

Measuring Development and Welfare: The Use of Night-Lights to Evaluate Programs and Formulate Policy

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This document explores the use of high-resolution nighttime satellite imagery as a tool to measure economic development and evaluate the impacts of public interventions, particularly in Latin America and the Caribbean (LAC). This is an efficient and alternative evaluation tool when there are no available traditional data sources such as household surveys and censuses in terms of coverage, frequency, accessibility, and representativeness to test results. Nighttime lights data emerge as a complementary and uniform source of information, capable of providing real-time and frequent, spatially detailed insights into human activity and economic outcomes, which is valuable for both academic research and Multilateral Development Banks (MDBs) evaluations.

KEYWORDS

Nighttime Lights, Satellite Data, Development.

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Medición del desarrollo y el bienestar: El uso de las luces nocturnas para evaluar programas y formular políticas

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Este documento analiza el uso de imágenes satelitales nocturnas de alta resolución como herramienta para medir el desarrollo económico y evaluar los impactos de las intervenciones públicas, especialmente en América Latina y el Caribe (ALC). Se trata de una herramienta de evaluación eficiente y alternativa cuando no se dispone de fuentes de datos tradicionales, como las encuestas de hogares y los censos, en términos de cobertura, frecuencia, accesibilidad y representatividad para validar los resultados. Los datos sobre luces nocturnas se perfilan como una fuente de información complementaria y uniforme, capaz de proporcionar información en tiempo real y con frecuencia, con detalles espaciales, sobre la actividad humana y los resultados económicos, lo cual resulta valioso tanto para la investigación académica como para las evaluaciones de los bancos multilaterales de desarrollo.

PALABRAS CLAVE

Luces nocturnas, datos satelitales, desarrollo.

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1 | INTRODUCTION

Measuring economic development and the impacts of public interventions remains a persistent challenge in many regions of the world. Traditional data sources often suffer from limited coverage, infrequent updates, restricted access, and heterogeneous methodological standards, constraining the ability to monitor development processes consistently across countries. These limitations are particularly pronounced in Latin America's rural or disperse areas and the Caribbean, where large parts of the region remain unseen or rely on outdated information.

As shown in Table 1, household surveys in LAC display substantial heterogeneity in frequency: some countries collect data monthly (e.g., Colombia, Ecuador, Uruguay), others annually (e.g., Bolivia, Costa Rica, Honduras), while some Caribbean countries rely on outdated surveys. Open access to microdata is common in much of Latin America (including Chile, Uruguay, Mexico, Colombia, and Peru), whereas access remains restricted in large countries such as Brazil and in several Caribbean nations. Representativeness likewise varies considerably. All surveys are nationally representative and most distinguish between urban and rural areas. At the subnational level, however, coverage differs markedly: roughly half of the countries provide estimates at the departmental or state level (typically between 9 and 32 units), while others are representative only for broader planning regions or urban clusters. Only very few surveys produce estimates for major metropolitan areas or capital cities, generally covering fewer than 15 cities. Municipal-level representativeness is almost entirely absent across the region.

Census data provides the population framework but shows even greater disparity in terms of frequency. In most Latin American countries, censuses have been conducted roughly every ten to twelve years, with recent rounds concentrated between 2020 and 2025 and preceding censuses largely dating from 2010–2012. In contrast, a subset of countries, particularly in the Caribbean, exhibits much longer inter-censual gaps. In extreme cases, such as Trinidad and Tobago, the most recent census dates to 2011 following a prior census in 2000. These disparities underscore uneven demographic baselines across the region.

These data constraints are particularly consequential for the evaluation of place-based infrastructure interventions, whose impacts are often spatially localized and therefore unlikely to be captured by aggregate indicators or coarse administrative units. Furthermore, when evaluation relies on municipality-level data, economically meaningful effects occurring within targeted neighborhoods may be diluted or entirely masked.

This challenge is illustrated by the case of *Canoas for Everyone*, an urban infrastructure program implemented between 2014 and 2017 in selected neighborhoods of Canoas, Brazil. The program financed road rehabilitation, construction of public facilities, and improvements to drainage and flood-protection systems. A previous evaluation conducted by CAF using municipal-level indicators and synthetic control methods finds no statistically significant effects on local GDP or urban expansion, despite documented improvements in health-related outcomes [Da Mata \(2025\)](#). While informative, this result may reflect data aggregation rather than the absence of economic effects, given that the intervention operated within a limited subset of the municipality.

Thus, this paper leverages high-resolution nighttime light data to reassess the economic effects of the Canoas for Everyone program, serving as a first application of this approach within CAF's project evaluation framework. In contexts characterized by limited traditional data availability or insufficient spatial granularity, nighttime lights offer a powerful complement to official statistics. They provide high-frequency, spatially detailed measures of human activity and economic development, reaching areas with limited institutional capacity for data collection, and allowing for consistent measurement across regions and over

TABLE 1 Household surveys and population censuses in Latin America and the Caribbean

Country	Name	Household / income survey			Census
		Latest survey	Representativeness	Open access	Last two censuses
Argentina	Encuesta Permanente de Hogares	2025 (jun)	Urban clusters (31)	Yes	2022, 2010
Bolivia	Encuesta de Hogares	2024 (dec)	Departmental (9), urban–rural	Yes	2024, 2012
Brazil	Pesquisa Nacional por Amostra de Domicílios (PNAD)	2025 (oct)	State (27), urban–rural	No	2022, 2010
Chile	Encuesta de Caracterización Socioeconómica Nacional	2024 (dec)	Regional (16), urban–rural	Yes	2024, 2017
Paraguay	Encuesta Permanente de Hogares	2024 (dec)	Departmental (17), urban–rural	Yes	2022, 2012
Uruguay	Encuesta Continua de Hogares	2025 (oct)	Departmental (19)	Yes	2023, 2011
Colombia	Gran Encuesta Integrada de Hogares	2025 (sep)	Departmental (32) and departmental capital cities, urban–rural	Yes	2018, 2005
Ecuador	Encuesta Nacional de Empleo, Desempleo y Subempleo	2025 (oct)	Monthly: national. Quarterly: national and main cities (5). Annual: provincial (24). All urban and rural areas	Yes	2022, 2010
Panamá	Encuesta de Mercado Laboral	2024 (oct)	Provincial and indigenous regions with provincial status (13), urban–rural	No	2023, 2010
Perú	Encuesta Nacional de Hogares	2025 (jun)	Annual: departmental and urban–rural by region (3). Quarterly: national, urban–rural	Yes	2025, 2017
Venezuela	Encuesta Nacional sobre Condiciones de Vida	2024 (jul)	National	No	2011, 2001
Costa Rica	Encuesta Nacional de Hogares	2025 (jul)	Planning regions (6), urban–rural	Yes	2022, 2011
El Salvador	Encuesta de Hogares de Propósitos Múltiples	2024 (dec)	Departmental (14) and metropolitan area of San Salvador, urban–rural	Yes	2024, 2007
Mexico	Encuesta Nacional de Ingresos y Gastos de los Hogares	2024 (dec)	State (32), urban–rural	Yes	2020, 2010
Honduras	Encuesta Permanente de Hogares de Propósitos Múltiples	2024 (dec)	Domains (4), urban–rural	Yes	2025, 2013
Antigua and Barbuda	Survey of Living Conditions and Household Budgets	2005/2006	National	No	2025, 2011
Bahamas	Bahamas Household Expenditure Survey	2025	National	No	2022, 2010
Barbados	Survey of Living Conditions	2016	National	Yes	2021, 2010
Jamaica	Survey of Living Conditions	2021	National	No	2022, 2011
Dominican Republic	Encuesta Nacional Continua de Fuerza de Trabajo	2025 (jun)	National, urban–rural	No	2022, 2010
Trinidad and Tobago	Multiple Indicator Cluster Survey	2022	National	Yes	2011, 2000

Notes: “Latest survey” reports the most recent wave available at the time of writing; the month of reference is shown in parentheses. “Representativeness” refers to the lowest geographic level for which the survey produces reliable estimates, with the number of units in parentheses. “Open access” indicates whether microdata are publicly downloadable without a formal request.

Source: Own elaboration based on national statistical offices.

time. These characteristics make nighttime lights especially well-suited for the evaluation of geographically concentrated interventions, such as urban infrastructure programs.

This approach is therefore relevant for both academia and Multilateral Development Banks (MDBs), enabling the evaluation of large-scale programs. In line with this potential, CAF, through its DADMI division, which is responsible for assessing the development contributions and impacts of CAF-financed projects, has begun incorporating high-resolution satellite data into its project evaluation framework. The Canoas case illustrates how this emerging approach can complement traditional evaluations and uncover economically meaningful effects at finer spatial scales.

Taking this into account, the remainder of this document is organized as follows. Section 2 reviews the relevant literature on satellite-based measurement and its applications. Section 3 describes the data sources and construction of satellite-based indicators used in the analysis. Section 4 outlines the methodological approach. Section 5 presents the results. Section 6 discusses limitations and proposes avenues for future work. Section 7 concludes.

2 | LITERATURE REVIEW

2.1 | Evolution of the use of nighttime lights

The systematic incorporation of nighttime luminosity into economic analysis was pioneered by [Henderson et al. \(2012\)](#), who combined official national accounts data with satellite-recorded changes in light intensity to improve the measurement of economic activity. Their approach demonstrated that integrating nighttime lights with GDP statistics yields more accurate growth estimates, particularly in countries with weak or incomplete statistical systems, such as Liberia, Burundi, Congo, and Iraq. Beyond improving aggregate measurement, the use of luminosity data enables subnational analyses that are largely infeasible with traditional sources. An example is their identification of systematically slower growth in coastal regions of Sub-Saharan Africa relative to inland areas.

This line of inquiry was expanded by [Pinkovskiy and Sala-i Martin \(2016\)](#), they used nighttime lights to compare the reliability of national accounts and household surveys. Their findings show that national accounts track the evolution of luminosity more closely than survey-based measures do, suggesting that they might provide a more credible basis for assessing poverty and development trends in low-income settings. Both studies rely on a key methodological assumption: that measurement errors in traditional economic statistics are independent from those embedded in nighttime light data.

More recent applications illustrate the growing sophistication of this research agenda. [Rossi-Hansberg and Zhang \(2025\)](#) construct a global dataset of subnational GDP based on a random forest model that combines nighttime lights, population, CO emissions, land use and other variables. This approach generates an annual panel of estimated GDP from 2012 onward, achieving an R^2 above 0.92 for GDP levels and maintaining robust correlations in out-of-sample validations, even in the face of shocks such as the COVID-19 pandemic in China.

2.2 | Correlation with conventional economic indicators

As literature evolved, nighttime luminosity became widely used as a proxy for economic development because it correlates closely with traditional indicators such as GDP per capita, urbanization, or the presence of basic infrastructure [Michalopoulos and Papaioannou \(2018\)](#). A large body of empirical evidence supports this association. Hodler and Raschky (2014) found a positive relationship between the logarithm of luminosity and the logarithm of

regional output for 126 countries; [Gennaioli et al. \(2013\)](#) estimated an average elasticity of 0.25 for this relationship in a sample of 1,500 regions across 83 countries; and [Michalopoulos and Papaioannou \(2013\)](#) documented positive correlations with DHS household well-being indicators in Zimbabwe, Tanzania, Nigeria, and the Democratic Republic of the Congo. For Brazil, an elasticity of 0.30 was found between municipal income and luminosity, with an R^2 of 0.25 for the period 2000–2011. Together, these findings have contributed to the widespread use of nighttime lights in interdisciplinary research combining economics with geography, history, and environmental science (Michalopoulos and Papaioannou, 2018)

In recent applications, [Woo-Gómez and Woo-Mora \(2025\)](#) show that, in Mexico, per capita nighttime light intensity is strongly correlated with municipal GDP estimates from Rossi-Hansberg and Zhang (2025), as well as with household income and food poverty measures taken from López-Calva et al. (2022), exhibiting a positive correlation with the former and a negative correlation with the latter (Figure 1).

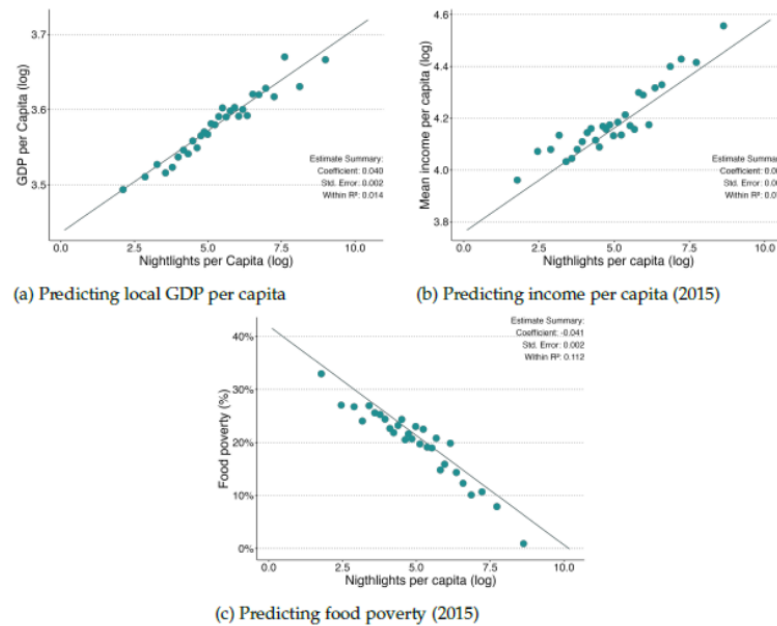


FIGURE 1 Nightlight intensity per capita and economic development in Mexico. Source: [Woo-Gómez and Woo-Mora \(2025\)](#)

[Woo-Gómez and Woo-Mora \(2025\)](#) also demonstrate how nighttime lights can be used to analyze empirical questions that would be infeasible with traditional data. Using a 10×10 km panel for Mexico between 2015 and 2023, the study estimates the impact of cooperative entry on local economic activity and finds persistent increases in luminosity between 2.7% and 8%, depending on the specification. Such analysis is difficult using conventional statistics, which are released infrequently, available at coarse administrative levels, and often lack coverage for rural or Indigenous territories where cooperatives operate. In this context, nighttime lights allow researchers to observe localized economic change and program effects at a granular level.

2.3 | Beyond economic measurement

Satellite-based methodologies have moved beyond measuring economic activity. A notable example is the work of [Chen et al. \(2024\)](#), who combine nighttime luminosity data with daytime image features (MOSAICS) through machine-learning models to predict local well-being and estimate subnational Human Development Index (HDI) measures in nine Eastern Caribbean countries. Their results show that these satellite-derived indicators exhibit high accuracy and can significantly improve the targeting of social assistance programs by reducing aggregation biases, allocating resources more efficiently across geographic areas, and serving as credible proxies for information that is difficult to verify, such as informal income.

Alternatively, [Mahadevan \(2024\)](#) uses nighttime lights paired with electricity billing records to detect corruption in electricity provision in India. Leveraging a close-election regression discontinuity design, the study shows that constituencies narrowly won by the ruling party consume significantly more electricity (captured through satellite luminosity) while reporting substantially lower billed consumption. The pattern emerges immediately after elections and areas the ruling party lost show no similar billing anomalies. The results suggest systematic undercharging for politically aligned voters, leading to an estimated efficiency loss of about USD 900 million due to higher use, lost revenue, and strain on the electricity grid.

Finally, satellite-based luminosity measures have also been used to study heterogeneous impacts of randomized social programs and their mechanisms. In the context of a large-scale housing lottery in Colombia, [Camacho González et al. \(2022\)](#) use nighttime lights to capture local economic activity around beneficiaries' residential locations. First, luminosity is used to assess whether program impacts vary across areas with different levels of economic activity, allowing the identification of geographically heterogeneous treatment effects that survey data alone cannot capture. Second, nighttime lights are used to study mechanisms by comparing luminosity levels in participants' current locations prior to the lottery. The results show that lottery winners were already located in more luminous and, thus, more economically active areas before the lottery, indicating that the program primarily relocated beneficiaries to neighborhoods with higher baseline economic activity rather than generating new local activity.

2.4 | From satellite data to impact evaluation

Beyond academic research, MDBs have also begun adopting satellite data for large-scale evaluation. One example is HUELLA, a methodology developed by the Inter-American Development Bank (IADB) to evaluate the impact of their project portfolios. *HUELLA* combines nighttime lights, settlement growth, and pollution indicators with quasi-experimental methods such as generalized synthetic controls and difference-in-differences ([Ruiz-Arranz et al. \(2025\)](#)), studying impacts at the municipal level. Applications in Mexico and Costa Rica show that this approach can produce credible evidence of changes in economic activity, settlement patterns, and environmental conditions.

3 | DATA

To characterize electricity access, we rely on the High-Resolution Electricity Access (HREA) dataset, a geospatial product that combines VIIRS nighttime satellite imagery with machine-learning-derived settlement maps. HREA was developed through a collaboration between the University of Michigan, the World Bank, and NOAA, and uses the full global archive

of nightly VIIRS-DNB observations from 2012 onward. This starting date is dictated by data quality considerations: VIIRS offers substantially higher radiometric precision, on-board calibration, and finer spatial resolution, allowing the detection of electricity-driven luminosity even at very low intensity levels, particularly in rural areas. By contrast, earlier DMSP-OLS nightlight data (used prior to 2013) suffer from coarse spatial resolution and the absence of calibration, which generates blooming in sparsely populated areas and saturation in large cities, thereby compressing regional variation. Consistent with these limitations, evidence from Indonesia, China, and South Africa shows that the relationship between nighttime lights and GDP is roughly twice as imprecise when estimated using DMSP-OLS compared to VIIRS data (Gibson et al. (2021)).

A central feature of HREA is its capacity to distinguish the light emitted by inhabited settlements from the natural background of brightness present in uninhabited areas. To achieve this, the methodology combines nightly VIIRS-DNB observations with high-resolution, machine-learning-generated maps of human-built settlements. These settlement maps pinpoint the location of buildings and population concentrations, allowing the system to separate anthropogenic light from radiance produced by moonlight, atmospheric reflectance, overglow, lightning, or other non-electricity sources (Min et al. (2024)). This distinction is crucial: it ensures that electricity access is inferred only for pixels containing settlements rather than for the entire land surface.

HREA produces annual indicators of electricity usage, access, and reliability. The dataset has global coverage, although data is not available for all countries. Specifically, for Latin America and the Caribbean (LAC), the dataset includes 24 countries and provides annual rasters for 2013–2020. Each raster is a grid of pixels ranging from 30×30 meters to 420×420 meters, depending on data availability. These rasters serve as the basis for constructing four key indicators: average radiance, z-score (usage), light score (access), and the proportion of nights with detectable artificial light (reliability).

3.1 | Radiance

This variable captures the annual average level of nighttime brightness in each settlement pixel. Because raw radiance values are right-skewed and can take slightly negative values (down to -1.5), HREA adds a constant of 2.5 before applying the natural logarithm. This transformation ensures that the variable is defined for all pixels and reduces the influence of extreme values (Min et al. (2024)). As a result, unlit or sparsely populated areas typically register values close to 1, while large metropolitan areas tend to have values around 3. For example, Rio de Janeiro has an average value of 3.2 during the period examined, and São Paulo an average of 3.1. Values above 8 are uncommon.

3.2 | Usage: Z-score

The settlement z-score measures how unusually bright a settlement pixel is relative to what would be expected in the absence of electricity use and is constructed in two steps (Min et al., 2024). First, a statistical model of background radiance is estimated using pixels located in isolated, non-settlement areas. Second, for settlement pixels, the difference between observed radiance and the predicted background level is standardized to obtain a z-score, which captures the presence and intensity of electricity use.

3.2.1 | Modeling background radiance

First, a statistical model of background radiance is estimated using pixels located in isolated, non-settlement areas, which are assumed to have no access to electricity. The goal is to characterize how non-anthropogenic factors affect observed light levels.

Let i denote pixels and j denote nights. For each calendar year, we estimate the following linear mixed-effects model:

$$\begin{aligned} \text{radiance}_{i,j} = & \beta_{0,j} + \beta_{1,j} \text{ lunar illumination}_{i,j} + \beta_{2,j} \text{ time}_{i,j} \\ & + \beta_{3,j} \text{ month}_{i,j} + \beta_{4,j} \text{ landcover}_{i,j} \\ & + \beta_{5,j} (\text{landcover} \times \text{lunar illumination})_{i,j} + e_{i,j} \end{aligned} \quad (1)$$

Here, radiance is the satellite-observed light intensity at pixel i on night j . Lunar illumination, local mean time, month, and land cover capture exogenous variation in light levels unrelated to human activity. The model includes a date-level random effect to account for night-specific shocks common across pixels.

Using the estimated coefficients from non-settlement pixels, the expected radiance for every pixel–night observation is predicted (Min et al., 2024).

3.2.2 | From radiance to electricity use

For settlement pixels, the difference between observed radiance and expected radiance measures light that is present only because humans are using artificial lighting. The expected radiance is estimated from areas with no settlements, where there is no electricity and therefore no artificial light. As a result, any additional light observed in settlement areas cannot come from natural sources.

In settlements, artificial nighttime lights are produced almost exclusively by electricity-powered sources such as streetlights, homes, and businesses. Therefore, when observed radiance in a settlement exceeds the expected background level, this excess light directly indicates that electricity is being used on that night.

This excess radiance is standardized by the standard deviation of the model residuals to obtain a z-score. A z-score close to zero indicates no detectable electricity use, while higher positive z-scores indicate stronger and more widespread electricity use. Higher z-scores are thus interpreted as reflecting a higher likelihood and intensity of electricity use in a settlement on a given night.

3.3 | Access: light score

For each settlement pixel, HREA aggregates all nightly z-scores within the calendar year and computes their average. This annual mean is then translated into a probability which represents the estimated likelihood that the settlement was electrified during that year.

3.4 | Reliability: proportion of nights lit

This variable represents the share of nights in which a settlement's standardized residual exceeded a given z-score threshold (i.e., nights when observed radiance was clearly brighter than the model-predicted background). Therefore, values range from 0 to 1. A value such as 0.10 indicates that the settlement exhibited detectable artificial light on only one out of ten nights, consistent with highly unreliable or sporadic service. In contrast, values near 0.90

suggest that artificial lighting was observed almost every night, reflecting stable electricity availability.

3.5 | Processing

After downloading nightly satellite rasters from either Amazon Web Services (AWS) or the HREA platform, processing is restricted to municipalities where project interventions occurred. For these municipalities, each TIFF raster for the four key variables is transformed into a pixel-level dataset, where every pixel becomes an observation with its corresponding spatial coordinates and year. This procedure produces four annual pixel-level panels (one per variable) for the period 2013–2020, limited to the intervention and respectively control municipalities.

4 | METHODOLOGY

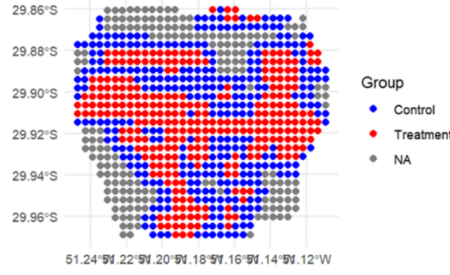
The empirical strategy assesses whether CAF-funded project *Canoas for Everyone* led to measurable changes in nighttime luminosity and, by extension, economic activity. The approach combines precise geospatial identification of intervention areas with the estimation of treatment effects using event-study models.

4.1 | Canoas for Everyone – Brazil

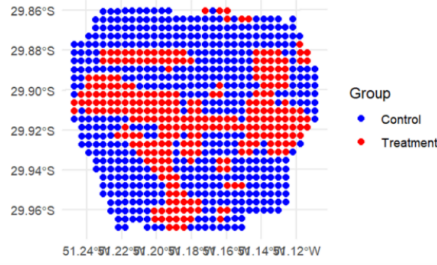
Canoas for Everyone is an urban infrastructure program implemented in selected neighborhoods of Canoas, Brazil, between 2014 and 2017. The project focused on road rehabilitation, construction of public facilities such as squares and gyms, and upgrades to drainage and flood protection systems. The program was financed with approximately USD 100 million, equivalent to an investment of USD 296 per capita.

4.2 | Definition of treated and control areas

Interventions were georeferenced and all pixels located within 250 meters of any intervention segment were classified as treated. Then, to identify appropriate counterfactuals, two complementary exercises were conducted. The first approach compares treated pixels to all other pixels within the municipality (Figure 2a). A second specification restricts controls to pixels located between 250 and 1,000 meters from the intervention sites (Figure 2b). This buffer ring comparison ensures that treated and control pixels share similar urban characteristics and spatial contexts.



(a) Full municipality comparison



(b) Buffer ring comparison (250–1,000 meters)

FIGURE 2 Spatial distribution of treatment and control areas in Canoas. *Notes:* Treated pixels are located within 250 meters of an intervention segment. Panel (a) compares treated pixels to all other pixels within the municipality; panel (b) restricts controls to pixels located between 250 and 1,000 meters from intervention sites. NA denotes pixels excluded from both the treatment and control groups. *Source:* Authors' elaboration based on HREA data.

In both exercises, an additional step is taken to improve baseline comparability. Specifically, control pixels are excluded if they fall outside the baseline or pre-treatment values for the variables of interest. This trimming rule is based on the distribution of luminosity prior to the intervention. We compute the minimum and maximum baseline luminosity values among treated pixels and exclude all control pixels with values below the treated minimum or above the treated maximum. This ensures common support between pixels in the treated and control areas before the intervention.

4.3 | Empirical Strategy

To examine the evolution of effects and test for pre-treatment parallel trends, we estimate the following event-study model:

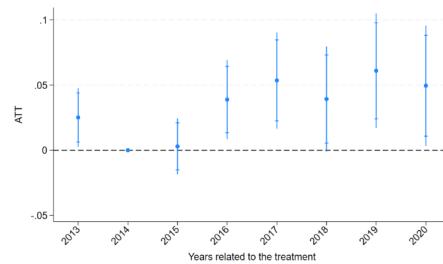
$$y_{it} = \alpha_i + \delta_t + \left(\sum_{j \neq 0} \gamma_j \cdot D_{i,t-j} \right) + \varepsilon_{it} \quad (2)$$

Where $D_{i,t-j}$ is an indicator equal to 1 if pixel i is j periods away from treatment in year t . The coefficients γ_j trace the trajectory of outcomes for each j period, before and after the intervention. The first treatment period ($j = 0$) is omitted and serves as the baseline category. This specification allows visualization of treatment dynamics and verification of whether treated and control pixels follow parallel trends before the intervention.

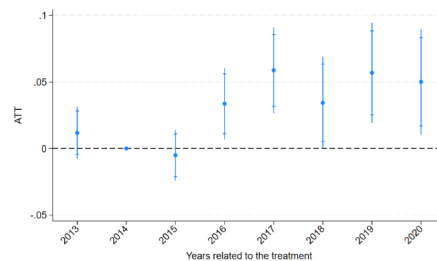
TABLE 3 Descriptive statistics for nighttime radiance after trimming and with buffer

		2013	2014	2015	2016	2017	2018	2019	2020
Control group	Min	1.63	1.63	1.67	1.64	1.63	1.64	1.59	1.60
	Mean	2.96	3.04	3.07	3.09	3.11	3.05	3.04	3.08
	Max	4.37	4.32	4.31	4.31	4.21	4.08	4.20	4.18
	Std. Dev	0.80	0.77	0.71	0.71	0.71	0.68	0.74	0.72
	Obs.	274	274	274	274	274	274	274	274
Treatment group	Min	1.61	1.70	1.79	1.80	1.74	1.71	1.65	1.80
	Mean	3.14	3.20	3.24	3.29	3.32	3.25	3.26	3.29
	Max	4.41	4.42	4.31	4.34	4.33	4.21	4.32	4.27
	Std. Dev	0.65	0.61	0.58	0.58	0.59	0.57	0.61	0.59
	Obs.	255	255	255	255	255	255	255	255

Figures 3a and 3b present the event study estimates for average radiance. In both specifications, pre-treatment coefficients are small and statistically indistinguishable from zero. This supports the validity of the parallel-trends and no-anticipation assumptions and indicates that treated and control pixels were evolving similarly prior to execution of Canoas for Everyone.



(a) Full municipality comparison



(b) Buffer ring comparison (250–1,000 meters)

FIGURE 3 Event study excluding outliers: estimated effects on nighttime radiance (2013–2020). *Notes:* Inner bars correspond to 90% confidence intervals and outer bars to 95% confidence intervals. Standard errors are clustered at the pixel (pixel ID) level. Panel (a) compares treated pixels to all other pixels within the municipality; panel (b) restricts controls to pixels located between 250 and 1,000 meters from intervention sites. *Source:* Authors' elaboration based on HREA data.

Following implementation, estimated effects become positive and grow gradually over time. By 2018–2020, the magnitude of the effect ranges from approximately 3% to 6%. Overall, the radiance results suggest that Canoas for Everyone generated incremental and persistent increases in light emissions in the treated neighborhoods. To gauge the economic relevance of these magnitudes, evidence for Brazil discussed in the literature review is informative. Using municipal income data for nearly 3,500 municipalities over the period 2000–2011, [Michalopoulos and Papaioannou \(2018\)](#) document an elasticity of approximately 0.30 between log income and log nighttime luminosity, even after controlling for year and state fixed effects. Applying this elasticity as a benchmark implies that the estimated post-intervention increases in radiance observed here correspond to local income gains on the order of 0.9% to 1.8% per year. While this calibration relies on DMSP-based luminosity measures rather than VIIRS or the HREA dataset used in this study, it suggests that the observed changes in nighttime lights are consistent with economically meaningful improvements in localized economic activity.

5.2 | Effects on usage

Tables 4 and 5 report descriptive statistics for the electricity usage indicator (z-score) between 2013 and 2020 under two sample definitions: trimming only (Table 4) and trimming with the additional spatial buffer (Table 5). Across both samples, average electricity usage is lower in treated areas than in control areas throughout the period. Mean usage in control areas ranges between approximately 227 and 267 standard deviations, while treated areas exhibit lower averages, between 204 and 230. Dispersion is relatively large in both groups but declines steadily over time. In the control group, average electricity usage shows a gradual decline over the period, whereas in the treated group usage increases up to 2017 and then decreases thereafter. This motivates a more formal analysis of treatment effects.

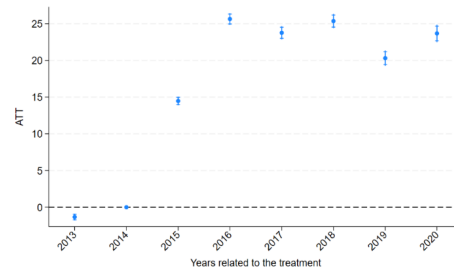
TABLE 4 Descriptive statistics for electricity usage after trimming

		2013	2014	2015	2016	2017	2018	2019	2020
Control group	Min	29.83	25.92	27.03	27.72	21.29	23.22	19.15	21.72
	Mean	266.78	254.13	240.62	253.01	246.38	227.42	235.75	231.43
	Max	747.68	706.97	545.11	557.06	436.92	412.49	438.84	398.52
	Std. Dev	102.64	95.22	85.74	85.77	79.93	70.85	75.59	73.56
	Obs.	23,714	23,714	23,714	23,714	23,714	23,714	23,714	23,714
Treatment group	Min	28.87	30.81	32.60	31.45	30.03	27.69	25.33	24.96
	Mean	216.43	204.12	207.19	230.12	223.11	205.87	208.61	205.82
	Max	747.68	706.97	545.11	557.06	436.92	412.49	438.84	398.52
	Std. Dev	103.20	88.74	81.89	82.17	76.07	69.30	74.44	68.87
	Obs.	15,283	15,283	15,283	15,283	15,283	15,283	15,283	15,283

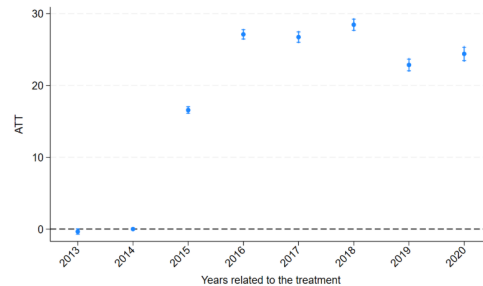
Figures 4a and 4b report the event-study estimates for electricity usage. As with the radiance measure, pre-treatment coefficients remain close to zero and statistically indistinguishable from the baseline period across both model specifications, indicating no evidence of differential trends or anticipation prior to project implementation. This reinforces the credibility of the identification strategy and the identification assumptions.

TABLE 5 Descriptive statistics for electricity usage after trimming and with buffer

		2013	2014	2015	2016	2017	2018	2019	2020
Control group	Min	29.90	27.97	27.03	29.00	21.29	23.41	19.15	21.98
	Mean	261.60	247.96	236.55	248.31	243.19	224.35	232.14	225.99
	Max	747.68	706.97	545.11	547.06	436.92	412.49	438.84	398.52
	Std. Dev	106.69	97.02	88.41	88.21	82.34	73.34	77.97	74.39
	Obs.	17,723	17,723	17,723	17,723	17,723	17,723	17,723	17,723
Treatment group	Min	28.87	30.81	32.60	31.45	30.03	27.69	25.33	24.96
	Mean	216.43	204.12	207.19	230.12	223.11	205.87	208.61	205.82
	Max	747.68	706.97	545.11	557.06	436.92	412.49	438.84	398.52
	Std. Dev	103.20	88.74	81.89	82.17	76.07	69.30	74.44	68.87
	Obs.	15,283	15,283	15,283	15,283	15,283	15,283	15,283	15,283



(a) Full municipality comparison



(b) Buffer ring comparison (250–1,000 meters)

FIGURE 4 Event study: estimated effects on electricity usage (2013–2020). *Notes:* Inner bars correspond to 90% confidence intervals and outer bars to 95% confidence intervals. Standard errors are clustered at the pixel (pixel ID) level. Panel (a) compares treated pixels to all other pixels within the municipality; panel (b) restricts controls to pixels located between 250 and 1,000 meters from intervention sites. *Source:* Authors' elaboration based on HREA data.

Following implementation, estimated effects increase more sharply than those observed for raw radiance. Between 2018 and 2020 the estimated impact ranges from approximately 20 to 28 standard deviations. In both the full-municipality and buffer-ring specifications, effects remain positive and statistically significant through 2020, suggesting that program-induced improvements did not dissipate and instead supported stable and higher electricity consumption during nighttime hours.

The stronger effects observed for electricity usage relative to raw radiance align with

its interpretation: by normalizing against expected background brightness, the indicator better captures changes in how intensively electricity is used in treated settlements, such as increased household lighting, enhanced street illumination, or higher levels of nighttime commercial and mobility activity.

Overall, these findings indicate that *Canoas for Everyone* produced lasting improvements in nighttime electricity usage in intervention areas, consistent with the program's objective of enhancing public infrastructure and improving urban living conditions.

5.3 | Spatial disaggregation and comparison with municipal-level evaluations

As mentioned in the introduction, previous analyses conducted at the municipal level find no statistically significant effects on aggregate economic indicators such as GDP or urban expansion (Da Mata, 2025), despite documented improvements in health-related outcomes. The positive and persistent effects observed here suggest that the program generated localized changes in economic activity and infrastructure use that remain spatially concentrated within treated neighborhoods. Such effects are unlikely to translate into detectable shifts in municipality-wide aggregates but become visible when outcomes are measured at a finer geographic scale. This comparison underscores how higher levels of spatial disaggregation can complement traditional evaluation approaches in the assessment of place-based urban interventions.

6 | LIMITATIONS AND NEXT STEPS

Despite its growing use, nighttime luminosity is not without limitations. One of the most frequently noted is that it does not adequately capture productive sectors with low light intensity, such as agriculture or forestry (Keola et al., 2015), which can lead to underestimations of development in rural areas. This limitation is illustrated by a pilot evaluation conducted by CAF in the context of this research agenda, using the rural irrigation program *Mi Riego* in Bolivia. While the ex-post evaluation rated the program's overall performance as high, with strong pertinence and effectiveness, nighttime lights did not detect associated economic changes, and the identification assumptions required for causal inference were more difficult to corroborate in low-density rural settings. There are also technical issues such as saturation in large cities, where light intensity stops capturing additional increases in activity, or blooming, which disperses light into surrounding areas and generates overestimations.

Furthermore, recent work by Huber and Mayoral (2025), focusing on sub-Saharan Africa, shows that nighttime lights suffer from non-classical measurement error. While their empirical emphasis is on poor and unlit regions, the underlying logic extends naturally to very rich and highly illuminated areas as well. When luminosity is extremely low, economically active locations may be misclassified as poor; when luminosity is extremely high, saturation limits the ability of nightlights to capture meaningful variation in economic activity. In both cases, measurement error may bias estimates in unknown directions.

Thus, in the case of *Canoas*, concerns arise as it is a highly illuminated municipality. Average nighttime radiance (2.9) during the period examined is comparable to that of major metropolitan areas such as Rio de Janeiro (3.2) and São Paulo (3.1), and two luminosity-based variables could not be used because they are equal to one for all observations. This suggests that saturation may limit the ability of nightlights to capture within-area variation in economic activity, but even with this constraint we are finding positive and significant increases.

Our analysis is also temporally constrained, as additional pre-treatment periods would strengthen the assessment of identifying assumptions. As mentioned before, this constraint is driven by data availability and quality considerations, since reliable, high-resolution measures of electricity-related luminosity are only available with the advent of VIIRS data starting in 2013. While combining DMSP-OLS and VIIRS data remains challenging, recent work has developed inter-calibration methods that improve consistency across satellite systems (Hsu et al., 2015; Li et al., 2017).

Taken together, these limitations point to a clear agenda for future work. From CAF's evaluation perspective, a key next step is to continue implementing pilot studies across different types of interventions and contexts to systematically assess when nighttime lights provide reliable signals of economic change and when they do not. Building this evidence base will allow the development of operational criteria to guide the use of luminosity-based indicators in project evaluation, clarifying the settings in which they can complement traditional data sources and those in which alternative measurement strategies are required.

7 | CONCLUSION

This study provides evidence that high-resolution satellite data, specifically nighttime luminosity derived from VIIRS and processed through the HREA framework, can be a valuable tool for evaluating the local impacts of development interventions. Focusing on the Canoas for Everyone program, the analysis shows that CAF-financed urban infrastructure investments led to persistent increases in nighttime radiance and, more markedly, in electricity usage intensity within treated areas. The absence of differential pre-trends and the stability of post-treatment effects across specifications support the credibility of the identification strategy and suggest that the observed changes are attributable to the intervention.

Beyond the specific case study, the findings underscore the broader potential of satellite-based indicators for MDBs. Nighttime lights allow for granular, timely, and comparable measurements of development outcomes at spatial scales that are typically inaccessible with household surveys or cannot study changes with census data given their frequency, particularly for urban projects with localized impacts. At the same time, the analysis highlights important caveats: saturation in highly illuminated areas, non-classical measurement error (present in other types of data as well), and limited temporal coverage can constrain inference and must be carefully addressed in empirical designs.

Taken together, the results suggest that these data can meaningfully enhance project evaluation frameworks and expand the scope of evidence available for policy decisions in Latin America and the Caribbean. At the same time, continued pilot applications across different types of interventions and territorial contexts are essential to better understand the conditions under which satellite-based indicators provide reliable signals of economic change. Future work that integrates multiple satellite products, extends temporal coverage, and addresses possible measurement errors will be key to consolidating the role of satellite data in development and poverty reduction impact evaluation.

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