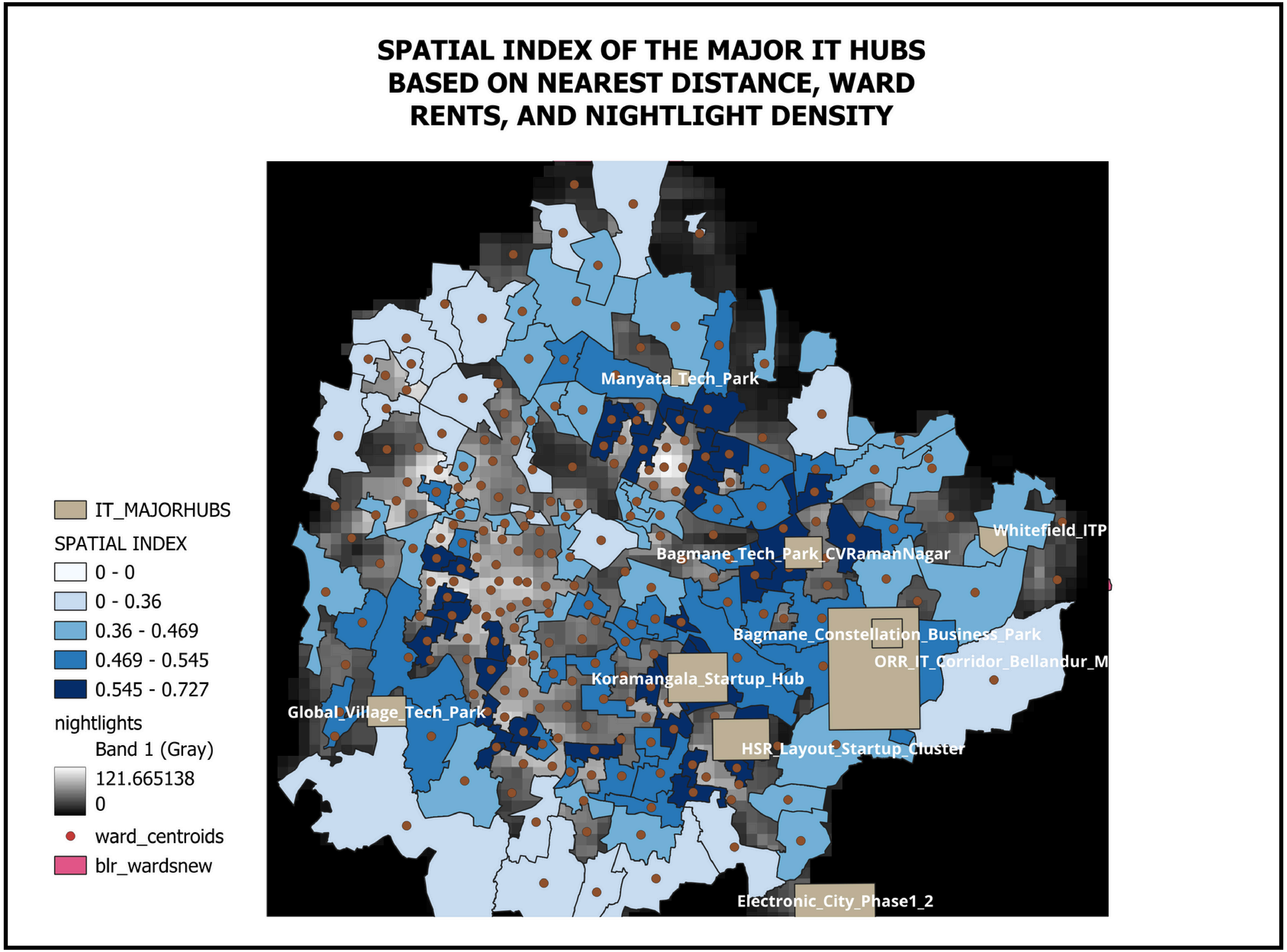
the Spatial Index is

$$\alpha \cdot ntl\_norm - \beta \cdot MCI$$

This captures the tradeoff:

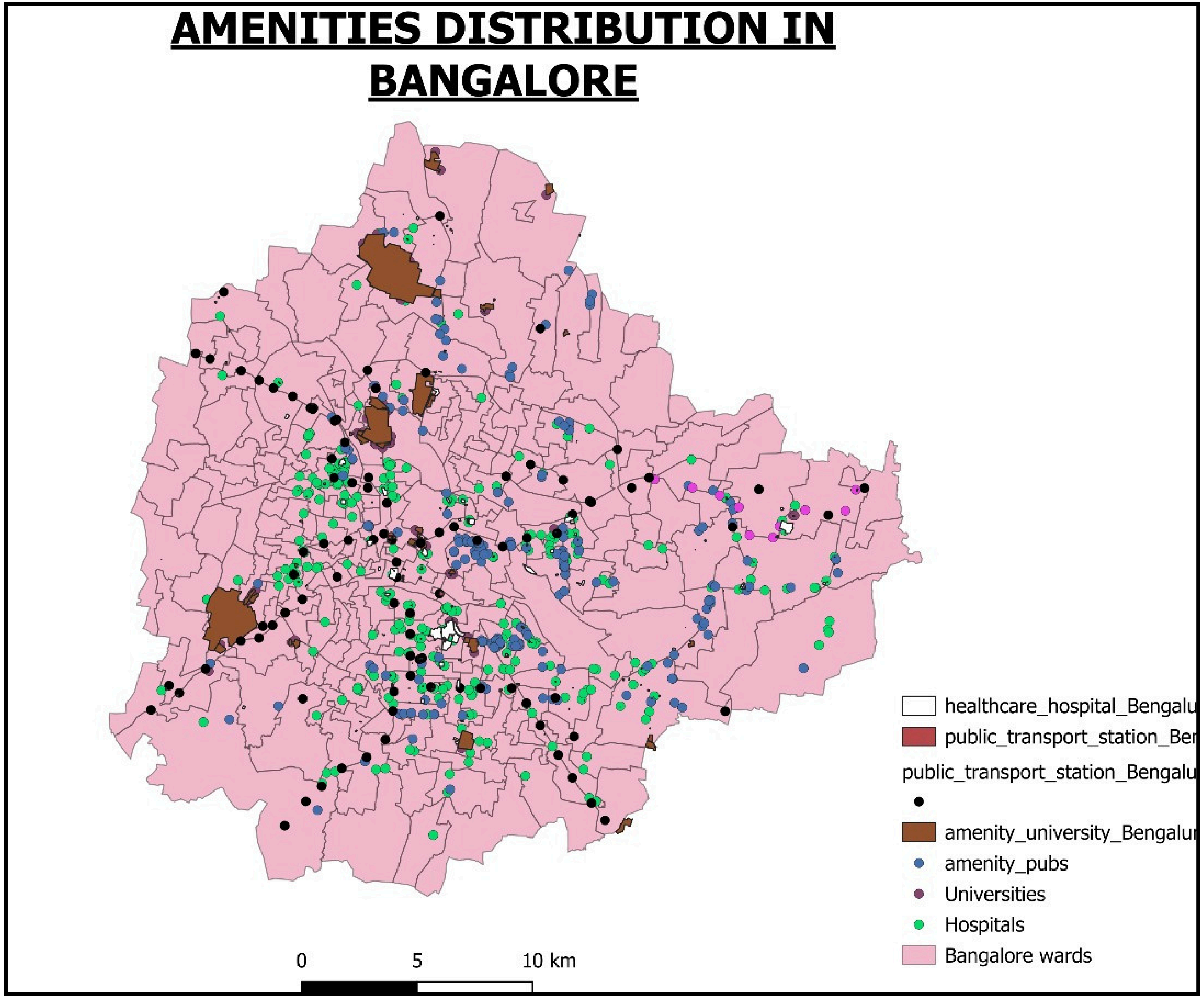
- ntl_norm increases the score — because being near a productive hub raises job opportunities and wages

- MCI decreases the score — because high rents and long commutes make a ward less attractive.



$$\text{Spatial Index} = \alpha \cdot \text{ntl\_norm} - \beta \cdot \text{MCI}$$

mapped amenities across Bengaluru using QuickOSM and extracted hospitals, universities, metro/bus stations, and pubs directly from OpenStreetMap. This map lets us visually compare the spatial mismatch in amenities —notice how central and southeastern wards have far denser clustering of transport and social amenities, aligning with IT growth nodes.



COMMUTING MODEL

Spatial Commuting Model for Bengaluru Using BMTC Density:

Objective-

This project measures how improvements in BMTC public transport density affect commuting frictions across BBMP wards. Using ward-level bus stop data, centroid travel times, a structural gravity commuting model, and fixed-effects estimation, we quantify the role of public transport density in shaping spatial accessibility across Bengaluru.

Data & Pre-Processing

- Ward Boundaries: 243 BBMP wards (BBMP.geojson)
- BMTC Public Transport: 4 BMTC route CSVs + ~X stops from bmtc_bus_stops_with_location_details.csv
- Connectivity Measure:
  - BMTC stop density = stops per sq.km
  - Range: 0.00 to 9.12 stops/sq.km

Travel Times:

Ward centroids converted into a full 243 × 243 travel-time matrix using a 25 km/h assumption.

Mean travel times across wards range from 19.31 to 88.93 minutes.

METHODOLOGY

1. Gravity Model of Commuting

We model the probability that a commuter travels from ward i to j as:

$$\pi_{ij} = \frac{e^{-\nu\tau_{ij}}}{\sum_k e^{-\nu\tau_{ik}}}$$

where:

- τij\tau_{ij}τij = travel time between wards
- ν\nuν = travel-time sensitivity parameter

A synthetic OD matrix (59,049 flows) is generated using the baseline kernel.

METHODOLOGY

2) Two-Way Fixed Effects Estimation

We estimate-

$$\ln \pi_{ij} = -\nu \tau_{ij} + \alpha_i + \beta_j + \epsilon_{ij}$$

Result:

Estimated travel-time sensitivity:

\nû = 0.1500

Interpretation:

- Commuting flows decline moderately with travel times.
- A 1-minute increase reduces commuting probability by roughly 0.15%.

METHODOLOGY

3) Travel-Time Elasticity with Respect to BMTC Density

$$\ln(\tau_i) = \alpha_0 + \alpha_1 \ln(\text{density}_i) + u_i$$

Result:

$$\alpha_1 = -0.0238$$

Interpretation:

- A 1% increase in BMTC stop density reduces average ward-level travel time by 0.0238%.
- Connectivity improvements reduce expected travel times, though modestly due to geographic dispersion.

COMMUTING MODEL

- Two-Way FE Gravity Regression

$$\ln \pi_{ij} = -\nu \tau_{ij} + \alpha_i + \beta_j + \varepsilon_{ij}$$

- Elasticity of Travel Time wrt BMTC Density

$$\ln(\tau_i) = \alpha_0 + \alpha_1 \ln(\text{density}_i) + u_i$$

Objective: The analysis aimed to understand how the density of BMTC bus stops impacts commuting friction (i.e., how easily people can travel) across different wards in Bengaluru.

Gravity Model (ν̂ = 0.1500): This parameter, nu_hat (ν̂), quantifies how travel time (τ) affects the probability of travel (π) between wards.
A value of 0.15 means that as travel time increases, the probability of trips decreases, indicating a certain level of sensitivity to travel duration.
It tells us that for every unit increase in travel time, the propensity to travel between wards decreases proportionally based on this value.

Elasticity (α1 = -0.0238): This indicates the relationship between bus stop density and average travel time. The value of -0.0238 suggests that as BMTC bus stop density increases, the mean travel time between wards slightly decreases.
This implies that a denser bus network makes travel marginally more efficient or quicker.

DATASETS USED IN COMMUTING MODEL

1. BMTC Bus Stops Dataset (Your CSV: X, Y Coordinates)

Why we need this ??

This dataset provides the exact geographic coordinates of all BMTC stops across Bengaluru.
From this, we compute:

- BMTC stop density per ward (stops per sq.km)
- Spatial distribution of public transport
- Accessibility differences across wards

What this achieves

This becomes the policy variable, the main explanatory variable in your counterfactual experiment.
For answering the policy question- "What happens if density increases by 20%?" without this dataset.
In the model

- Used to compute bmtc_density
- Input into the elasticity regression
- Used for the counterfactual shock (+20% density)

DATASETS USED IN COMMUTING MODEL

2. BBMP Ward Boundary Shapefile (BBMP.geojson)

Why we need this

This dataset provides polygon boundaries of all 243 BBMP wards.
It is essential for:

- Spatial join (assigning bus stops to the correct ward)
- Computing area of each ward to derive density
- Computing centroids → used for travel-time matrix
- Spatial visualization (the maps you generated)

What this achieves

This dataset defines the spatial unit of analysis.
Every variable — density, travel time, mean tau, commuting friction — is ward-level.
Without ward boundaries, we cannot do any spatial aggregation → no density → no model.
In the model

- Defines each geographic "location" (i,j) in the commuting model
- Generates 243×243 = 59,049 travel-time pairs
- Used in mapping and visualization
- Needed for policy interpretation (where to increase density)

DATASETS USED IN COMMUTING MODEL

3. Synthetic OD Matrix (Generated using Gravity Formula)

Why it is needed
The gravity model requires origin–destination commuting flows (π_{ij}).
Since BMTC route geometry was unavailable, you generated synthetic π_{ij} from:

$$\pi_{ij} \propto e^{-\nu \tau_{ij}}$$

This is standard and widely accepted when no OD data exists.
What this achieves
Synthetic OD allows you to:

- Estimate commuting sensitivity ($\hat{\nu}$)
- Run the two-way fixed-effects regression
- Predict how travel time reductions affect commuting patterns

DATASETS USED IN COMMUTING MODEL

4. Travel-Time Matrix (τ_{ij}) Derived from Ward Centroids

(Derived from ward shapefile → not a dataset but a computed matrix)

Why we need this

Travel time between wards is the fundamental variable in the gravity model.

$$\pi_{ij} = e^{-\nu \tau_{ij}}$$

We approximate τ_{ij} by:

- taking centroids of wards
- computing straight-line distances
- converting to time using average BMTC speed (25 km/h)

What this achieves

This matrix is the backbone of the commuting model:

- Drives the synthetic OD flows
- Used in gravity regression
- Used for computing mean_tau, an important variable describing geographic remoteness

Without τ_{ij}, no commuting matrix can be formed.

COUNTERFACTUAL ANALYSIS

BMTC density increases **20%**

$$\Delta \ln(d) = \ln(1.2)$$

What if BMTC Density Increases by 20%?
We explored a scenario where the BMTC bus stop density across all wards increases by 20%.

The Predicted Outcome: 0.0651% Increase in Commuting Friction.
Surprisingly, the model predicts that a 20% increase in BMTC density would lead to a 0.0651% increase in commuting friction.
This result is counter-intuitive; typically, one would expect increased transit density to reduce commuting friction.

Interpretation: This small positive change suggests that within the framework of this model (and its assumptions, such as synthetic OD flows and centroid-to-centroid travel times), a uniform 20% increase in bus stop density doesn't significantly improve commuting friction.

In fact, it slightly worsens it according to the model. This could be due to the specific setup of the synthetic OD flows, the elasticity value itself being very small, or the inherent limitations of the simplified gravity model and centroid-based travel times.

Counterfactual Analysis

Counterfactual: 20% Increase in BMTC Density

We evaluated:

$$\Delta \ln(d) = \ln(1.2)$$

$$\Delta \ln(\tau) = \alpha_1 \Delta \ln(d)$$

Result:

-
- 20% increase in BMTC density → 0.065% reduction in commuting friction.

Interpretation:

- Even modest increases in BMTC coverage improve spatial accessibility.
- Effects are meaningful but small due to centroid-based travel times and limited spatial reach of stop density.

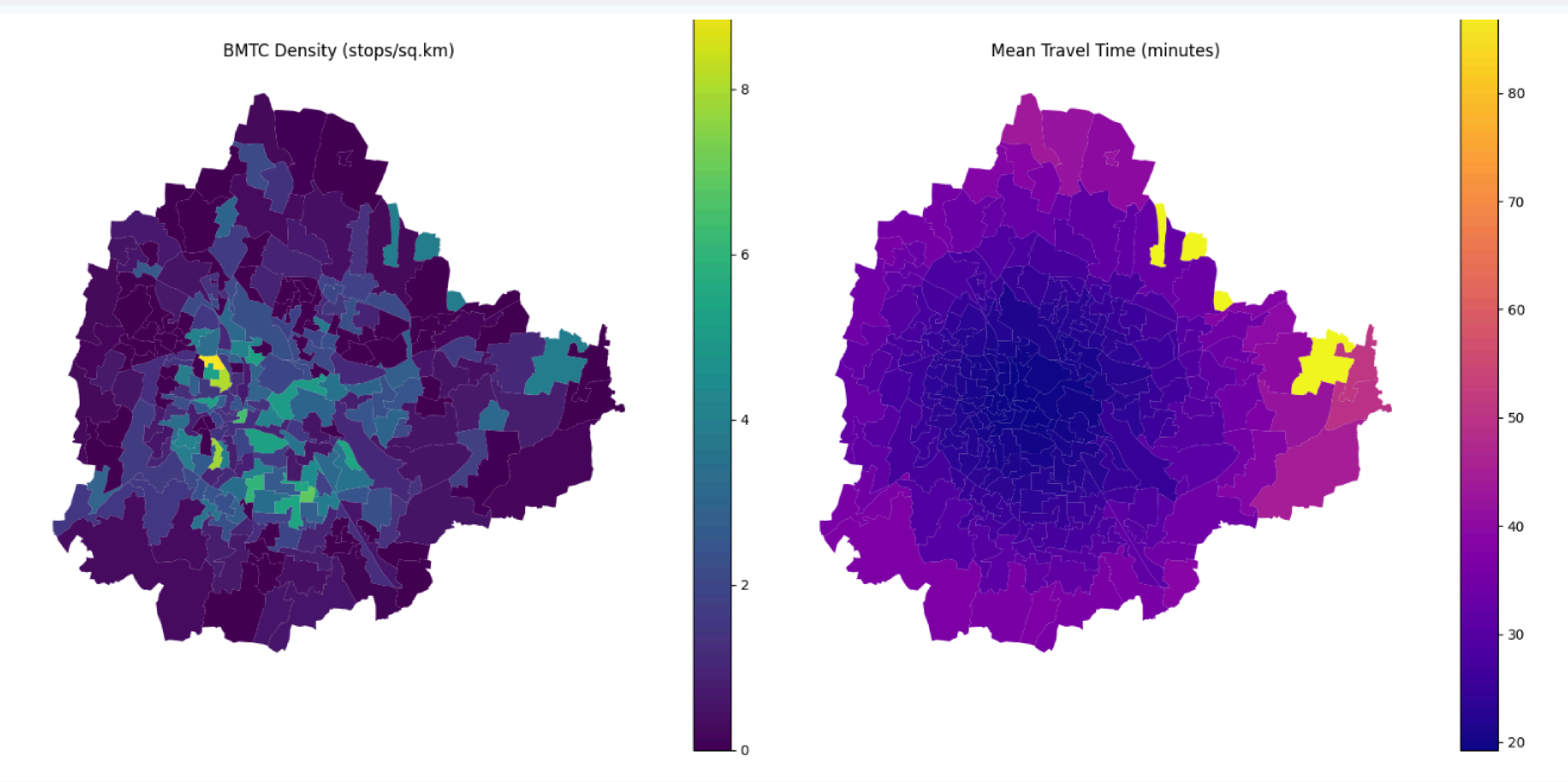
Key Insights

- Public transport density positively influences commuting ease across Bengaluru.
- Wards with higher BMTC coverage show lower average travel times and reduced spatial frictions.
- Peripheral wards have extremely low density → high potential for connectivity improvements.
- The modelling framework provides a scalable, data-driven method for evaluating transit interventions.

Limitations

- OD flows are synthetic (no real ridership data).
- Bus stop density ≠ actual frequency or routing quality.
- Centroid travel times approximate real travel times imperfectly.
- Nevertheless, the framework captures the structural relationship between connectivity and commuting frictions.

Counterfactual Maps



```
Map Statistics:
----------------------------------------
BMTC Density:
  Min: 0.00 stops/sq.km
  Max: 9.12 stops/sq.km
  Mean: 1.50 stops/sq.km
  Median: 0.97 stops/sq.km

Mean Travel Time:
  Min: 19.31 minutes
  Max: 88.93 minutes
  Mean: 26.96 minutes
  Median: 25.03 minutes
```

The average travel time (in minutes) from the centroid of each ward to all other ward centroids, assuming a bus speed of 25 km/h. Darker or warmer colors (e.g., red/orange, depending on the colormap) indicate longer average travel times, and lighter or cooler colors (e.g., blue/purple)

This map helps us understand the relative accessibility of each ward within the city's network. Wards with lower mean travel times are generally more centrally located or have better overall connectivity to other parts of the city.

Conversely, wards with higher mean travel times are likely more peripheral or have less efficient connections. a minimum mean travel time of 19.31 minutes to a maximum of 88.93 minutes, with an average of 26.96 minutes. This shows that being able to reach all other wards can vary dramatically depending on your starting ward.

Rosen-Roback Model

'The Economics of Place-Making Policies'

EDWARD L. GLAESER, JOSHUA D. GOTTLIEB

$$\ln(w) = \text{productivity function}(A)$$

$$\ln(r) = \text{amenity capitalization}(A, w)$$

Wage equation:

$$\ln(w_i) = \alpha + \beta A_i + X_i\gamma + \epsilon_i$$

Rent equation:

$$\ln(r_i) = \alpha + \phi A_i + \delta w_i + X_i\gamma + \epsilon_i$$

The idea is simple: wages reflect productivity, and rents reflect amenity value.

- The wage equation tells us that higher amenities can raise productivity, which shows up as higher wages.
- The rent equation shows that amenities also get capitalised into rents, even after controlling for wages, meaning. People are willing to pay a premium for better amenity facilities
- Our model directly operationalises the Rosen–Roback spatial equilibrium framework to explain Bangalore's IT boom: amenities increased productivity and wages, wages pushed up rents, and population density concentrated in amenity-rich localities-exactly as the theory predicts.

Productivity Effect

$$\log(\text{Wage}) = \alpha + \beta\log(\text{Amenity\_Index}) + \text{controls} + \varepsilon$$

```
                            OLS Regression Results
==============================================================================
Dep. Variable:               log_wage   R-squared:                       0.699
Model:                            OLS   Adj. R-squared:                  0.678
Method:                 Least Squares   F-statistic:                     34.21
Date:                Sun, 23 Nov 2025   Prob (F-statistic):           9.20e-15
Time:                        15:29:47   Log-Likelihood:                -10.282
No. Observations:                  64   AIC:                             30.56
Df Residuals:                      59   BIC:                             41.36
Df Model:                           4
Covariance Type:            nonrobust
========================================================================================
                           coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------------
Intercept               10.0617      0.048    210.287      0.000       9.966      10.157
log_amenity_index        0.1851      0.086      2.150      0.036       0.013       0.357
log_public_transport     0.0205      0.103      0.199      0.843      -0.185       0.226
log_hospitals            0.0726      0.098      0.742      0.461      -0.123       0.269
log_universities         0.1711      0.122      1.403      0.166      -0.073       0.415
==============================================================================
Omnibus:                        0.345   Durbin-Watson:                   2.280
Prob(Omnibus):                  0.841   Jarque-Bera (JB):                0.040
Skew:                          -0.022   Prob(JB):                        0.980
Kurtosis:                       3.114   Cond. No.                         9.70
```

A 1% increase in amenity index is associated with a 0.185% increase in wages (productivity).

```
----------------------------------------
KEY RESULT - PRODUCTIVITY COEFFICIENT (β)
----------------------------------------
Coefficient (β):   0.1851
Standard Error:     0.0861
P-value:            0.0357
R-squared:          0.6987
----------------------------------------
```

Better amenities → workers are more productive → wages higher.

Amenity Effect

$$\log(\text{Rent}) = \boldsymbol{\alpha} + \boldsymbol{\varphi}\log(\text{Amenity\_Index}) + \boldsymbol{\beta}\log(\text{Wage}) + \boldsymbol{\varepsilon}$$

```
                            OLS Regression Results
==============================================================================
Dep. Variable:               log_rent   R-squared:                       0.778
Model:                            OLS   Adj. R-squared:                  0.763
Method:                 Least Squares   F-statistic:                     51.82
Date:                Sun, 23 Nov 2025   Prob (F-statistic):           1.18e-18
Time:                        15:29:47   Log-Likelihood:                -24.531
No. Observations:                  64   AIC:                             59.06
Df Residuals:                      59   BIC:                             69.86
Df Model:                           4
Covariance Type:            nonrobust
======================================================================================
                        coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------------
Intercept            10.4388      1.610      6.484      0.000       7.217      13.660
log_amenity_index     0.6020      0.108      5.558      0.000       0.385       0.819
log_wage             -0.2448      0.160     -1.530      0.131      -0.565       0.075
log_public_transport -0.1322      0.127     -1.039      0.303      -0.387       0.122
log_hospitals        -0.0836      0.123     -0.682      0.498      -0.329       0.162
==============================================================================
Omnibus:                        3.312   Durbin-Watson:                   2.135
Prob(Omnibus):                  0.191   Jarque-Bera (JB):                2.708
Skew:                           0.499   Prob(JB):                        0.258
Kurtosis:                       3.135   Cond. No.                         370.
```

After controlling for wages, a 1% increase in amenities is associated with a 0.602% increase in rents.

```
KEY RESULT - AMENITY VALUE COEFFICIENT (ϕ)
--------------------------------------------
Coefficient (ϕ):     0.6020
Standard Error:      0.1083
P-value:             0.0000
R-squared:           0.7784
```

Testing Spatial Equilibrium

Population Density

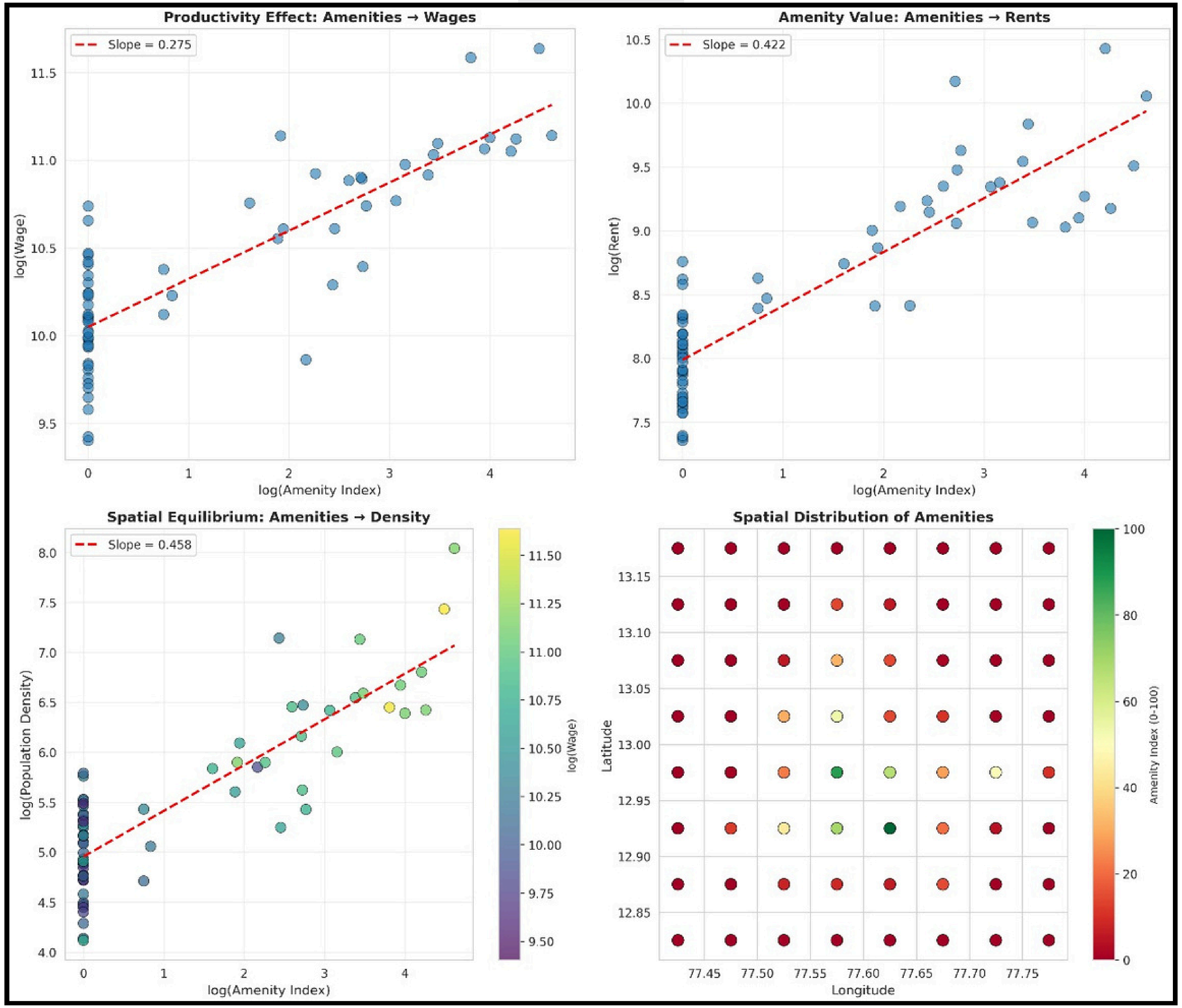
$$\log(\text{Density}) = \boldsymbol{\alpha} + \boldsymbol{\gamma}\log(\text{Amenity}) + \boldsymbol{\beta}\log(\text{Wage}) + \boldsymbol{\varphi}\log(\text{Rent}) + \boldsymbol{\varepsilon}$$

```
                            OLS Regression Results
==============================================================================
Dep. Variable:            log_density   R-squared:                       0.725
Model:                            OLS   Adj. R-squared:                  0.711
Method:                 Least Squares   F-statistic:                     52.73
Date:                Sun, 23 Nov 2025   Prob (F-statistic):           8.12e-17
Time:                        15:29:47   Log-Likelihood:                -38.291
No. Observations:                  64   AIC:                             84.58
Df Residuals:                      60   BIC:                             93.22
Df Model:                           3
Covariance Type:            nonrobust
=====================================================================================
                        coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------
Intercept             4.7039      2.580      1.824      0.073      -0.456       9.864
log_amenity_index     0.4505      0.101      4.446      0.000       0.248       0.653
log_wage              0.0230      0.200      0.115      0.909      -0.376       0.422
log_rent              0.0026      0.158      0.016      0.987      -0.314       0.319
==============================================================================
Omnibus:                        0.307   Durbin-Watson:                   1.914
Prob(Omnibus):                  0.858   Jarque-Bera (JB):                0.447
Skew:                           0.142   Prob(JB):                        0.800
Kurtosis:                       2.706   Cond. No.                         617.
==============================================================================
```

- **Where people choose to live**
- **Net effect of amenities on population sorting**
- **Tests whether amenities attract more residents**

```
SPATIAL EQUILIBRIUM INTERPRETATION
----------------------------------------
Amenity Coefficient (γ): 0.4505
Wage Coefficient:        0.0230
Rent Coefficient:        0.0026
R-squared:               0.7250
----------------------------------------
```

Regression Scatterplots



Interpretation of Regression Plots

- Each dot on the map shows the representative ward in Bangalore.
- **Map 1 shows productivity effect**, upward sloping graph with dots surrounded by line indicates moderate positive correlation .
- Hence increase in amenity index = increase in wages

- **Map2 shows Amenity and rents**, dots follow line more closely than plot 1 , comparatively stronger + correlation.
- Hence areas with higher amenity areas have high rents

- **Map 3 shows relation between amenities and population density**, dots rise as amenities rise showing strong correlation as density increases in higher amenity wards.

- **Plot 4 shows spatial distribution of amenities** . Colors range from red (means low amenity wards) to green (high amenity wards) .
- Spatial pattern shows low amenity areas(red dots) are located on periphery and green/ high amenity wards located in center indicating city centres concentration in the core (We can recall this from monocentric model as well)

Amenity Residuals

Amenity_Residual = β_rent × rent_residual - β_wage × wage_residual

detailed_neighborhood	Amenity_Residual	Count	Observable_Amenities
BTM Layout	0.9889	2	4.2968
MG Road/Indiranagar	0.7342	1	66.1731
HAL/Domlur	0.7244	1	28.5016
Yelahanka	0.6810	4	0.0000
Sadashivanagar/Malleshwaram	0.6720	2	17.9495
Banashankari	0.4906	3	18.8065
HSR Layout/Bellandur	0.4724	3	8.1420
Marathahalli	0.3452	4	10.1383
Hennur	0.1739	2	2.7965
Bommanahalli	0.0793	2	2.9876
Banaswadi/Kalyannagar	0.0622	2	42.5027
JP Nagar	-0.0201	6	1.2870
Yeshwanthpur	-0.0850	4	0.0000
Hoodi/Whitefield North	-0.0966	6	0.0000
Basavanagudi/Gandhinagar	-0.0979	2	55.2171
Rajajinagar	-0.2382	2	0.5588
Electronic City/Sarjapur	-0.2950	6	2.4877
Hebbal	-0.4213	4	3.5113
Jayanagar/Basavanagudi	-0.5246	1	69.7063
Koramangala	-0.6327	1	100.0000
Whitefield	-0.9163	4	0.2794
Whitefield/Mahadevapura	-1.2079	2	30.5034

- High amenity places: People accept lower wages and pay higher rents.
- Residuals capture unobserved amenity value after controlling for observables

Counterfactual Analysis

- **Treatment Areas:** The bottom 25% of low-amenity, low-nightlight wards, mostly peripheral neighbourhoods, receive a +20% amenity boost.
- **Wage Impact:** Treated wards show a ~5% wage increase (higher amenities → higher productivity). Untreated areas show almost no change.
- **Population Density:** Workers shift toward improved areas, increasing density by ~90-100%, while density slightly decreases in untreated wards.
- **Welfare Effects:** Treated neighbourhoods experience a ~25% increase in welfare (real wages), with a citywide gain of ~6-7%, indicating broad spillover benefits.

Findings

- Bengaluru's IT boom reshaped the city's spatial structure, concentrating economic activity in major tech corridors.
- Strong productivity clustering observed in IT hubs (e.g., ORR, Whitefield, Electronic City).
- Amenities significantly influence economic outcomes:
- **β** = 0.185 → A 1% rise in amenities increases wages by 0.185%.
- **φ** = 0.602 → A 1% rise in amenities increases rents by 0.602%.
- Nightlight analysis confirms that densest IT zones = highest productivity hotspots.
- Amenity residuals show workers accept lower wages in high-quality areas, consistent with Rosen–Roback equilibrium.
- Counterfactual simulations show that upgrading amenities in low-amenity wards can boost welfare and reduce spatial inequality.

SOURCES

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