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Assessing Nighttime Light as a Proxy for Income Index with Gendered Insights in North East India

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***Abstract*—North East India has eight states. It has a varied situation regarding income growth, changes in different sectors, and ongoing inequality. Over recent decades, the region has experienced varied economic trajectories, with some states like Sikkim and Mizoram witnessing rapid income growth, while others, such as Assam and Manipur, still lag behind the national average. Nighttime light (NTL) data are commonly used as proxies for economic activity and income, especially in areas where traditional statistics are limited or unreliable. In Northeast India, with its hilly terrain and reliance on agriculture, the connection between NTL and income index is often weak or negative at detailed spatial levels. Studies consistently indicate that women in Northeast India earn less and have lower labor force participation than men, with the wage gap remaining significant. In this paper, an effort has been made to quantify how Nighttime light can serve as a proxy for the income index for both men and women.**

***Index Terms*—Nighttime Light Data (NTL) , Income Proxy , Gender Disparities , North East India, Regional Economic Inequality, JEL Classifications : C43, J16 , O12 , O13 , O18**

I. INTRODUCTION

North East India includes eight states. It shows a complex situation involving income growth, sector shifts, and persistent inequality. Over the past few decades, the region has taken different economic paths. Some states, like Sikkim and Mizoram, have seen rapid income growth. Meanwhile, others, such as Assam and Manipur, still fall behind national averages (Taloh, 2024; Sarma, 2015; Singh, 2018; Singha & Raj, 2021). Despite policy interventions and increased central assistance, income inequality, both within and between states, remains a significant challenge. Recent evidence shows a rise in disparities since 2010-11 (Thangjam & Das, 2022; Sarma, 2015; Rajeev & Nagendran, 2016). Sector shifts from agriculture to services have helped the economy grow. However, the benefits are not shared equally. Multidimensional poverty remains a challenge, particularly in Assam and Meghalaya (Hazarika, 2025; Chakrabarti, 2018; Konwar, 2020; Singh, 2018). Northeast India is often seen as having better gender equality than the national average. However, noticeable gaps still exist in labor force participation, income, and opportunities between men and women. While some states in the region show promising trends in women's educational achievement and workforce participation, deep-rooted disparities persist, especially in rural areas and specific states. Studies consistently show that women in Northeast India earn less and participate less in the labor force than men, with the wage gap remaining substantial. The primary drivers include lower educational attainment among women, limited access to higher education, and persistent social stigma and discrimination against women working outside the home. These factors result in both lower participation rates and significant wage differentials, particularly in rural areas (Singh & Ningthoujam, 2022; Hussain, 2025; Bordoloi & Bedamatta, 2022; Mahanta & Nayak, 2013). Satellite-derived nighttime light data provides a powerful, high-resolution proxy for estimating the income index in North East India, bridging critical data gaps and supporting more effective development strategies. However, we need to interpret the information carefully. We must consider local context, electrification, and sector composition to make sure our assessments of income and human development are accurate. However, ongoing gender gaps in income and labor force participation, along with the limitations of NTL data in capturing informal and low-light economic activity, show the need for gender-sensitive approaches in both data interpretation and policy design.While a positive correlation between NTL and income is well documented, a growing body of research highlights contexts where this relationship is weak, inconsistent, or even adverse (negative). These adverse relationships often emerge at fine spatial scales, in specific urban or rural settings, or due to sectoral and methodological biases. For example, studies have found that at the census tract or block group level, NTL can show a weak or negative correlation with per capita income, particularly in areas where commercial activity or high-density, lower-income housing emits more light than affluent, low-density neighborhoods (Liu et al., 2022; Yu et al., 2024; Mirza et al., 2021).The use of satellite-derived nighttime light (NTL) data as a proxy for economic activity and income has revolutionized the measurement of development, especially in regions where traditional data collection is challenging. In North East India, characterized by rugged terrain, data scarcity, and a large informal economy, NTL data offers a unique lens to estimate the income index one of the core components of the Human Development Index (HDI), which measures per capita income. Research demonstrates a strong correlation between NTL intensity and income-related indicators at subnational levels, enabling the mapping of economic disparities and regional inequality even in data-poor environments (Singhal et al., 2020; Mathen et al., 2023; Mirza et al., 2021; Elvidge et al., 2012; Asher et al., 2021). The Night Light Development Index (NLDI), derived from NTL and population data, further enhances the spatial understanding of human development and income distribution (Elvidge et al., 2012; Singhal et al., 2020). However, the relationship is nuanced, with factors such as electrification, urbanization, and sectoral composition influencing the strength and interpretation of NTL as a proxy for income (Singhal et al., 2020; Yu et al., 2024; Keola et al., 2015). Nighttime light (NTL) data, captured by satellites, has become a transformative tool for estimating economic activity and income, especially in regions where traditional data is sparse or unreliable. In North East India, a region marked by challenging geography, data scarcity, and a large informal economy, NTL data offers a unique lens to estimate the income index one of the core components of the Human Development Index (HDI), which measures per capita income. While NTL data has proven effective in mapping economic disparities and regional inequality at fine spatial scales, its ability to capture gendered dimensions of income is more complex. Gender disparities in labor force participation, wage levels, and sectoral employment persist in North East India, and these differences can influence how well NTL data reflects the true economic status of men and women (Asher et al., 2021; Bordoloi & Bedamatta, 2022; Choudhury & Kumar, 2021). In this paper, we aim to assess how nighttime light can serve as a proxy for the income index for both men and women.

II. NIGHTTIME LIGHT DATA AND THE INCOME INDEX: GENDERED INSIGHTS FROM NORTH EAST INDIA

Nighttime light (NTL) data, derived from satellite imagery, has become a widely used proxy for economic activity and development, especially in regions where reliable income data are scarce. In India, and particularly in the North-east, researchers have leveraged NTL to estimate local income, map poverty, and assess regional inequality at fine spatial scales (Asher et al., 2021; Singhal et al., 2020; Mathen et al., 2024; Mathen et al., 2023; Weidmann &Theunissen, 2021; Pradhan & Agrawal, 2025). However, the relationship between NTL and income indices is complex and context-dependent, with evidence suggesting that the strength and trend of this relationship can vary by geographic scale, sector, and demographic factors such as gender (Asher et al., 2021; Singhal et al., 2020; Dhamija et al., 2023; Choudhury & Kumar, 2021). Recent studies highlight that while NTL correlates with economic indicators, its ability to capture gendered disparities and nuanced socioeconomic outcomes such as women's empowerment or intra-household income dynamics remains limited and sometimes adverse, particularly in the diverse and underdeveloped regions of North East India (Asher et al., 2021; Dhamija et al., 2023; Choudhury &Kumar, 2021; Debnath & Devarani, 2025). This review synthesizes the literature on the relationships between NTL and income indices, with a focus on gendered insights from North East India.

A comprehensive search was conducted across over 170 million research papers in Consensus, including sources such as Semantic Scholar and PubMed. The search strategy targeted foundational concepts, regional studies, gender disparities, and methodological critiques related to nighttime light data, income indices, and gender in North East India. In this process, 1007 papers were identified, 557 were screened, 244 were deemed eligible, and 32 were included in this review.

2.1 Results

2.1.1) Nighttime Light Data as a Proxy for Economic Activity

NTL data is a significant proxy for employment, population, per capita consumption, and electrification at local levels in India, but the strength of this relationship varies by geographic scale and sector (Asher et al., 2021; Singhalet et al., 2020; Mathen et al., 2024; Weidmann & Theunissen, 2021; Pradhan & Agrawal, 2025). At the village level, elasticities between NTL and employment or population are much lower than at district or subdistrict levels, and the relationship is particularly weak for manufacturing employment (Asher et al., 2021; Singhal et al., 2020; Mathenet et al., 2024).

2.1.2) Regional and Gendered Disparities in North East India

Studies focusing on North East India reveal that while NTL can highlight regional disparities in development, it does not consistently capture gendered economic outcomes. For example, urbanization, as measured by NTL, is associated with mixed effects on women's empowerment improving mobility and financial autonomy but not labor participation or agency, and sometimes increasing vulnerability to violence (Dhamija et al., 2023; Choudhury & Kumar, 2021; Debnath & Devarani, 2025). Intra-household gender dynamics further complicate the relationship, with women-headed households showing higher vulnerability and lower income indices (Debnath & Devarani,2025).

2.1.3) Limitations and Adverse Relationships

Several research articles demonstrate that nighttime light data may not fully reflect the complexity of economic development or gender differences. The link between NTL and income can be non-linear or even negative at small spatial scales. This is especially true in rural or underdeveloped areas where access to electricity and economic activity are not evenly spread (Asher et al., 2021; Singhal et al., 2020; Pradhan & Agrawal, 2025). Additionally, NTL is not very effective at representing sectors like agriculture and informal economies. These sectors are important in North East India and often employ many women (Asher et al., 2021; Singhal et al., 2020; Keola et al., 2015; Pradhan & Agrawal, 2025).

2.1.4) Methodological Advances and Critiques

Recent advances, such as the use of VIIRS data and machine learning, have improved the accuracy of NTL-based proxies for economic activity and inequality (Mathen et al., 2024; Mathen et al., 2023; Pradhan & Agrawal, 2025). However, even with these improvements, NTL alone is insufficient to predict socioeconomic inequality or gendered outcomes without integrating additional demographic and contextual data (Pradhan & Agrawal, 2025; Weidmann & Theunissen, 2021; Singhal et al., 2020).

2.2 Discussion

The literature shows that nighttime light data is a helpful way to estimate economic activity and regional inequality. However, its connection to income indices is not always clear. This problem is clear in small regions and areas of the north-eastern states of India. The socioeconomic structures here are complex (Asher et al., 2021; Singhal et al., 2020; Mathen et al., 2024; Pradhan & Agrawal, 2025). Negative or unclear relationships can occur because NTL cannot capture informal economic activities, household dynamics, and gender-based labor(Asher et al., 2021; Singhal et al., 2020; Dhamija et al., 2023; Debnath & Devarani, 2025; Pradhan & Agrawal, 2025). Observations on gender indicate that improvements in NTL, such as urbanization or electrification, do not always lead to better economic outcomes for women; instead, these changes may even heighten vulnerabilities. (Dhamija et al., 2023; Debnath & Devarani, 2025). More data sources and context need to be incorporated to achieve better and fairer assessments. While using machine learning and adding more factors can improve how well NTL data predicts outcomes, these methods do not entirely solve its limitations (Pradhan & Agrawal, 2025; Mathen et al., 2024; Weidmann & Theunissen, 2021).

In conclusion, nighttime light data is a useful resource for studying the economy. Although its limitations, particularly related to small-scale and gender differences, need more detailed research methods for the North-Eastern states of India.

1) Objectives of the study

To quantify how well a proxy for income, nighttime lights data, performs in the north-eastern Indian states for both men and women.

2) Data collection

The data used in this analysis were obtained from various secondary sources. The year range is from 2012 to 2022. The data has been collected for all eight northeastern states of India. This Dataset contains year and state-wise cumulative radiance of nighttime light over India from space. The source is the National Remote Sensing Center of the Indian Space Research Organization. The unit is nanowatts per square centimeter per steradian per square kilometer. Additionally, income index data have been obtained from the Subnational HDI Database of the Global Data Lab. Their Subnational Human Development Index (SHDI) is a translation of the UNDP's official HDI to the subnational level.

The income index is a key component of the Human Development Index (HDI) used by the United Nations Development Program (UNDP) to measure a country's level of human development. It shows the standard of living based on Gross National Income (GNI) per capita, adjusted for purchasing power parity (PPP). The income index ranges from 0 to 1, following the United Nations Development Program's Human Development Index (HDI) framework. A low income index value (near 0) indicates very low income and poor living standards. A high income index value (near 1) reflects very high per capita income and superior living standards.

III. RESEARCH METHODOLOGY

The whole analysis of this paper is based on the mean, the correlation coefficient, and linear regression.

3.1) Linear Regression

A simple linear regression tries to predict the value of a dependent variable from one or more independent variables. The substantial the linear relationship between the independent and dependent variables, the more precise the prediction. This goes along with the fact that the more significant the proportion of the dependent variable's variance that the independent variable can illustrate, the more accurate the prediction. Undisguisedly, the relationship between the variables can be exhibited in a scatter plot. The more prominent the linear relationship between the dependent and independent variables, the better the data points represent a straight line.

The following equation can describe the regression line:

$$\hat{y} = bx + a + \in$$

Here, $\hat{y}$ is estimated dependent variable

b is the gradient of the straight line

x is the independent variable

a is the point of intersection with the y-axis

$\in$ is the residual or error parameter

The regression coefficient b can have different signs, which can be elucidated as follows

b > 0: positive correlation between x and y (the greater x, the greater y)

b < 0: negative correlation between x and y (the greater x, the smaller y)

b = 0: There is no correlation between x and y

3.2) Mean

The mean represents the central or typical value of a dataset and is computed by dividing the sum of all observations by the number of observations. If you have data points $x_1, x_2, \ldots x_n$, the mean — usually denoted as $\underline{x}$ — is given by:

$$\underline{x} = \frac{x_1 + x_2 + x_3 + \cdots + x_n}{n}$$

For a population mean, the symbol μ is used, with the same formula applied to all observations in the population.

3.3) Correlation Coefficient

The correlation coefficient is a statistical calculation that quantifies the strength and direction of the relationship between two variables. The correlation coefficient takes a value between -1 and 1. Positive values (close to 1) imply a strong positive relationship, meaning both variables increase together. Negative values (close to -1) indicate a strong negative relationship, implying that as one variable increases, the other decreases. A value of 0 implies no relationship between the variables.

For variables x and y, the formula (Pearson's r) is:

$$r = \frac{\sum (x_i - \underline{x})(y_i - \underline{y})}{\sqrt{\sum (x_i - \underline{x})^2 \sum (y_i - \underline{y})^2}}$$

Where $\underline{x}$ and $\underline{y}$ denote the mean of the x and y variables, respectively.

IV. ANALYSIS AND INTERPRETATION

The analysis starts by calculating the mean of all four variables in the dataset, accompanied by scatter plots of these variables (Table 1 and Figure 1).

States	mean_NTL_radiance	mean_income_index	mean_income_index_men	mean_income_index_women
Arunachal Pradesh	0.8873	0.6486	0.7179	0.5055
Assam	12.2036	0.5505	0.6146	0.4177
Manipur	3.3455	0.6162	0.6837	0.4765
Meghalaya	4.5509	0.6179	0.6857	0.4781
Mizoram	0.7645	0.7125	0.7849	0.5624
Nagaland	3.9518	0.6510	0.7203	0.5075
Sikkim	2.8773	0.6681	0.7385	0.5227
Tripura	17.3327	0.5737	0.6392	0.4385

Table 1

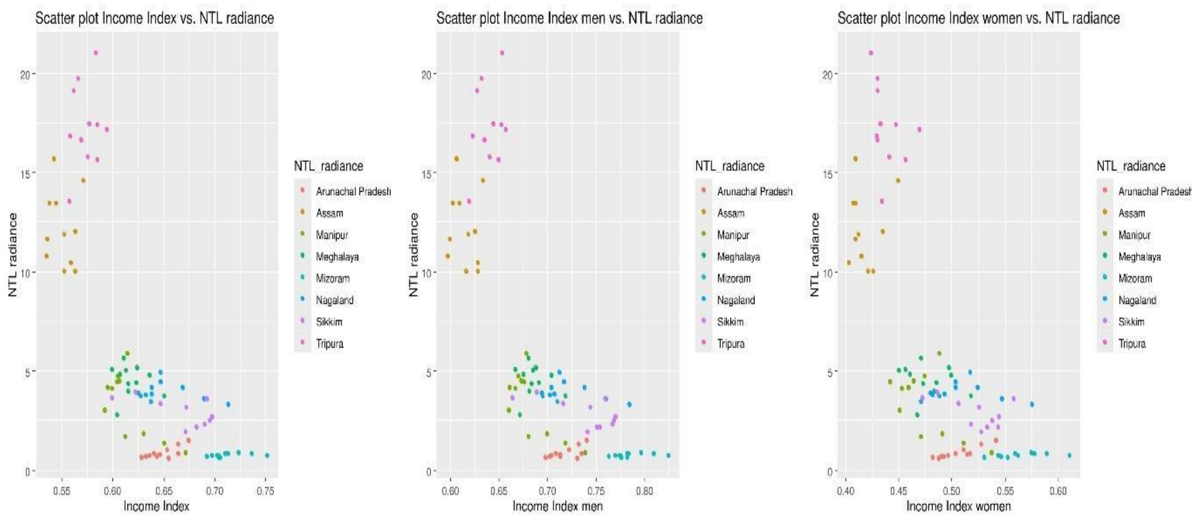

Figure 1

After that, the correlation coefficient between nighttime light radiance data and income indices, along with the P-value, was calculated for all variables state-wise over the given period (Table 2).

State	Correlation_Overall	P_value_Overall	Correlation_Women	P_value_Women	Correlation_Men	P_value_Men
Overall (Pooled)	-0.76297	0.00000	-0.74008	0.00000	-0.76415	0.00000
Arunachal Pradesh	0.76282	0.00632	0.91040	0.00010	0.66693	0.02499
Assam	-0.09034	0.79167	0.10980	0.74792	-0.13395	0.69458
Manipur	-0.70080	0.01630	-0.59835	0.05181	-0.72624	0.01138
Meghalaya	-0.12634	0.71128	-0.22552	0.50493	-0.09750	0.77551
Mizoram	0.43128	0.18537	0.53954	0.08672	0.39091	0.23455
Nagaland	-0.29221	0.38325	-0.10527	0.75805	-0.34118	0.30450
Sikkim	-0.64326	0.03274	-0.51687	0.10351	-0.66023	0.02704
Tripura	0.18194	0.59235	-0.35098	0.28991	0.29937	0.37114

Table 2

Feature	Model 2: Income.Index	Model 1: Income.Index_men	Model 3: Income.Index_women
Dependent Variable	NTL_radiance	NTL_radiance	NTL_radiance
Intercept Estimate	57.347	60.345	47.745
Intercept Std. Error	4.731	4.986	4.136
Income Index Coefficient	-81.943	-78.221	-85.971
Coefficient Std. Error	7.486	7.12	8.424
t-value	-10.95	-10.99	-10.21
p-value	< 2e-16	< 2e-16	< 2e-16
Residual Std. Error	3.685	3.677	3.833
Degrees of Freedom	86	86	86
Multiple R-squared	0.5821	0.5839	0.5477
Adjusted R-squared	0.5773	0.5791	0.5425
F-statistic	119.8 on 1 and 86 DF	120.7 on 1 and 86 DF	104.1 on 1 and 86 DF
F-statistic p-value	< 2.2e-16	< 2.2e-16	< 2.2e-16

Table 3

In the analysis chronology, three linear regression models were developed to estimate the impact of income indices on nighttime light radiance data (Table.3). After that, these three linear regression models have been broken down by state and year (Tables 4 and 5).

States	intercept.all	slope.all	p_value_slope.all	r_squared.all
Arunachal Pradesh	-8.9300	15.1353	0.0063	0.5819
Assam	19.8302	-13.8550	0.7917	0.0082
Manipur	32.5042	-47.3217	0.0163	0.4911
Meghalaya	8.7704	-6.8287	0.7113	0.0160
Mizoram	-0.5786	1.8853	0.1854	0.1860
Nagaland	7.1111	-4.8530	0.3832	0.0854
Sikkim	12.1712	-13.9111	0.0327	0.4138
Tripura	-0.2904	30.7170	0.5924	0.0331
	intercept.men	slope.men	p_value_slope.men	r_squared.men
Arunachal Pradesh	-8.6563	13.2935	0.0250	0.4448
Assam	24.4154	-19.8683	0.6946	0.0179
Manipur	36.4297	-48.3881	0.0114	0.5274
Meghalaya	8.1853	-5.3001	0.7755	0.0095
Mizoram	-0.5500	1.6748	0.2345	0.1528
Nagaland	7.9110	-5.4968	0.3045	0.1164
Sikkim	12.6622	-13.2505	0.0270	0.4359
Tripura	-13.2993	47.9238	0.3711	0.0896
	intercept.women	slope.women	p_value_slope.women	r_squared.women
Arunachal Pradesh	-6.4055	14.4282	0.0001	0.8288
Assam	5.9808	14.8968	0.7479	0.0121
Manipur	20.0226	-35.0027	0.0518	0.3580
Meghalaya	8.7174	-8.7149	0.5049	0.0509
Mizoram	-0.2372	1.7813	0.0867	0.2911
Nagaland	4.7393	-1.5516	0.7580	0.0111
Sikkim	10.1478	-13.9088	0.1035	0.2672
Tripura	40.6009	-53.0686	0.2899	0.1232

Table 4

Year	intercept.all	slope.all	p_value_slope.all	r_squared.all
2012	38.5116	-52.8197	0.0161	0.6466
2013	51.4006	-72.4758	0.0145	0.6580
2014	64.5009	-93.0887	0.0152	0.6532
2015	72.7326	-106.1399	0.0174	0.6381
2016	55.2477	-79.9255	0.0351	0.5502
2017	58.4775	-84.2281	0.0287	0.5775
2018	66.7591	-96.2946	0.0459	0.5124
2019	62.4183	-90.0646	0.0232	0.6042
2020	57.0872	-83.7991	0.0243	0.5986
2021	63.6061	-91.7601	0.0098	0.6978
2022	73.0836	-103.4955	0.0069	0.7299
	intercept.men	slope.men	p_value_slope.men	r_squared.men
2012	40.1791	-50.1737	0.0161	0.6465
2013	53.7782	-68.8512	0.0153	0.6522
2014	67.8682	-88.8023	0.0152	0.6531
2015	76.3858	-100.8436	0.0172	0.6398
2016	58.2263	-76.2386	0.0340	0.5546
2017	61.5187	-80.1977	0.0290	0.5760
2018	70.2554	-91.2580	0.0449	0.5155
2019	65.2785	-85.2957	0.0240	0.5999
2020	60.0553	-79.8951	0.0239	0.6003
2021	66.4491	-87.1255	0.0097	0.6986
2022	76.5479	-98.8747	0.0071	0.7279
	intercept.women	slope.women	p_value_slope.women	r_squared.women
2012	34.4287	-58.3754	0.0165	0.6442
2013	45.4290	-80.4083	0.0148	0.6560
2014	57.1982	-104.6068	0.0149	0.6550
2015	63.8421	-118.9028	0.0170	0.6407
2016	48.4187	-89.9234	0.0349	0.5510
2017	51.3202	-95.5615	0.0280	0.5806
2018	57.2562	-110.0347	0.0463	0.5109
2019	54.3310	-100.0660	0.0249	0.5953
2020	50.2836	-93.7743	0.0241	0.5995
2021	56.4923	-102.1913	0.0097	0.6994
2022	65.6878	-115.1519	0.0066	0.7333

Table 5

The analysis used data from 2012 to 2022. It combined nighttime light (NTL) radiance data from the Indian Space Research Organization (ISRO) with income index components from the Subnational Human Development Index Database. The study used statistical methods like the mean, correlation coefficients, and linear regression. It looked at differences in mean NTL radiance and income indices across the overall population, men, and women in the northeastern states of India.The correlation results demonstrated a significant positive association between NTL radiance and income indices in Arunachal Pradesh, but negative or weak correlations were observed in other states, such as Manipur, Assam, and Meghalaya, indicating inconsistent performance of NTL as an income proxy. Three linear regression models analyzed the impact of income indices on NTL radiance for the overall population and separately for men and women, with all models producing statistically significant coefficients. However, the strength of these relationships varied across states and over time. The findings highlight that while NTL can be a valuable proxy for aggregate income at regional levels, its effectiveness for gender-specific income estimation is complex and sometimes inconsistent. The study underscores significant gender gaps in income and labor force participation in Northeast India and cautions against interpreting NTL data as an economic proxy, given regional and demographic complexities. This comprehensive analysis illustrates both the utility and limitations of satellite-derived nighttime light data for estimating income indices, particularly regarding gender disparities in development in Northeast India.

V. CONCLUSION OF THE STUDY

This study reaffirms the utility of nighttime light data as an innovative proxy for assessing economic activity and regional income disparities in Northeast India. In this region, traditional economic data often lack granularity and reliability. However, the relationship between NTL and income is complex. It depends on the situation, and there are clear differences between states and genders. Research shows that NTL is closely linked to income at larger geographic areas. However, its ability to predict income drops a lot at smaller levels, like villages or districts. In these areas, the economic structures are more complex. The context of Northeast India reveals distinct regional differences. For instance, Arunachal Pradesh has a positive connection between NTL brightness and income levels.In contrast, states like Manipur, Meghalaya, Mizoram, and Nagaland often show weak or even negative relationships. This difference points out the challenges from uneven population densities, the dominance of informal economies, and economic structures that are harder to see in nightlight data. Particularly in low-density or affluent areas with less dense lighting, NTL may underestimate true financial well-being.

In contrast, bustling but less affluent areas with higher light emissions might be misleadingly interpreted as wealthier. Moreover, the study underscores a significant gap in the current literature—the absence of direct gender-disaggregated insights from NTL data. Nighttime lights measure the light related to economic activity, but they overlook the differences in income and workforce participation between genders. This issue is important in Northeast India, where gaps in earnings and workforce involvement between men and women remain significant. Relying on NTL alone may miss the deeper social and economic inequalities that women and underrepresented groups face. Other issues, such as light saturation in urban areas, calibration problems between different satellite sensors, and timing mismatches, make it harder to use NTL as a dependable measurement tool. Taken together, these factors caution against uncritical use of nighttime lights as a standalone economic proxy in small-area or gender-sensitive analyses.

In conclusion, the study backs a more integrated approach that integrates satellite NTL data with ground-collected demographic, socio-economic, and gender-specific information. This combination will help better assess economic status and inequalities in Northeast India. Such an approach would improve the quality of regional economic assessments, support development policies that consider gender, and reduce the chance of ignoring vulnerable populations. This research contributes to a nuanced understanding of the promises and pitfalls of using satellite-derived proxies and calls for future investigations to bridge significant gender and regional data gaps through mixed-methods and multi-source datasets. This synthesis includes worries about negative and varied relationships between NTL and income. It also highlights the lack of analysis focused on gender and emphasizes the need for policies that consider context. This aligns with recent academic findings on the topic.

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