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Spatiotemporal Estimation of the Potential Adoption of Photovoltaic Systems on Urban Residential Roofs

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Abstract: The adoption of residential photovoltaic (PV) systems to mitigate the effects of climate change has been incentivized in recent years by government policies. Due to the impacts of these systems on the energy mix and the electrical grid, it is essential to understand how these technologies will expand in urban areas. To fulfill that need, this article presents an innovative method for modeling the diffusion of residential PV systems in urban environments that employs spatial analysis and urban characteristics to identify residences at the subarea level with the potential for installing PV systems, along with temporal analysis to project the adoption growth of these systems over time. This approach integrates urban characteristics such as population density, socioeconomic data, public environmental awareness, rooftop space availability, and population interest in new technologies. Results for the diffusion of PV systems in a Brazilian city are compared with real adoption data. The results are presented in thematic maps showing the spatiotemporal distribution of potential adopters of PV systems. This information is essential for creating efficient decarbonization plans because, while many households can afford these systems, interest in new technologies and knowledge of the benefits of clean energy are also necessary for their adoption.

Keywords: energy transition; geographical information systems; geographically weighted regression; logistics growth model; moving average; residential photovoltaic systems; spatiotemporal estimation

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1. Introduction

Electricity consumption in urban areas has increased due to rapid urbanization and the widespread use of modern electrical appliances that promise to improve people's comfort [1]. This increase in electricity consumption poses significant environmental challenges, especially if the energy supply remains solely based on nonrenewable resources [2]. The dependence on fossil fuels exacerbates greenhouse gas emissions and intensifies global environmental issues [3]. Integrating sustainable and distributed energy sources is vital for reducing reliance on traditional energy and its detrimental environmental effects [4].

Photovoltaic (PV) systems represent an important renewable energy source for distributed generation because they can be installed on residential rooftops in urban areas, enabling more efficient utilization of clean energy [5]. Despite the enormous potential of solar energy, economic and technological barriers have impeded its widespread adoption [6]. The high initial installation costs are particularly prohibitive for middle- and low-income households [7]. Additionally, technical limitations, such as inadequate infrastructure or structural challenges in multi-apartment buildings, complicate installation [8]. However, with technological advancements and improvements in construction materials,

building-integrated photovoltaic (BIPV) solutions have become increasingly common in urban areas. BIPV solutions allow PV systems to be integrated into the building's structure, such as facades, windows, and roofs, without occupying additional space, thus optimizing available space [9]. This trend is driven by the growing demand for clean energy and the need to enhance the energy efficiency of buildings in urban settings [10]. Moreover, BIPV solutions contribute to the architectural esthetics of buildings, as they can be customized to fit the building's design, reducing the visual impact of conventional PV systems [11]. The implementation of BIPV solutions has been further supported by governmental policies and regulations that encourage the use of renewable energy in urban environments [12], boosting its adoption and development in smart cities.

To effectively address the barriers and challenges in the adoption of PV systems, it is critical to accurately identify subareas with the greatest potential for the adoption of this technology and to understand the factors influencing users' decisions. A promising tool in this context is spatiotemporal analysis, which integrates spatial and temporal factors to examine the evolution of new technology adoption across various urban environments over time [13]. This approach identifies optimal areas for PV system installation and elucidates how socioeconomic and geographical factors impact decision-making. Recent studies suggest that proximity to areas where these technologies have already been deployed may serve as a critical factor in their expansion, generating contagion or imitation effects within neighboring communities [14].

Moreover, utilizing spatiotemporal analysis provides valuable insights for designing policies that promote the adoption of technologies in areas with the highest potential. Identifying the most suitable subareas enables authorities to optimize resource and infrastructure distribution, directing investments to locations that yield the most significant impact [8]. This strategy benefits citizens by enhancing access to clean energy and assists utilities in achieving more efficient demand management while mitigating the risk of distribution network overloads [15]. Collectively, these strategies foster a more balanced, resilient, and sustainable energy transition, equipping urban areas to confront future challenges better.

PV systems play a pivotal role in enhancing energy resilience, reducing the urban carbon footprint, and driving sustainable energy transitions in urban environments. These decentralized systems provide a reliable renewable energy source that decreases dependence on vulnerable power grids, particularly during natural disasters or energy disruptions [14]. Furthermore, by generating clean energy, PV systems significantly reduce greenhouse gas emissions, which is critical for combating climate change and mitigating environmental impacts in urban areas [2].

In the context of sustainable energy transitions, PV systems enable urban communities to integrate into a more distributed and efficient energy model, aligning with global sustainability goals. However, modeling the spatiotemporal adoption of PV systems is essential to maximize their impact. This approach identifies areas with high potential for implementation, evaluates their economic feasibility, and informs strategies that promote equitable and efficient adoption in cities [4]. Current energy research focuses on refining these models to support urban planning efforts and accelerate the transition to resilient and sustainable energy systems.

1.1. Literature Review

Understanding the spread of residential PV systems in urban areas is essential for assessing the impact of these technologies on the distribution system and designing environmental policies to encourage their use. Various modeling approaches have emerged in the specialized literature. For instance, ref. [16] presents a spatial econometric model analyzing the adoption of residential PV systems across 402 counties in Germany from 2000 to 2013. This model utilizes autoregressive spatial and error regression techniques, incorporating data on economic incentives, socioeconomic differences, and environmental attitudes. Similarly, ref. [17] evaluates the economic profitability of PV systems by examining self-consumption and storage through a financial analysis approach. This study focuses

on the costs of PV systems, electricity tariffs, and battery prices in Portugal. While economically sound, this approach lacks spatial analysis and fails to account for socioeconomic factors or local heterogeneity.

Reference [18] expands the scope by developing a hierarchical Bayesian model that estimates residential PV potential both spatially and temporally. This model integrates technical criteria and socioeconomic conditions, offering a more comprehensive understanding of factors influencing PV adoption.

Reference [19] takes a different approach by proposing a logistic regression model to identify critical factors affecting PV adoption in Tehran. This research assesses household income, environmental concerns, and renewable energy awareness. Complementarily, [20] introduces a subsidy scheme based on CO_2 emission prices, using a discounted cash flow model to promote PV adoption in mature markets in Italy while analyzing self-consumption levels and economic variables.

Reference [21] combines artificial neural networks with agent-based models to study PV adoption through spatiotemporal patterns. This method examines spatial, temporal, and socioeconomic data to model adoption spread. Further exploration in [22] presents a fuzzy logic-based method for modeling the spatiotemporal dynamics of PV adoption, integrating data on early adopters' characteristics. Applied to a Brazilian city, this approach illustrates how early adopters influence neighboring areas. Moreover, ref. [23] develops a spatiotemporal model for estimating PV adoption, incorporating temporal and spatial modules alongside energy potential. The analysis includes socioeconomic variables like monthly income and electricity consumption, focusing on rooftop PV systems in Ecuador.

Reference [24] reviews machine learning applications for estimating PV system potential in urban areas, classifying methods, and identifying key variables across spatial, temporal, and socioeconomic parameters. In a related study, ref. [25] compares various machine learning methods for predicting the installed power of PV systems using spatiotemporal data, including climatic patterns and energy performance, achieving accurate short-term predictions across five cities.

Building on these foundational studies, this article introduces a novel model for estimating the spatiotemporal diffusion of residential PV systems in urban areas. The model comprises two modules: one spatial and one temporal. The spatial module utilizes socioeconomic characteristics such as monthly income, type of residence (house or apartment), ownership status, environmental awareness, and interest in new technologies to estimate the number of residences with potential for PV adoption by census tracts. A hybrid approach combines a logistic growth model with a moving average prediction model to represent the temporal growth of potential buyers, capturing three stages of technology adoption (initiation, growth, and saturation) and allowing for adjustments based on new PV adoption data.

1.2. Contributions

This article presents the following significant contributions to the modeling of PV system adoption in urban areas:

- An innovative combination of spatial and temporal analysis to model the adoption of PV systems in urban environments. This dual approach allows for more accurate predictions of the adoption potential of PV systems over time and space.
- A new method for more realistically modeling PV system adoption dynamics in urban areas by incorporating factors such as population density, socioeconomic data, environmental awareness, population interest in new technologies, and urban rooftop space.
- A novel spatial analysis module that not only calculates the number of residences with the potential to purchase PV systems based on the socioeconomic characteristics of the local population but also considers the influence of neighboring subareas.
- A hybrid approach for PV adoption that combines a logistic growth model with a moving average prediction model. This innovative combination captures the

three phases of technology adoption (initiation, growth, and saturation) while allowing for adjustments based on new data. This flexibility enhances the robustness and reliability of the proposed model compared to more rigid methods employed in prior studies.

Collectively, these contributions advance the state of the art in modeling the diffusion of residential PV systems in urban areas, offering a more comprehensive and applicable approach to the current urban reality. Table 1 summarizes the main differences between the proposal presented in this article and previous research addressing the modeling of residential PV system diffusion; symbols "✓" and "×" respectively indicate whether a particular aspect is considered or not. Below is a brief explanation of the aspects considered in the comparison and a justification of their importance.

Table 1. Summary of the literature review.

Reference	Spatiotemporal Analysis	Estimation at Subarea Level	Socioeconomic Variables	Neighboring Subareas Influence	Technology Adoption Interest	Environmental Awareness	Adjusting the Estimate with New Data	Comparison with Real Data
[16]	×	✓	×	×	×	×	×	✓
[17]	×	×	×	×	×	×	×	×
[18]	✓	×	✓	×	×	×	×	×
[19]	×	×	×	✓	×	✓	×	×
[20]	×	×	×	×	×	×	×	×
[21]	✓	×	×	×	×	×	×	×
[22]	✓	✓	✓	×	×	✓	×	×
[23]	✓	×	✓	×	×	✓	×	✓
[24]	×	×	×	×	×	✓	×	✓
[25]	×	×	✓	×	×	×	×	✓
This work	✓	✓	✓	✓	✓	✓	✓	✓

The spatiotemporal analysis encompasses both spatial and temporal dimensions in the adoption of PV systems, examining how adoption varies across different regions and over time. This approach is decisive for capturing patterns and trends in the distribution of adoption, enabling planners to devise more effective and tailored strategies for each area and period. Neglecting this aspect may result in inadequate policies that fail to adequately address regional and temporal variations, leading to inefficient management and less effective promotion of PV technology. Articles that do not consider this aspect include [16], which focuses solely on spatial analysis, and [17,19,20,24,25], which exclusively addresses temporal analysis.

Estimating residences with the potential to adopt PV systems at the subarea level involves identifying small areas with higher potential for PV installation. This approach allows for more detailed and focused planning, pinpointing specific areas with greater potential. Ignoring this aspect could lead to ineffective resource allocation and a lack of initiatives in high-potential areas, reducing the overall impact of adoption policies. Articles that do not consider this aspect include [17–21,23–25], which make estimates at the regional level without breaking them down into subareas.

Utilizing local socioeconomic data to estimate the potential adoption of PV systems involves considering factors such as income levels and socioeconomic status, which affect residents' ability and willingness to invest in PV technology. This aspect is key for designing policies adapted to local economic realities and promoting adoption among groups with higher potential. Neglecting socioeconomic data could result in ineffective strategies that fail to capture differences in capability and willingness among various socioeconomic groups. Articles that do not consider this aspect include [17], which does not incorporate socioeconomic variables in its analysis, and [20], which focuses on environmental data without considering socioeconomic context, as well as [16,19,21,24].

The influence of neighboring subareas on the estimation of PV system adoption considers how adoption in nearby areas can affect the willingness of residents in adjacent zones to adopt similar technology. This aspect is important for capturing spatial spillover effects that may accelerate adoption in neighboring areas. Failure to account for these influences could lead to underestimating adoption potential and a lack of synchronization

in promotional strategies. Articles that do not consider this aspect include [17,19,20,23–25], which do not examine spatial spillover effects between areas, and [18,21], which focus on global-level analysis without considering neighboring influences, as well as [22].

Public interest in acquiring new technologies is a critical factor in estimating the potential adoption of PV systems, as residents with a higher inclination towards technological innovations are more likely to invest in PV technology. Assessing this interest helps design strategies that align with consumer desires and expectations. Ignoring this aspect may result in inadequate marketing strategies that fail to capture the necessary enthusiasm to drive adoption. None of the articles [16–25] described above consider this aspect.

The environmental awareness of the population influences the willingness to adopt PV systems, as residents who are more concerned about environmental issues are more likely to invest in clean technologies. Including this aspect in estimations helps identify areas where ecological concerns may drive adoption. Neglecting environmental awareness could result in underestimating the real interest in PV systems and designing policies that do not leverage the potential of environmentally conscious consumers. Articles that do not consider this aspect include [17], which does not assess residents' environmental awareness, and [20], which focuses on economic variables without considering ecological concerns, as well as [16,18,21,25].

Adjusting estimated values with newly observed data is essential for improving the accuracy of predictions regarding PV system adoption. Updating estimates based on real data allows for refining models and reflecting current conditions more accurately. Failure to make these adjustments may result in outdated predictions, affecting the effectiveness of implemented policies and strategies. None of the articles [16–25] described above consider this aspect.

Comparing the results of the proposed method with actual data is essential for evaluating the accuracy and effectiveness of the PV adoption estimation model. This comparison validates the model's utility and allows for identifying possible improvements. Not performing this comparison may result in inaccurate models that do not accurately reflect adoption realities. Articles that do not consider this aspect include [16], which does not compare model results with real data, and [20], which focuses on theoretical simulations without empirical validation, as well as [18,19,21,22].

These aspects are integral to building a robust and precise model for predicting the adoption of residential PV systems. Their inclusion ensures that the model can adequately capture the complexities of the urban and socioeconomic environment, providing a solid foundation for effective policies and strategies.

1.3. Manuscript Structure

This paper is structured as follows: Section 2 provides a theoretical contextualization of spatiotemporal estimation. Section 3 details the proposed method to model the spatiotemporal diffusion of residential PV systems in urban areas. Section 4 presents a case study applying the technique to a medium-sized Brazilian city. Section 5 discusses the results obtained, while Section 6 concludes the paper with the main conclusions derived from the study.

2. Overview of Spatiotemporal Estimation

Spatial forecasting estimates the geographic distribution of phenomena within urban areas, aiding in the identification of subareas with high potential for technology adoption based on demographics, socioeconomic status, and infrastructure availability [26]. For example, it can predict where residential PV systems are likely to be installed, allowing policymakers to focus resources on high-potential subareas [14]. However, a fundamental limitation is its failure to capture the temporal dynamics of adoption, leading to static predictions that may hinder decision-making in fast-changing urban environments.

In contrast, temporal forecasting estimates how phenomena evolve over time, providing insights into growth trends and adoption patterns [14]. This approach aids in long-term

planning and resource allocation, allowing authorities to adjust policies and infrastructure in response to anticipated growth in residential PV installations [14]. Nonetheless, it often overlooks spatial heterogeneity, reducing accuracy and leading to uneven policy effects across diverse urban subareas.

To address these limitations, spatiotemporal estimation integrates both spatial and temporal dimensions, providing a comprehensive estimation of phenomena [21]. This approach not only identifies where adoption is likely to occur but also when, thus capturing the dynamic landscape of technological innovation [22]. By combining geographical and temporal variables, spatiotemporal forecasting enhances our understanding of adoption trends, enabling precise interventions such as modeling the growth of PV systems over time in various subareas [23]. Ultimately, this method offers a holistic framework that better reflects the complexities of real-world adoption processes, making it highly effective for strategic urban planning.

2.1. Tools and Techniques for Spatiotemporal Analysis

Spatial modeling analyzes the distribution and relationships of phenomena within geographic areas, employing various tools and techniques to explore how spatial patterns are configured and vary across locations. A prominent technique is geographically weighted regression (GWR), which allows for a local estimation of model parameters rather than a global estimation. This is essential for data exhibiting spatial heterogeneity, where processes influencing observed phenomena differ across geographic space [27]. By applying GWR, researchers can identify relationship variations between variables based on location, providing a detailed view of the phenomenon under study. In the context of residential PV system adoption, spatial modeling using GWR helps identify subareas with socioeconomic and environmental characteristics influencing adoption propensity. Key variables include average monthly income, housing type, tenure status, environmental awareness, interest in new technologies, and the influence of neighboring subareas, each potentially having different effects across various locations [13].

In addition to spatial modeling, understanding temporal changes is critical. Temporal modeling focuses on how phenomena evolve over time, which is vital for predicting future trends based on historical data [28]. The logistic growth model is a mathematical framework to describe growth constrained by resources [29]. In modeling the temporal growth of new residential technologies, this model effectively represents three distinct stages: the initial stage, characterized by gradual growth due to limited early adoption [30]; the rapid growth stage, where technology adoption accelerates; and the saturation stage, where growth stabilizes upon reaching maximum adoption levels [24]. The logistic model's primary advantage lies in capturing these dynamic adoption patterns within urban environments.

The moving average model is another valuable statistical technique that smooths time series data by averaging values within a sliding window, revealing underlying trends and patterns. This model assists in adjusting adoption estimates by incorporating newly observed data, enhancing prediction accuracy by reflecting recent changes in adoption behavior [31]. A hybrid temporal growth model combining logistic growth and moving averages offers a powerful tool for estimating the expansion of residential properties adopting PV systems.

A comprehensive spatiotemporal analysis integrates both spatial and temporal methods to provide a dynamic understanding of phenomena. Combining a spatial module based on GWR with a temporal module employing a logistic growth model and a moving average model effectively captures spatial variations and temporal trends in the overall model [13]. This integration is essential for accurately predicting the expansion of residential PV systems in urban areas, enhancing our understanding, and providing practical tools for decision-making and strategic planning.

2.2. The Role of Geographic Information Systems in Spatiotemporal Analysis

Geographic information systems (GISs) are essential tools for capturing, storing, manipulating, analyzing, and visualizing geospatial data. By integrating geographic information with non-spatial data, such as demographic and socioeconomic characteristics, GIS provides a comprehensive understanding of the relationships between variables and their spatial manifestations [32]. The ability to perform advanced spatial analyses, including interpolation and pattern identification, further establishes GISs as fundamental assets across various disciplines, from geography to urban planning. Thus, employing GISs is central to addressing issues involving the location and distribution of variables within defined geographic spaces [33].

The application of GIS in spatiotemporal analysis is particularly relevant for studying phenomena that evolve over both space and time, especially in the context of adopting new technologies in urban areas. These systems facilitate the modeling of technology adoption, such as residential PV systems, by integrating spatial and temporal data from multiple sources [32]. By employing techniques like GWR, GIS can identify adoption patterns that vary according to factors such as income levels and openness to new technologies [33]. This ability to visualize and analyze trends as they shift over time and space provides a more accurate and dynamic understanding of the adoption process, thereby aiding more efficient planning for technology implementation in urban settings.

2.3. Case Studies Using Spatiotemporal Analysis

Recent studies illustrate the practical applications of spatiotemporal analysis in different contexts. One notable study conducted in a highland city in Ecuador evaluated the adoption of electric induction stoves as part of a national policy to reduce liquefied petroleum gas consumption. The analysis utilized a spatiotemporal model based on GWR to capture spatial variability, complemented by a logistics growth model for the temporal component. Key variables included socioeconomic status, access to government subsidies, available electrical infrastructure, and the distribution of awareness campaigns. The results revealed that the spatiotemporal approach allowed researchers to accurately identify areas with rapid adoption, linking them to socioeconomic and infrastructural factors. Additionally, the temporal analysis provided robust predictions regarding future adoption patterns, optimizing the allocation of government resources and efforts [13].

In several European cities, the adoption of electric vehicles has been analyzed, highlighting the important role of expanding charging stations. One study employed a combined spatiotemporal approach alongside agent-based modeling (ABM). The spatiotemporal component examined the relationship between the locations of charging stations and EV adoption across different urban areas, while the ABM simulated residents' decision-making processes, considering governmental incentives, vehicle costs, and accessibility to charging stations. This comprehensive approach allowed for identifying areas with insufficient charging infrastructure, thereby informing strategies for strategically expanding stations in underserved districts [34]. Ultimately, the spatiotemporal analysis proved vital in capturing geographic and temporal variations in EV adoption, enabling more effective infrastructure planning.

In southern U.S. cities, rising temperatures attributed to climate change have resulted in increased demand for air conditioning systems in regions that historically did not require them. A relevant study utilized a spatiotemporal approach to analyze this phenomenon by combining GWR with network theory to model technological diffusion. Key variables considered included rising average temperatures, population density, electricity costs, and household income. The analysis successfully identified areas where the electrical infrastructure was becoming overloaded due to increased demand, highlighting the necessity for grid modernization. Furthermore, the temporal component enabled projections of future demand increases linked to global warming trends. This spatiotemporal approach was essential in correlating adoption with both socioeconomic and environmental factors, facilitating better infrastructure and energy policy planning [35].

In the United Kingdom, the adoption of heat pumps has been incentivized through public policies promoting renewable energy technologies. A study focused on this process in a UK city employed a spatiotemporal approach using Poisson regression to capture adoption rates across various urban areas. The analysis considered factors such as housing age, governmental incentives, building energy efficiency, and access to subsidies. This spatiotemporal analysis identified areas with lower adoption rates, primarily due to high installation costs in older homes. Consequently, the findings underscored the need for targeted policies, such as additional subsidies or accessible financing, to facilitate adoption in these regions. This study highlighted the importance of capturing spatial and temporal variability to design more effective public policy interventions [36].

In conclusion, the adoption of new technologies in urban areas can be effectively modeled using spatiotemporal approaches, which adeptly capture both spatial variability and temporal dynamics. The reviewed studies illustrate the successful application of this method to model technology adoption across diverse geographic and socioeconomic contexts. Spatiotemporal analysis has proven critical in identifying adoption patterns, local barriers, and the effectiveness of public policies, ultimately contributing to improved infrastructure planning and the promotion of sustainable technologies.

3. Proposed Method

The proposed method enables the modeling of PV system adoption in urban environments by considering the complex interplay between spatial and temporal factors. From a spatial perspective, the adoption of these systems is heterogeneous and heavily influenced by socioeconomic variables that vary geographically. On the temporal side, the adoption of new technologies generally follows diffusion patterns that can be captured and modeled through predictive techniques. Thus, the proposed model begins by identifying subareas with the highest potential for PV system adoption, utilizing GWR to assess how the local population's socioeconomic characteristics influence adoption across different parts of the city. Subsequently, the temporal module projects the annual growth in the number of residences with the potential to adopt these systems, using a hybrid temporal growth model that combines the strengths of logistic growth and moving average models. The logistic model effectively captures the three typical stages of new technology adoption in urban areas: the initial phase, rapid growth phase, and saturation phase. Meanwhile, the moving average model adjusts predictions based on newly observed data, thereby enhancing the accuracy of the results. The mathematical formulation and the details of each module are presented below.

3.1. Spatial Analysis Module

The spatial module is based on GWR, a spatial analysis technique that estimates the relationships between independent and dependent variables locally, i.e., based on their geographic location [37]. GWR is particularly suitable when the relationships between variables are not expected to be constant across the geographic space, which is common in the adoption of new technologies in urban areas.

The choice of GWR as a technique for spatial analysis is due to its ability to capture local variations that other spatial models cannot. In an urban environment, socioeconomic characteristics and technology adoption behavior vary significantly between different subareas. Factors such as income, housing type, or interest in new technologies do not affect each subarea equally, and, therefore, it is important to have a model that can reflect this spatial heterogeneity. GWR is an extension of linear regression that allows for the local estimation of regression parameters based on the geographic location of the observations. The mathematical formulation of GWR is defined in (1).

$$y_{t,s} = \sum_{i=1}^{\rho} \beta_{i,t,s} \chi_{i,s} + \varepsilon_{t,s} \quad (1)$$

Note that $y_{t,s}$ is the value of the dependent variable; in this case, it is the number of residences with the potential to adopt PV systems in year t and subarea s. $\beta_{i,t,s}$ is the coefficient of the variable $\chi_{i,s}$, which can vary depending on year t and subarea s. $\chi_{i,s}$ is the value of the i^{th} independent variable. ρ is the total number of independent variables used in the model. $\varepsilon_{t,s}$ is the estimation error term in year t and subarea s. $\beta_{i,t,s}$ is calculated by (2).

$$\beta_{i,t,s} = \left({\chi_{i,s}}^T W_s \chi_{i,s}\right)^{-1} {\chi_{i,s}}^T W_s \hat{y}_{t,s} \tag{2}$$

Note that W_s is a square weight matrix that defines the weight that the results obtained in the neighboring subareas have in subarea s. $\hat{y}_{t,s}$ is the number of residences with the potential to adopt PV systems in year t and subarea s. $\hat{y}_{t,s}$ values do not include the weight that the results obtained in the neighboring subareas have in the subarea s. Moreover, this value does not consider the set of variables $\chi_{i,s}$.

3.2. Temporal Analysis Module

The temporal growth of the number of residences with the potential to adopt PV systems is modeled using a hybrid approach that combines a logistic growth model with a moving average model. This approach offers several significant advantages. The logistic growth model accurately captures the three classic phases of technology adoption: an initial slow phase, a rapid growth stage, and a saturation phase, making it ideal for modeling the diffusion of emerging technologies in urban environments. Meanwhile, the moving average model provides a critical advantage by continuously adjusting predictions based on recent data, improving accuracy and responsiveness to changes in adoption trends. Compared to other models available in the specialized literature, which often focus on only one aspect of growth, this hybrid approach allows for a more realistic and adaptable representation of the diffusion process by capturing both long-term trends and short-term fluctuations. This makes it a robust choice for modeling residential technology adoption.

The logistics growth model emerges as an improvement to exponential growth models, which assume continuous and unlimited growth, which is not realistic when it comes to populations or the adoption of technologies since there are factors that limit growth, such as available resources or market saturation [38]. The mathematical formulation of the logistics growth model is defined in (3).

$$\dot{y}_{t,s} = \frac{\overline{y}_s}{1 + e^{-\psi_s (t - \hat{t}_s)}} \tag{3}$$

Note that $\dot{y}_{t,s}$ is the estimated number of residences with the potential to adopt PV systems at year t and subarea s. $\overline{y}_s$ is the maximum capacity or the total number of residences that will eventually adopt PV systems (saturation) at subarea s. ψ_s is the growth rate, measuring how quickly technology is adopted at subarea s. $\hat{t}_s$ is the inflection point, where the growth shifts from slow to rapid at subarea s. This model captures the three critical phases of adoption: the initial slow phase, the rapid growth phase, and the saturation phase. ψ_s can be calculated as a function of historical adoption data of other electrical appliances, such as air conditioners, dishwashers, electric induction stoves, etc., in each subarea. Thus, ψ_s is calculated by (4).

$$\psi_s = f(\theta_s, \eta_s, \mu_s, \ldots) \tag{4}$$

Note that θ_s denotes the historical adoption of air conditioners in subarea s. η_s refers to the historical adoption of dishwashers in subarea s. μ_s stands for the historical adoption of electric induction stoves in subarea s. Historical data on the adoption of other technologies whose historical adoption can influence the adoption of PV systems may be used. In this way, the local population's interest in adopting new technologies is considered.

On the other hand, the moving average model adjusts temporal predictions using recent data. The simple moving average for n periods is defined by (5).

$$\hat{y}_{t,s} = \frac{1}{n}\sum_{k=0}^{n-1} \dot{y}_{t,s}(t-k) \tag{5}$$

$\hat{y}_{t,s}$ is the adjusted PV adoption value at year t and subarea s. n is the number of periods considered in the moving average window. $\dot{y}_{t,s}(t-k)$ is the real number of residences with the potential to adopt PV systems in previous years.

3.3. Socioeconomic Variables: Importance and Selection Criteria

The adoption of residential PV systems in urban areas is expected to be heterogeneous, reflecting the diverse socioeconomic profiles of the population [39]. Factors influencing this heterogeneity include household income, which directly affects the financial capacity for investing in PV technology; higher-income families tend to be more inclined to adopt such systems [19]. Additionally, the type of residence plays a significant role; single-family homes are generally more suitable for PV system installation than apartments due to their structural characteristics [40]. Ownership status is another important consideration; homeowners typically have more incentives to invest in long-term energy efficiency solutions than renters [41]. Furthermore, environmental awareness can significantly influence adoption, particularly in households with young children, as parents are often more concerned about their children's environmental future [39]. The general population's interest in new technologies also plays a substantial role; those more inclined to embrace technological innovations are more likely to install PV systems [40]. Finally, the influence of neighboring sectors can create a peer effect, where the adoption of PV systems by a significant number of households within a community encourages others to follow suit [39]. Understanding these interrelated factors is essential for creating more accurate and effective models of PV adoption.

The selection of socioeconomic variables is carried out in two steps. First, the planner's logical criteria are considered, selecting variables that make logical sense with the problem addressed. Second, a statistical correlation analysis is performed to avoid redundant variables and those that do not have statistical significance with the observed data on the adoption of PV systems.

3.4. Model Validation

The validation of the proposed model is executed by applying four error metrics that facilitate the assessment of the accuracy of the PV system adoption estimations. These metrics are as follows:

Mean absolute error (MAE), shown in (6), measures the average magnitude of errors in a set of predictions, disregarding their direction.

$$MAE_t = \frac{1}{m}\sum_{s=1}^{m} |y_{t,s} - \hat{y}_{t,s}| \tag{6}$$

where $y_{t,s}$ represents the observed value and $\hat{y}_{t,s}$ denotes the estimated value for each subarea s.

Mean squared error (MSE), shown in (7), calculates the mean of the squared errors, penalizing larger discrepancies and providing an indicator of the variance in the estimations.

$$MSE_t = \frac{1}{m}\sum_{s=1}^{m} (y_{t,s} - \hat{y}_{t,s})^2 \tag{7}$$

Root mean squared error (RMSE), shown in (8), serves as the square root of the MSE, thereby rendering the error in the same units as the original data, facilitating interpretation.

$$RMSE_t = \sqrt{\frac{1}{m}\sum_{s=1}^{m}(y_{t,s} - \hat{y}_{t,s})^2} \tag{8}$$

Mean absolute percentage error (MAPE), shown in (9), expresses the error as a percentage, offering an intuitive means to evaluate the model's performance, particularly useful when comparing different data scales.

$$MAPE_t = \frac{100}{m}\sum_{s=1}^{m}\left|\frac{y_{t,s} - \hat{y}_{t,s}}{y_{t,s}}\right| \tag{9}$$

The utilization of these metrics not only enables the evaluation of the model's quality but also aids in identifying areas for improvement in the estimations. Furthermore, it allows for adjusting parameters to optimize the accuracy of predictions.

3.5. Algorithm Development and Implementation

Figure 1 shows a flowchart of the proposed method. Its main steps are described below.

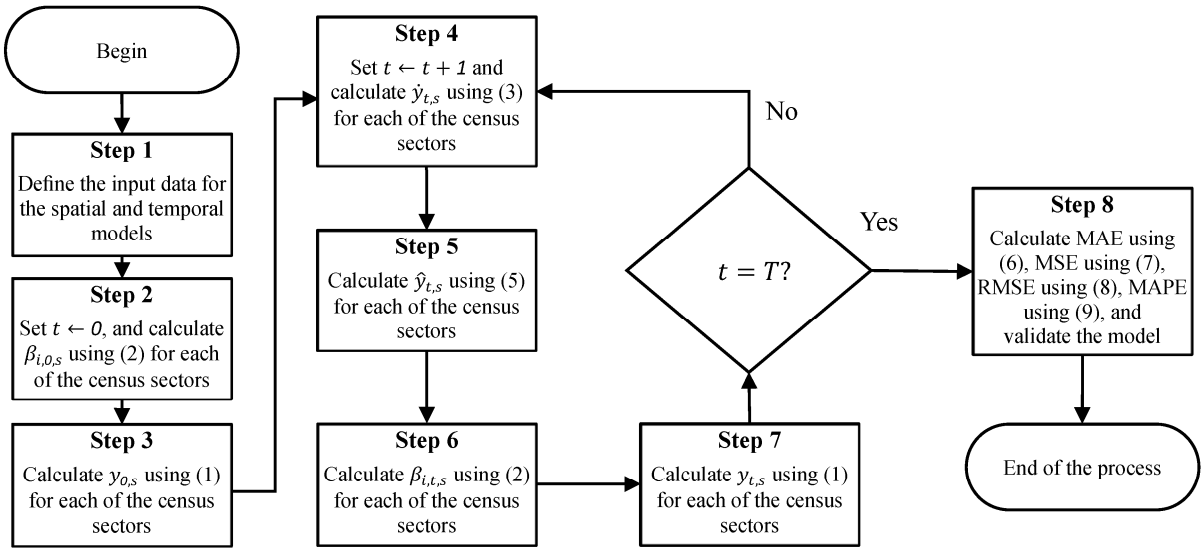


Figure 1. Flowchart of the proposed method.

Step 1. Define the variables and input data

- Spatial module:
  - $\chi_{i,s}$: Socioeconomic data set of the population.
  - W_s: Spatial weight matrix of the influence of neighboring subareas.
  - $\hat{y}_{0,s}$: Number of residences with the potential to adopt PV systems in the base year $(t = 0)$ for each subarea s.
- Temporal module:
  - $\overline{y}_s$: Maximum capacity or the total number of residences that will eventually adopt PV systems (saturation) at the subarea s.
  - n : Number of periods considered in the moving average window.
  - T : Estimation horizon.
  - $\dot{y}_{t,s}(t-k)$: Real number of residences with the potential to adopt PV systems in previous years.

Step 2. Set $t \leftarrow 0$, calculate $\beta_{i,0,s}$ using (2), and go to Step 3.

Step 3. Calculate $y_{0,s}$ using (1) and go to Step 4.
Step 4. Set $t \leftarrow t+1$, calculate $\dot{y}_{t,s}$ using (3) and go to Step 5.
Step 5. Calculate $\hat{y}_{t,s}$ using (5) and go to Step 6.
Step 6. Calculate $\beta_{i,t,s}$ using (2) and go to Step 7.
Step 7. Calculate $y_{t,s}$ using (1) and return to Step 4 until $t = T$.
Step 8. Calculate MAE using (6), MSE using (7), RMSE using (8), and MAPE using (9) and validate the model.

The method presented establishes a framework for modeling the spatiotemporal adoption of residential photovoltaic systems in urban areas. Through the application of the proposed approach, the study seeks to identify key adoption patterns and evaluate the factors influencing their spatial and temporal distribution. The results section provides an overview of the outcomes, emphasizing critical trends, adoption dynamics, and the model's predictive performance.

4. Tests and Results

This research focuses on Presidente Prudente, a city in São Paulo state, Brazil. Figure 2 shows a map of the urban area of the city of Presidente Prudente. This city has a population of around 230,000 people and is divided into 300 census tracts, or subareas, as defined by the Brazilian Institute of Geography and Statistics (IBGE) to facilitate census data collection. Figure 3 shows a map of the city divided into subareas. This study was conducted across the entire urban area, with the proposed method applied to each of these subareas.

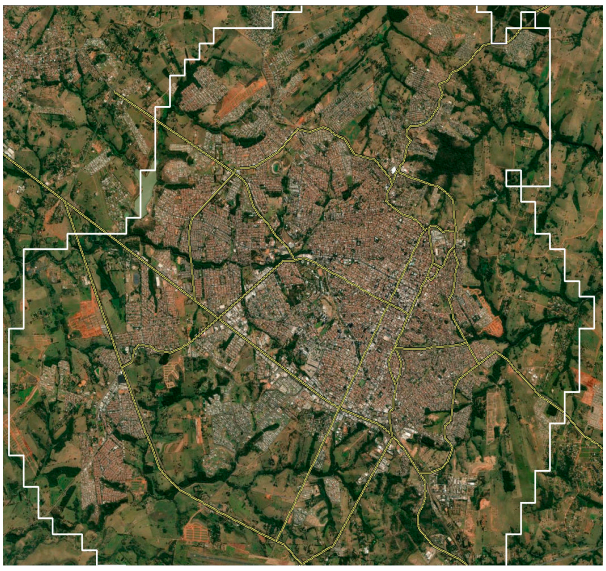


Figure 2. Map of the urban area of the city.

The method models residential PV system adoption through a combination of spatial and temporal analysis. The spatial component was implemented using GWR, which processed the city's georeferenced maps using ArcGIS 10.5 software [42]. ArcGIS made it easier to apply the model by automatically calculating the explanatory variables' distances and weights. The temporal module was written in Python and calibrated with historical data spanning 2019 to 2023.

The socioeconomic variables used in the GWR were selected in two stages. First, a logical criterion was used to select those that were directly related to the problem of adopting new technologies. The Pearson correlation coefficient was then used to eliminate redundancies among the selected variables. The data were obtained from the population census.



Figure 3. Map of the city divided into subareas.

4.1. Input Data

Five socioeconomic variables were used to calibrate the spatial model taken from the population census [43], available in the supplementary material. The variables taken are (1) number of residences in which the head of the household has an average monthly income greater than or equal to the average for the entire city, (2) number of residences that are of the permanent house type, (3) number of residences that the inhabitants own, (4) number of residences in which there is at least one child under 5 years old, and (5) level of education of the head of the household. It is worth highlighting that the GWR calculates the estimated value of candidate residences considering the influence of the neighboring subareas. The socioeconomic variables included in the spatial regression were the same for the three case studies, which guaranteed a consistent basis of comparison between the simulations. The parameters of the GWR were left in the predefined configuration of the ArcGIS toolbox.

For the calibration of the temporal module, historical data on the adoption of PV systems in the study area for the years 2019, 2020, and 2021 were used. These data allowed the adjustment of the model parameters, ensuring that the projections were aligned with the observed historical behavior. The adoption data for 2022 and 2023 were used exclusively to validate and compare the estimates generated by the model, allowing their accuracy to be measured. The initial calibration process was carried out using the 2019 values, while the 2020 and 2021 data helped to fine-tune the model for the simulations. In this regard, a three-data moving window was introduced for the temporal adjustment, allowing the model to correct the estimated values as new observed data become available.

4.2. Considerations for Simulations

Three simulations were run to assess the impact of various factors on PV system adoption. Two major aspects distinguish each case study: (1) whether or not it considers the population's willingness to adopt new technology, and (2) determining if the model allows for adjusting estimated values based on new observations. Table 2 summarizes the differences between the three cases.

Table 2. Summary of the cases considered in the simulations.

	Considers the Population's Willingness to Adopt New Technology	The Model Allows for Adjusting Estimated Values Based on New Observations
Case 1	×	×
Case 2	✓	×
Case 3	✓	✓

- Case 1. Does not use population interest in new technologies or the moving average method to adjust estimates.
- Case 2. Includes interest in new technologies but does not adjust estimated values using the moving average method.
- Case 3. Considers population interest in new technologies and uses the moving average method to adjust estimated values based on observed data.

4.3. Results

Figures 4–7 show the spatial distribution of residences with the potential to purchase PV systems obtained using the proposed method, i.e., considering the conditions established for case 3. These results illustrate how the number of residences with the potential to acquire PV systems increases both in space and time. The data presented correspond to the estimated values for the years 2020, 2021, 2022, and 2023, respectively.

The results show that the adoption of PV systems in the analyzed subareas presents a notable temporal and spatial heterogeneity. Each subarea presents a unique growth pattern for the adoption of these systems, reflecting significant differences in the socioeconomic factors that influence their implementation.

On the one hand, some subareas stand out for having a greater number of residences with the potential to acquire PV systems, which drives faster growth over the years. These areas usually benefit from favorable conditions, such as higher incomes, adequate infrastructure (available space on the roofs), interest in new technologies, environmental awareness, among others. On the other hand, there are subareas where growth is more moderate, possibly due to economic limitations for investment or barriers to technological adoption. Likewise, subareas are identified where the increase in the number of residences with purchasing potential is slow or practically non-existent. Even in certain cases, no residences with adequate conditions for installing PV systems are observed, which implies a total absence of growth in this sector.

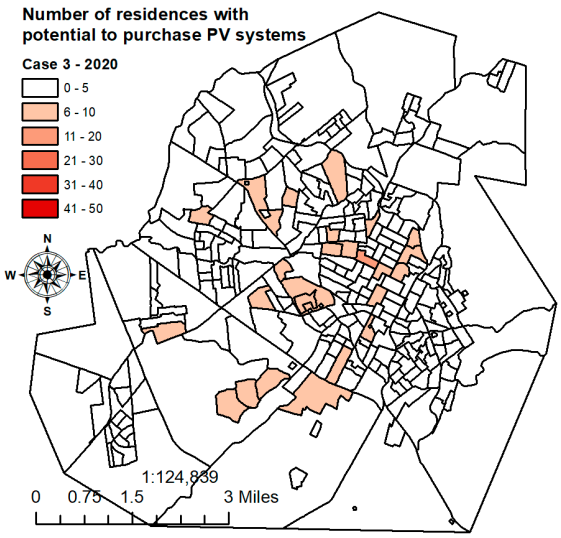


Figure 4. Spatial distribution of the results obtained for 2020.

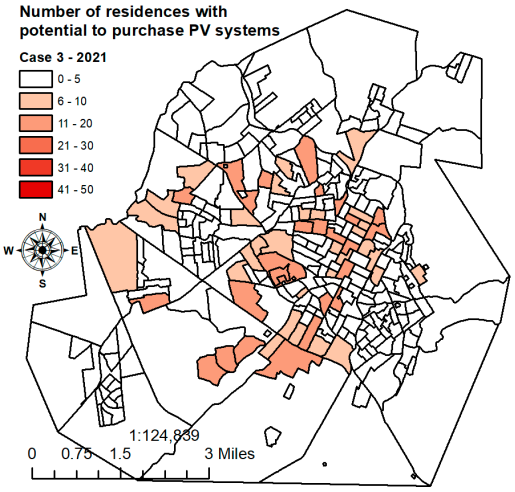


Figure 5. Spatial distribution of the results obtained for 2021.

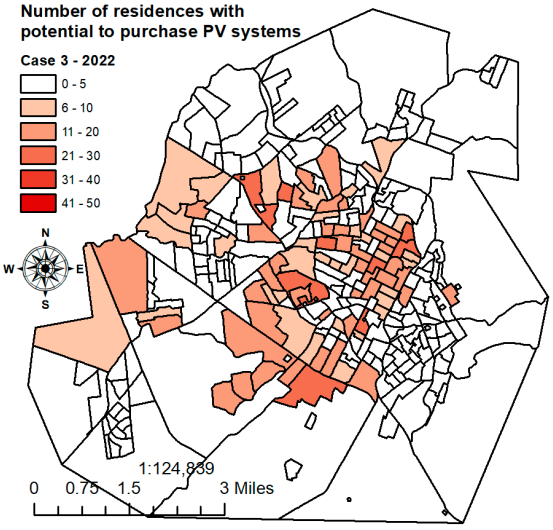


Figure 6. Spatial distribution of the results obtained for 2022.

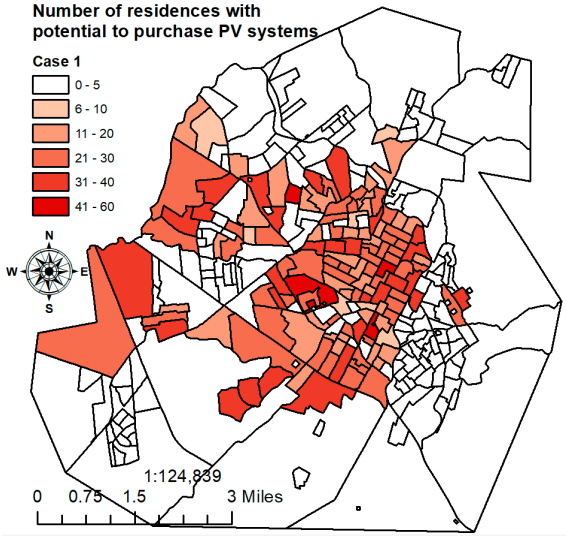


Figure 7. Spatial distribution of the results obtained for 2023.

This analysis highlights the importance of and need to design spatiotemporal estimation methods for the adoption of PV systems that consider the characteristics of the inhabitants of each subarea to design customized incentive programs that allow for a more equitable and sustainable energy transition.

4.4. Validation of Proposed Method

Figures 8–10 show the spatial distribution of residences with the potential to acquire PV systems in 2023, corresponding to Cases 1, 2, and 3, respectively. Furthermore, Figures 11–13 present the spatial distribution of the percentage error in the estimates for each case, comparing the results of the estimated values with the actual data of PV system adoption in 2023. Moreover, four error metrics were used to assess the accuracy of the simulations: MAE, MSE, RMSE, and MAPE. Table 3 summarizes the error metrics results obtained for the three cases.

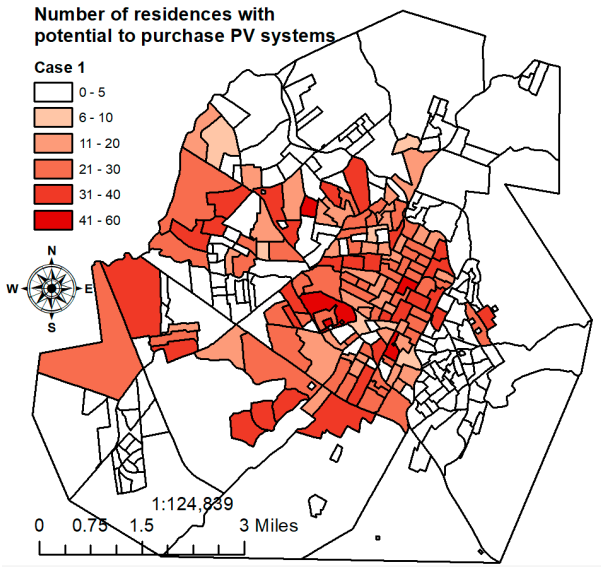


Figure 8. Spatial distribution of the results obtained in Case 1.

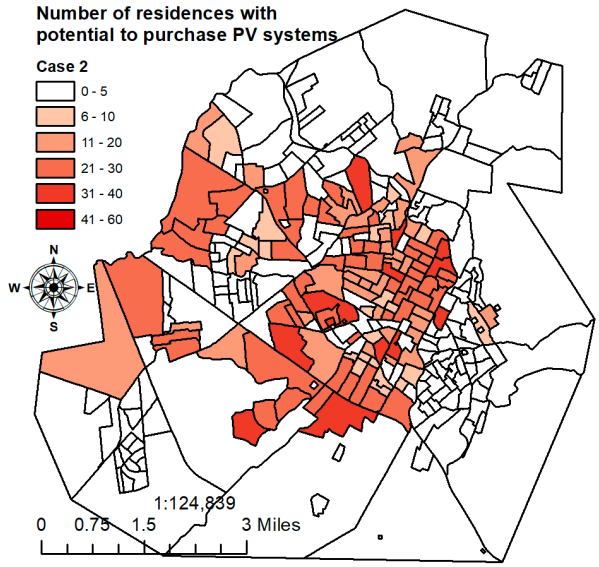


Figure 9. Spatial distribution of the results obtained in Case 2.

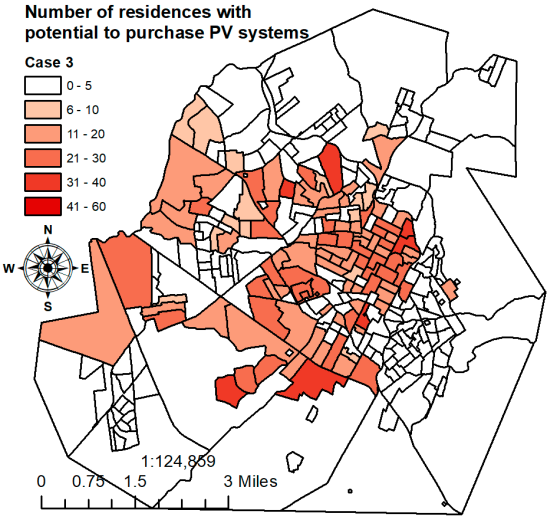


Figure 10. Spatial distribution of the results obtained in Case 3.

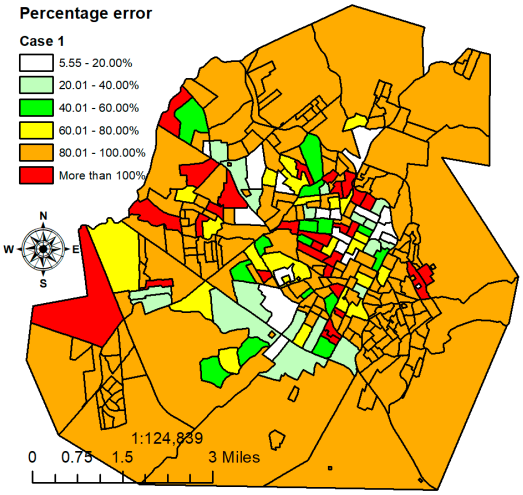


Figure 11. Percentage error between Case 1 versus 2023 real data.

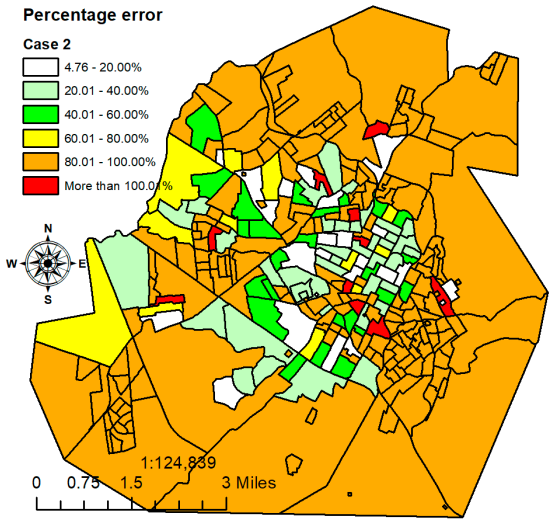


Figure 12. Percentage error between Case 2 versus 2023 real data.

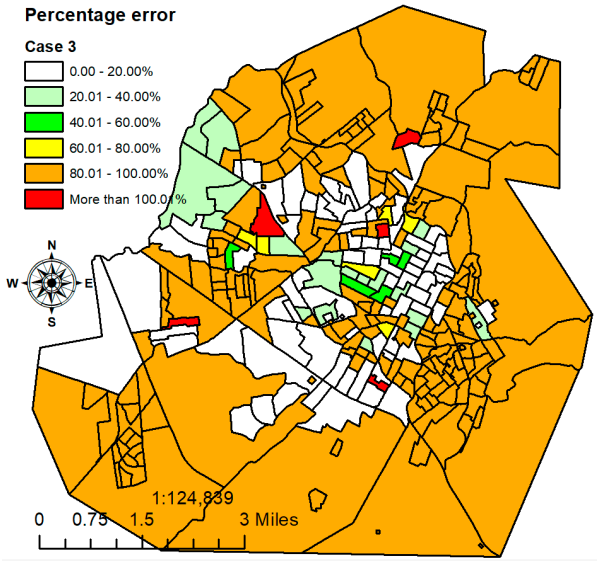


Figure 13. Percentage error between Case 3 versus 2023 real data.

Table 3. Error metrics results of simulated cases.

Metric	Case 1	Case 2	Case 3
MAE	4.86 [Residences]	2.71 [Residences]	1.17 [Residences]
MAPE	99.23 [%]	82.70 [%]	72.24 [%]
MSE	66.46 [Residences^2]	19.29 [Residences^2]	4.44 [Residences^2]
RMSE	8.15 [Residences]	4.39 [Residences]	2.11 [Residences]

As seen in Table 3, Case 3 presents the lowest values in all error metrics, indicating that, by considering both the interest in new technologies and the adjustment using the moving average method, more accurate results are obtained. Case 1, by not considering any of these factors, presents the highest error values, while Case 2, which only considers the interest in new technologies, presents an intermediate improvement.

The comparative analysis of the results obtained across the three cases highlights significant differences in the accuracy of the estimates, underscoring the advantages of incorporating both population interest in adopting new technologies and the adjustment of estimated values using newly observed data. These differences are clearly reflected in the error metrics, which are critical for assessing how closely the proposed method aligns with real-world data.

When comparing Case 1 to Case 2, it is evident that including population interest in new technologies (Case 2) significantly enhances the accuracy of the estimates. The MAE decreases from 4.86 to 2.71 residences, indicating a substantial reduction in the average error margin. Similarly, the MAPE drops from 99.23% to 82.70%, demonstrating that the predictions in Case 2 align more closely with actual values. Furthermore, the MSE and RMSE also show marked improvements, declining from 66.46 and 8.15 to 19.29 and 4.39, respectively. These findings suggest that incorporating this contextual variable enables the model to capture dynamics that Case 1 fails to account for.

Comparing Case 2 to Case 3, the additional impact of using the moving average method in Case 3 leads to even more notable improvements. The MAE reduces from 2.71 to 1.17 residences, while the MAPE declines from 82.70% to 72.24%, indicating more precise and consistent predictions. Likewise, the MSE decreases from 19.29 to 4.44 residences^2, and the RMSE falls from 4.39 to 2.11 residences. These enhancements reflect the moving average's ability to smooth fluctuations and adjust predictions based on observed patterns, resulting in outcomes that are more closely aligned with reality.

Finally, the comparison of Case 1 to Case 3 reveals the most significant differences, as Case 3 combines both improvements: the inclusion of population interest in new technologies and the adjustment of estimated values using observed data. The MAE in Case 3 (1.17) is nearly four times lower than that in Case 1 (4.86), while the MAPE drops from 99.23% to 72.24%. Similarly, the MSE and RMSE exhibit drastic reductions. These results confirm that integrating contextual variables with robust adjustment techniques enables the model to capture trends and variations in the data with greater accuracy, providing superior predictive performance.

5. Discussion

The simulation results show that the accuracy of the estimates varies significantly between the three cases. Three major aspects were identified in the obtained results:

Heterogeneity in adoption: Because of differences in the population's socioeconomic characteristics, the adoption of new technologies varies by subarea in the city. This variability is reflected in the results, which show that some subareas are more likely to adopt solar panels than others despite having similar socioeconomic characteristics.

Impact of interest in new technologies: In many subareas, residents have the financial resources to purchase solar panels but do not do so due to a lack of interest in adopting new technologies. When the results of Cases 1 and 3 are compared, it is clear that the accuracy of the estimates improves significantly when interest in new technologies is factored in.

Importance of adjusting estimated values based on new observations: The ability to adjust the estimated values through the moving average method significantly improves the quality of the estimates. When comparing Case 2 and Case 3, it is noted that Case 3 offers more accurate results due to its ability to correct the estimated values as newly observed data are incorporated, reducing errors introduced by external events that the logistic growth model cannot foresee.

The simulations provided significant insights into the adoption of PV systems in urban areas, highlighting three key points. First, it is observed that the adoption of these technologies varies considerably among different subareas. This variation is largely attributable to the socioeconomic characteristics of the population, which play a critical role in their willingness to embrace sustainable energy solutions.

Secondly, although specific individuals possess favorable economic conditions for purchasing PV systems, their lack of interest in new technologies may hinder their utilization. This phenomenon becomes evident when comparing the outcomes of two scenarios: Case 1, which does not account for the population's interest, and Case 3, which does. Such a comparison underscores the importance of not only examining economic resources but also understanding the attitudes and perceptions within the community regarding the adoption of clean technologies.

Lastly, the employed method must be capable of adjusting estimates based on newly observed data, as this is essential for achieving precise results. Should a model fail to accommodate such adjustments, it may lead to significant errors in projections. While the logistic growth model effectively depicts the diffusion of new technologies, it does not account for external factors that could influence the speed of adoption. This point is particularly clear when comparing Case 2, which does not allow for the recalibration of estimates, with Case 3, which does. In summary, adjusting estimates considering new observations is essential for enhancing the accuracy of projections concerning the adoption of PV systems and facilitating the transition towards more sustainable energy sources.

Table 4 highlights the varying degrees to which each variable contributes to the spatiotemporal adoption model. Socioeconomic factors such as income, housing type, and ownership strongly influence adoption rates, while education and demographic factors offer moderate contributions. Notably, the inclusion of population interest in new technologies adds a dynamic layer to the model, capturing behavioral trends that complement the socioeconomic variables.

Table 4. Summary of the variables and their influence on PV adoption.

Variable	Description	Influence on PV Adoption
Income	Number of residences where the head of the household has income greater than the city average	Higher income levels increase the likelihood of PV adoption due to greater financial capacity to invest in solar systems
Housing type	Number of residences classified as permanent houses	Permanent housing indicates stability and suitability for PV installation, positively influencing adoption
Ownership	Number of residences owned by their inhabitants	Homeownership encourages long-term investments like PV systems, as owners benefit directly from energy savings
Demographics (Children < 5)	Number of residences with at least one child under the age of 5	Families with young children may prioritize energy savings for future economic benefits, slightly influencing adoption
Education	Educational attainment of the head of the household	Higher education levels are correlated with greater awareness of renewable energy benefits, fostering PV adoption
Interest in new technologies	Population interest in acquiring new technologies	Strong interest drives adoption by reflecting a population's openness to innovation and sustainable solutions

While the GWR method effectively captures spatial heterogeneity, its performance may be limited in densely populated or irregularly shaped urban settings. These areas often exhibit overlapping or fragmented spatial influences, complicating the interpretation of localized coefficients and potentially reducing predictive accuracy.

5.1. Significance of the Findings

The results of this study have significant relevance for understanding the dynamics of the adoption of PV systems in urban environments. First, they underline that the adoption of clean technologies does not depend solely on economic conditions but also on sociocultural factors, such as the population's interest in innovation and sustainability. This finding suggests that strategies to encourage the adoption of PV technologies should be multifaceted, combining financial incentives with education and awareness programs.

Furthermore, the identification of heterogeneity in adoption implies that policies should be adaptive and consider the specific characteristics of each subarea. Promotion strategies should be customized, such as implementing grant programs or low-interest financing in communities with high environmental awareness and carrying out information campaigns in areas where a conservative mentality prevails.

In addition, the results highlight the importance of having estimation methods that allow for readjusting values based on newly observed data, thus improving the accuracy of predictions in the adoption of technologies. This adaptive capability in models can provide policymakers and researchers with a valuable tool for making more reliable forecasts, which is vital for long-term planning in the transition to sustainable energy.

5.2. Implications and Applications of Findings

The findings of this study have important implications and applications in various fields, especially in distribution system planning and public policy design.

The adoption of PV systems directly influences energy distribution networks. With an increase in the use of renewable energy technologies, power grids must adapt to manage greater variability in power generation. The results suggest that planners can better anticipate and model energy production and demand by integrating PV adoption into their projections. Furthermore, the identification of subareas with high economic capacity but low interest in adoption can guide companies to develop specific strategies to incentivize

these groups, such as the implementation of education and awareness programs. The capacity of networks to adapt to generation variability can also be benefited by using storage and demand management technologies, facilitating a more effective integration of renewable energy into the distribution system.

The results of this study have a significant impact on public policy formulation and urban planning. The need to consider the population's interest in adopting new technologies indicates that promotion strategies should be multifaceted, combining economic incentives with education and awareness programs. This duality in policies could increase the adoption rate of PV systems in urban areas, promoting a cultural shift towards greater acceptance of sustainable technologies.

Furthermore, the heterogeneity in adoption suggests that policies should be adaptive and consider the specific characteristics of each subarea. In communities with high environmental awareness, grant or low-interest financing programs could be implemented to reinforce the commitment to sustainability. In contrast, in areas where a conservative mindset prevails, it would be essential to carry out information campaigns that highlight the long-term benefits of adopting clean technologies. Policymakers could benefit from integrating these findings into urban planning, ensuring that strategies for charging infrastructure and energy distribution consider not only economic factors but also social and cultural aspects that affect the adoption of renewable technologies.

These results have significant implications for urban energy policy and grid planning. Understanding where and when adoption is most likely to occur can assist policymakers in designing more effective strategies to promote renewable energy use in cities. For instance, identifying potential areas for high adoption can guide the allocation of subsidies or tax incentives to lower economic barriers for potential adopters. In regions with low adoption rates, model outcomes could inform targeted awareness campaigns emphasizing the benefits of PV systems, tailored to communities demonstrating greater resistance to change.

From a grid planning perspective, predicting the spatiotemporal adoption of PV systems is critical for preparing electrical infrastructure for the integration of distributed renewable energy. For example, in urban areas with high predicted adoption density, grid planners can anticipate issues such as voltage instability or the need to upgrade local transformers to manage bidirectional energy flows. This also enables utility companies to optimize investments in energy storage infrastructure or microgrids at strategic locations, maximizing operational efficiency and minimizing the costs associated with grid adaptation.

A practical application of the model is its use in planning new urban developments or renovation projects. In an urban development scenario, the model can predict adoption levels at different project stages, guiding the design of electrical systems capable of accommodating high solar energy penetration. Similarly, it can identify areas with low adoption potential, which may be ideal for implementing pilot programs to demonstrate the feasibility of PV systems, creating a demonstration effect that encourages adoption in neighboring communities.

Additionally, the model could be employed in energy resilience scenarios, such as planning strategies to mitigate blackouts. For instance, areas with high PV adoption could be prioritized for the development of self-sufficient microgrids, reducing dependence on centralized grids during emergencies. Collectively, these applications demonstrate how the model's findings can translate into tangible benefits for urban energy sustainability while laying the groundwork for more equitable and resilient energy transitions.

5.3. Limitations of the Method

Despite the significant contributions and findings of this study, some limitations need to be acknowledged. First, the proposed method does not consider the impact of government incentive programs on the adoption of PV systems. These incentives can play a fundamental role in facilitating the acquisition of clean technologies, especially in diverse

socioeconomic contexts. Future research should incorporate this variable to assess how incentives can modify the adoption dynamics in different communities.

Another important limitation is data availability. The model requires detailed information on technology adoption in the population to adequately capture interest in new technologies. However, not all cities have complete and up-to-date databases, which may limit the model's applicability in specific contexts. To address this limitation, it is suggested that researchers use alternative methods, such as surveys or inferences based on socioeconomic characteristics, to model population interest in technology adoption.

In conclusion, although the proposed method has limitations, its significant contributions provide a solid basis for future research and the formulation of public policies that encourage the adoption of clean technologies in urban areas. Consideration of societal interest and heterogeneity in adoption as well as the integration of dynamic adjustments in the models can contribute to significant progress toward energy sustainability.

6. Conclusions

This study on the adoption of photovoltaic (PV) systems in urban areas has provided valuable insights into the factors influencing the implementation of sustainable technologies. By combining spatial and temporal analysis, an integrated method was developed to examine both the socioeconomic characteristics of the population and the interest of citizens in adopting clean energy solutions. This approach has proven effective in offering more accurate estimates regarding the potential for PV system adoption, highlighting the existing diversity among different urban subareas.

A key finding is that, although many residents in urban areas possess favorable economic conditions to acquire PV systems, their willingness to adopt these technologies does not depend solely on the availability of financial resources. This study revealed that a lack of interest and awareness regarding the benefits of solar energy can significantly hinder its implementation. Therefore, it is essential to conduct awareness campaigns that promote the advantages of solar energy and address any negative perceptions the community may hold toward new technologies.

Another important aspect of the study is the method's ability to readjust estimates based on newly observed data. This approach is decisive for enhancing the accuracy of projections, as it considers external factors that may influence adoption, such as changes in public policy or government incentives. The results demonstrate that a model incorporating such adjustments is fundamental for reflecting the dynamic reality of the clean technology market, ensuring that decisions are based on up-to-date data. Moreover, this research underscored the necessity of considering the socioeconomic characteristics of the population, which vary across different urban subareas. This diversity not only impacts the economic capacity of residents to acquire PV systems but also influences their attitudes toward adopting sustainable technologies. Public policies must be designed to adapt to these particularities, addressing the diverse needs and motivations of each community.

Furthermore, this study highlighted the importance of a holistic approach to the planning and adoption of renewable technologies. Strategies for the adoption of PV systems must be integrated into a broader framework that contemplates not only the technical infrastructure but also the public's awareness and the creation of effective public policies. This integration is critical for successfully transitioning towards more sustainable energy sources in urban areas. The investigation also revealed that the urban context presents a complex scenario where technology adoption depends on multiple factors. Variability in socioeconomic conditions and population interest creates a series of dynamics that must be understood to encourage the uptake of solar energy. Thus, continued research into these interactions is essential for developing policies that genuinely promote the adoption of clean technologies.

Despite the achievements realized in this study, several areas warrant further investigation. An essential focus for exploration is the development of a method that allows for the adequate sizing of solar panels to be adopted in various urban subareas. This

method must consider not only the socioeconomic characteristics of the population but also the potential for solar energy generation based on climatic conditions and geographic location. Additionally, it is essential to assess the impact of the adoption of these systems on the electricity distribution network. This entails conducting simulations that contemplate different adoption scenarios and analyzing how the integration of solar panels may affect the operation and stability of the electrical grid. Variables such as the variability of solar generation and the energy demand of the population must be considered to identify the best integration strategies.

The development of this method would not only contribute to improved planning of the necessary infrastructure but would also enable decision-makers to implement more informed and effective policies to promote the adoption of renewable energy. By correctly sizing solar panels and evaluating their impact, more suitable strategies can be designed to facilitate the transition toward a cleaner and more accessible energy future for all.

In future work, it is proposed to address the demographic impacts—such as age, educational level, and cultural factors—on the adoption of photovoltaic (PV) systems to broaden the scope of the study. This can be achieved by incorporating additional demographic variables into the model, enabling a more nuanced analysis of the social dynamics influencing technological adoption. For instance, households with higher educational attainment could be analyzed to understand their tendency to adopt sustainable technologies due to greater environmental awareness and the ability to evaluate long-term benefits. Similarly, age could be considered as a differentiating factor, as younger generations often exhibit greater openness to technological innovations, while older generations may prefer more traditional solutions. Cultural factors, such as perceptions of sustainability or attitudes toward shared energy systems, could also be integrated to account for regional differences in technology adoption.

Furthermore, it is proposed to explore the feasibility of applying the model to regions with varying levels of data availability, including potential adaptations for contexts with limited information. This could be achieved by using proxies for missing variables or implementing imputation techniques based on data available at regional or national scales. In resource-constrained contexts, alternative data sources, such as community surveys or information derived from satellite imagery, could be utilized to compensate for the lack of detailed census data. These strategies would not only extend the model's applicability to a broader range of regions but also underscore its adaptability to diverse socioeconomic and demographic realities, thereby enhancing its relevance for the design of equitable and sustainable energy policies.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/electronics13244939/s1, File S1: Socioeconomic variables used to calibrate the spatial model.

Author Contributions: Conceptualization, M.A.M. and J.F.F.; Methodology, M.A.M. and J.F.F.; Software, M.A.M. and L.H.M.; Validation, M.A.M. and L.H.M.; Formal analysis, L.H.M., T.P. and J.F.F.; Investigation, M.A.M., L.H.M., T.P. and J.F.F.; Resources, L.H.M. and J.F.F.; Data curation, M.A.M.; Writing—original draft, M.A.M.; Writing—review & editing, L.H.M., T.P. and J.F.F.; Visualization, M.A.M., L.H.M., T.P. and J.F.F.; Supervision, L.H.M., T.P. and J.F.F.; Project administration, L.H.M. and J.F.F.; Funding acquisition, L.H.M. and J.F.F. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflict of interest.

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