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Spatial Patterns of Household-Scale Solar PV Systems in Hungarian Districts

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Abstract

While total solar PV capacity in Hungary was only 1 MW in 2010, this figure had grown to 7551 MW by 2024 as a result of the favorable settlement system, subsidies, and the uncertainty caused by the Russo-Ukrainian war. At that time, more than 6.4% of households were already prosumers. In our study, we focus on Hungarian districts, examining the spatial patterns of household-scale solar PV systems and the main drivers of technology adoption in 2024. We use the Theil T index to examine spatial heterogeneity and the Moran's I statistic to test for spatial dependence. Spatial autocorrelation is further explored using maps based on Local Moran's I and Local Geary statistics. Finally, a spatial error model is applied to identify the factors influencing the share of household-scale solar PV systems per 100 households. Our results show that the spatial error variable has the largest effect, with household education, the age and size of the building stock, population growth, and built-up area also having significant effects. This confirms the need for a spatially sensitive policy approach and for incorporating space and spatial relations in energy economic studies.

Keywords: solar PV system; spatial econometrics; Theil T; Local Moran's I; Local Geary; prosumers; energy transition; solar energy

1. Introduction

The energy transition is a complex, multidimensional process and, contrary to all expectations, a nonlinear one [1,2]. It can be defined as a "switch from an economic system dependent on specific energy sources and technologies to a different economic system" [1]. Within this broader transition, the household sector plays a particularly important role, as energy consumption patterns and technological choices at the household level directly influence the pace and direction of decarbonization. In the household sector, new carbon-neutral technological solutions are required for all activities (e.g., heating, water heating, cooking, and lighting). During electrification, households replace fossil-fuel-based devices (e.g., gas stoves, gas boilers, mixed-fuel boilers) with modern, efficient electric alternatives. The resulting increase in household electricity demand can also be met by the use of renewable energy sources such as solar photovoltaic (PV) systems.

Solar energy technologies convert the sun's heat and light into electrical or thermal energy [3]. Among renewable energy sources, solar energy is growing the fastest, and solar-based electricity generation technologies are now considered the most affordable

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worldwide [4,5]. There are two ways to harness solar energy: solar collectors for hot water systems and conventional solar PV panels for electricity generation. According to the theory of the energy ladder [6], electricity produced from solar energy is the highest-quality secondary energy carrier, not only because of its safe use, cleanliness, and other physical characteristics but also because it is the only energy source that can be applied to all major household activities, and it is characterized by flexible use and substitutability [7].

Forecasts indicate further growth in solar PV capacity, primarily due to decreasing investment costs. In 2023, the total cost of installing a 1 kW solar PV system was USD 758 (global average), which represents an 86% decrease compared to the USD 5310 in 2010, making it highly competitive with any technology based on fossil energy sources [8–10]. Solar energy systems help reduce dependence on energy imports, contribute to mitigation efforts, and protect consumers from fluctuations in energy prices. They address the key dimensions of the energy trilemma: the expectations of energy security, environmental sustainability, and equity [11].

Solar PV systems can be installed at the household level and are widely available. The social acceptance of the technology is outstanding [12]; in addition to its affordability, other socio-economic advantages make its application extremely attractive to households. Those who become prosumers often become much more informed about energy issues, change and rationalize their energy-use habits with the help of smart meters, and become more supportive of environmental protection activities and movements [13]. In many cases, solar systems also offer an opportunity to eliminate energy poverty.

These relationships are particularly pronounced in Hungary, where the rapid uptake of solar PV systems is remarkable even by international standards. The year 2010 was considered a milestone when total solar PV capacity reached 1 MW [14]. After 2020, the installation of these systems accelerated significantly, driven by the newly adopted energy strategy, subsidies, the very favorable compensation system, the COVID-19 pandemic, the 2021–2022 energy crisis, and the uncertainty caused by the Russo-Ukrainian war.

The aim of the current paper is to build on existing research [14–16], describing how we conducted further, more in-depth spatial analyses of Hungarian household-scale solar PV systems. The study addresses the following research questions: (1) How can the spatial distribution of household-scale solar PV systems in Hungary be characterized? Is there evidence of a strong neighborhood effect? (2) Which spatial clusters of Hungarian districts can be identified in the distribution of these systems? (3) Which additional socio-economic and other factors explain the number of *household-scale solar PV systems per 100 households* in Hungary?

Analyzing the spatial distribution of household-scale solar PV systems is important for several reasons. First, the distribution of these systems is not even. Their output is highly weather-dependent, which poses serious challenges for electricity system operators. Understanding their spatial distribution can improve system predictability and planning [17]. Second, identifying the factors contributing to territorial heterogeneity within the country is crucial for effective policymaking.

The study addresses the research gap in two key ways. First, drawing on the most recent data, it provides an up-to-date and detailed exploration of the spatial distribution patterns of household-scale solar PV systems in Hungary—an area that has so far remained insufficiently examined in the literature. Second, it offers empirical evidence that supports the need for a decentralized, spatially sensitive energy policy approach, thereby advancing understanding of how territorial factors shape the diffusion of renewable energy technologies at the household level.

The remainder of the paper is structured as follows. Section 2 presents the expansion of household-scale solar PV systems in Hungary, highlighting the related trends and policies. International and Hungarian experiences with the spatial econometric analysis of household-scale PV systems are also summarized. Section 3 introduces the data and methodology, presents the spatial distribution of household-scale solar PV systems, analyzes their spatial heterogeneity and spatial dependence, and identifies the main drivers of their spatial differences. Finally, we summarize the results and draw conclusions.

Here, we note that details of this study have previously been published in Hungarian [18]. However, the present paper is a substantially expanded and revised version of the latter, in which the original analysis has been refined and complemented with the most recent data available (for the year 2024), and we have included a new section with policy recommendations.

2. Theoretical Background

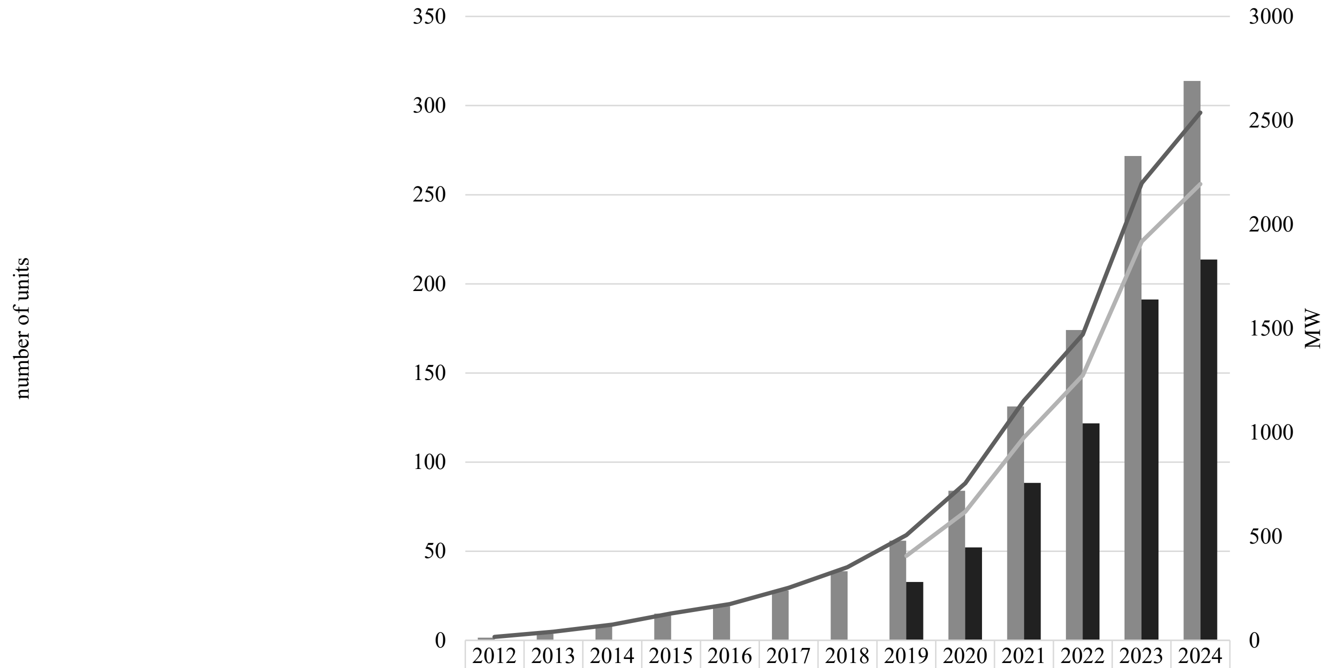
2.1. The Expansion of Household-Scale Solar PV Systems in Hungary—Trends and Policy

In 2024, solar energy accounted for 24% of gross electricity generation in Hungary, while in the EU Member States, this share was 11% on average [19,20]. This electricity is generated by both industrial-scale systems (above 50 kW) and household-scale solar PV systems (up to 50 kW). According to the official statistics of the Hungarian Energy and Public Utility Regulatory Authority [21], in 2024, total solar PV capacity was 7551 MW, of which 2690 MW was household-scale.

Private individuals owned 255,691 household-scale solar PV systems in 2024, while the remainder were owned by companies, institutions, and other non-natural persons (Figure 1). According to data from the 2022 census, the number of occupied dwellings in Hungary was 4008.5 thousand, of which more than 6.4% had a household-scale solar PV system [22]. It is noteworthy that the revised Hungarian National Energy and Climate Plan defined a target of 12,000 MW of total installed PV capacity by 2030 [23], and according to estimates in the National Energy Strategy 2030, more than 200,000 households were expected to have household-scale PV systems by 2030 [24]. This latter target was in fact already achieved by 2023, while the updated 2024 version of the National Energy and Climate Plan foresees further expansion [23].

However, a significant change in support schemes occurred in the second half of 2023, which, according to market assessments, is expected to lead to a substantial decline in the number of newly installed household-scale solar PV systems. Since 8 September 2023, the option of net metering is no longer available for newly installed household-scale solar PV systems (the applications for which were not submitted by 7 September 2023), with users instead subject to so-called gross metering [25]. Net metering refers to the yearly netting of electricity volumes fed into and withdrawn from the grid. In contrast, gross metering means separate metering and billing: the electricity withdrawn from the grid and electricity exported to the grid are measured and paid for separately (including grid fees), the latter at a selling price of 5 HUF/kWh (~0.01 EUR/kWh) [26]. Even with net metering, non-volume-based system usage fees must still be paid.

One of the reasons for the change is a modification in European Union legislation, which states that "*Member States that have existing schemes that do not account separately for the electricity fed into the grid and the electricity consumed from the grid shall not grant new rights under such schemes after 31 December 2023*" [27]. Net and gross metering schemes significantly affect the payback period for PV systems. According to our calculations, the latter is approximately 7 years under net metering, whereas under gross metering, it is around 15 years.



	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Household-scale solar panel capacity (MW)	13	31	68	128	164	240	332	479	719	1125	1492	2329	2690
Household-scale solar panel capacity in the residential sector (MW)								280	447	757	1044	1638	1832
Total number of household-scale solar panel units (1000 units)	2	5	9	15	20	30	41	59	88	134	172	256	296
Total number of household-scale solar panel units in the residential sector (1000 units)								47	72	114	149	224	256

Figure 1. Total installed capacity (MW) and number of household-scale solar PV systems in Hungary. Source: Authors' compilation based on [21].

2.2. International and Hungarian Experiences with the Spatial Econometric Analysis of Household-Scale PV Systems

The literature on residential solar energy use, the factors influencing it, and technological diffusion can be considered extensive; however, far fewer studies have addressed territorial relationships and spatial patterns. Table 1 summarizes the most relevant international literature regarding the current article, presenting the spatial dimension of the analysis, the models that were applied, and the explanatory variables found to be significant in determining the adoption of household-scale solar PV systems.

Based on the studies summarized in Table 1, the adoption of household-scale solar PV systems is influenced by a wide range of economic, socio-demographic, housing-related, and environmental factors [17,28–32]. All of the former highlight the importance of household income, education level, age, and other socio-demographic characteristics, as well as built-environment features such as population density, housing density, housing quality, and the share of detached houses. Environmental conditions, particularly solar irradiation, also play a significant role in explaining the spatial distribution of installations. In addition, most pieces of research (except [29]) emphasize the importance of spatial spillover or neighborhood effects (often referred to as peer effects), indicating that the diffusion of residential PV systems is often spatially clustered, as the presence of installations in neighboring areas can encourage further adoption.

Table 1. International literature review: the spatial econometrics of household-scale solar PV systems.

Study Authors/Year	Significant Variables	Applied Model	Spatial Dimension and Time Period
Dharshing, 2017 [28]	economic factors, socio-demographic and attitudinal adopter characteristics (age, income, education, unemployment), settlement structure, building stock (share of single-family homes and new buildings), regional spillover effects, annual global irradiation	Structural Equation Modeling (SEM)	Germany, 807,969 residential photovoltaic systems (2000–2013)
Jayaweera et al., 2018 [29]	social (age and education), demographic (population and housing density), residential (housing quality, size of residence), and environmental (irradiation) variables	Zero Inflated Negative Binomial Multilevel (ZINBM)	Srí Lanka, Colombo (2010–2016)
Pronti and Zoboli, 2024 [30]	housing market, electricity consumption, social capital, socio-demographic indicators, economic factors (average income), solar irradiation, policies on energy efficiency and renewable energy in the housing sector, spatial dependence	Spatial Error Model (SEM)	Italy, province-level data (2014–2021)
Zhang et al., 2023 [17]	spatial dependence, household income, property value, population density, housing type, and household type	Spatial Durbin model	Netherlands, 3205 Dutch neighborhoods
Graziano and Gillingham, 2015 [31]	demographics and built environment variables (housing density, share of renter-occupied dwellings), household income, political affiliation, spatial neighbor effects (often known as "peer effects")	Optimized Getis-Ord method (OGO) and Anselin's cluster and outlier analysis (COA)	USA, Connecticut (2000, 2010)
Kosugi et al., 2019 [32]	social attributes (population structure, population density, number of household members), living environment (share of detached houses), neighbor effect	Spatial Durbin model	Japan, Kyoto City (2003–2014)

Source: Authors' compilation.

The methodological approaches used in the literature are also diverse. Many studies apply spatial econometric and spatial statistical models, including Spatial Error Models, Spatial Durbin Models, and Structural Equation Modeling, while some analyses employ cluster detection techniques and multilevel regression models. These studies are conducted at different spatial scales, ranging from national-level analyses (e.g., examining more than

800,000 residential PV systems in Germany) to regional, city-level, or neighborhood-level investigations in countries such as the Netherlands, Japan, the United States, and Sri Lanka.

Relevant Hungarian studies [6,14–16,18,33] have analyzed the spatial distribution of different types of heating fuels and technologies in the residential sector, including solar PV systems, the factors influencing their installation, and the implementation process: refs. [16,17] applied Pearson correlation and Spearman rank correlation, a non-parametric method, and ref. [14] employed project management analysis (similar to the PM^2 model developed by the European Commission), while the rest [6,18,33] applied spatial econometric techniques (Global and Local Moran's I, spatial LAG model).

Beyond traditional economic factors, ref. [15] also highlights social, housing-related, and attitudinal factors, complemented by what they call a "small-settlement effect." This refers to the observation that villages often have a significant number of household-scale solar PV systems and substantial installed capacity, likely related to peer effects. However, refs. [16,18] did not find a significant relationship among GDP per capita, average monthly gross wages, and the location (density) of household-scale solar PV systems. These results clearly indicate that the installation of household-scale power plants (which in Hungary almost exclusively refers to solar PV systems) is generally concentrated in areas dominated by detached houses [15,16] and higher educated households [18,33]. Interestingly, in Budapest, the number of household-scale solar PV systems per 10,000 inhabitants is far below that of other NUTS2 regions in Hungary. The dense urban housing stock is one of the main barriers to installing conventional PV systems, due to limited space (roofs may be shaded by neighboring buildings) and high population density. In addition, roof orientation is often suboptimal, while regulatory frameworks and local rules may make it more difficult to establish resident-driven energy projects and energy communities (involving both owners and tenants) in large apartment buildings. In contrast, the Budapest agglomeration stands out for its significant concentration of household-scale PV systems both in terms of the number of installations and installed capacity, together with the Pécs and Balaton agglomerations [15,18,33].

3. Methodology and Results

3.1. Spatial Pattern of Distribution of Household-Scale Solar PV Systems

Territorial distribution is typically examined using topological maps. Based on the work of [34,35], the current approach uses special thematic maps or cartograms in which the basic elements of the original topology are retained; i.e., territorial units that were adjacent in the original map remain adjacent. However, the size of these units is made proportional to the socio-economic variable being depicted. Ref. [36] also employed a typology of cartograms. In the current study, we applied this method by adjusting district sizes based on the number of household-scale solar PV systems installed, and depicting the proportion of systems per 100 households by coloring the surfaces of maps created using ScapeToad 1.1 software (Figure 2). The number of household-scale solar PV systems is sourced from the district-level database of the Hungarian Energy and Public Utility Regulatory Authority (MEKH), which includes districts of Budapest. Data is available for the period 2019–2024 [21].

The capital and its agglomeration, the districts of county-level cities, and the Balaton region have the highest number of household-scale solar PV systems. By contrast, districts in the inner and outer peripheries along county borders have few systems. When we compare the number of household-scale solar PV systems with the number of households, setting aside the Budapest agglomeration and the Balaton region, the districts of Gárdony, Bóly, and Mórahalom stand out. Data from the latter two districts suggest that, in addition to the prominence of resorts, other factors may be relevant.

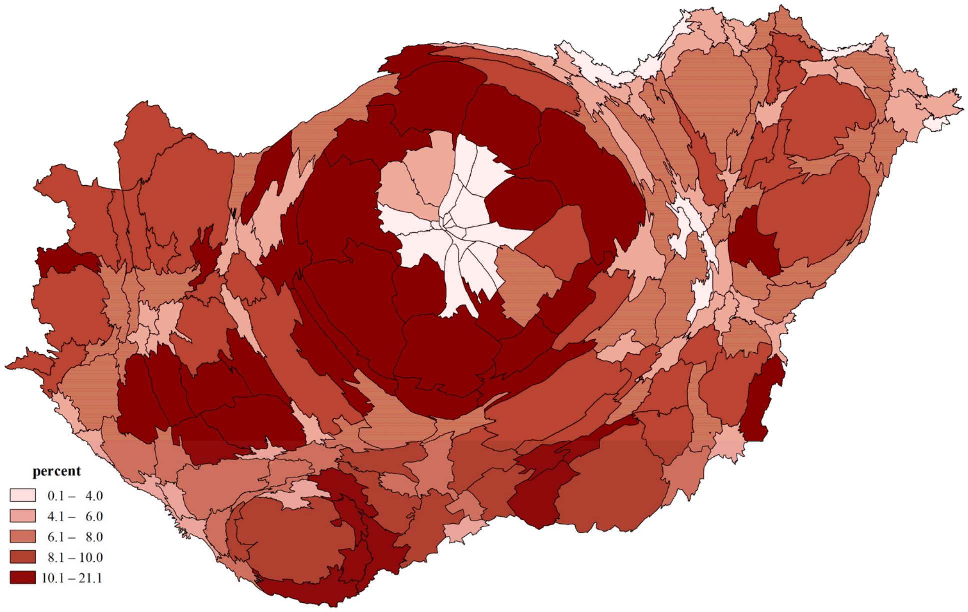


Figure 2. Spatial image of number of household-scale solar PV systems and their proportion per 100 households, 2024. Note: district sizes are adjusted based on the number of household-scale solar PV systems; color indicates the proportion of such systems per 100 households.

In 2019, 59,106 household-scale solar PV systems were in operation; this figure had increased to 296,231 by 2024. This represents a national average increase of 501%. The largest change occurred in the Aszód district (see Figure 3). The top ten districts with the greatest increase were Aszód, Cegléd, Mezőcsát, Kecskemét, Dabas, Gyál, Tét, Kalocsa, Eger, and Vecsés.

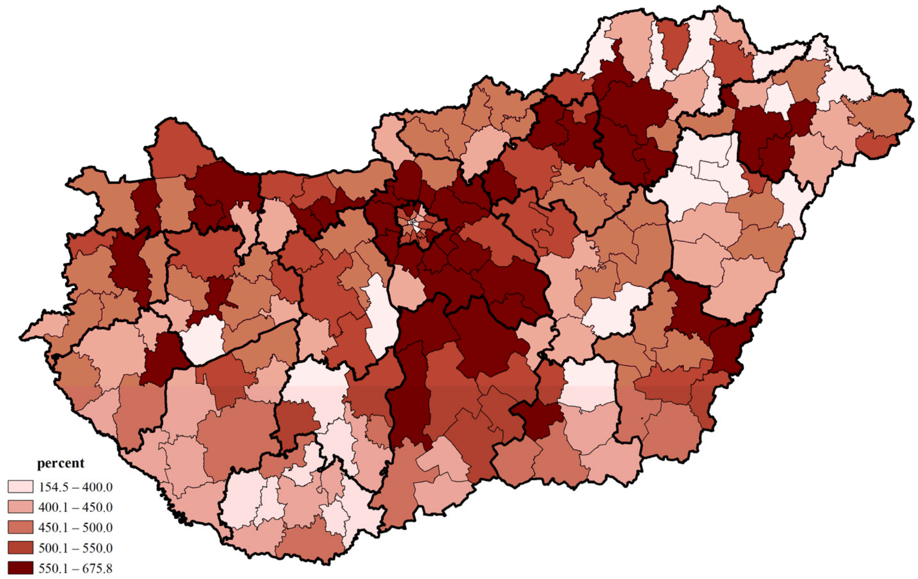


Figure 3. Percentage change in number of household-scale solar PV systems per district, 2024 (2019 = 100%).

3.2. Spatial Heterogeneity and Dependence of Household-Scale Solar PV Systems

The analysis of spatial data continues with an examination of heterogeneity and dependence. Spatial heterogeneity refers to the variability of spatial phenomena that arises from the characteristics of spatial units and their differences from one another. Spatial dependence essentially denotes a functional relationship between the values of the same variable measured at different locations [37].

In what follows, we focus on these two factors together. Our approach is similar to that of [38], who performed calculations on income data for US states and state groupings. To examine spatial heterogeneity, we used the Theil T index [39–41] (Equations (1) and (2)):

$$T_T = \frac{1}{N}\sum_{i=1}^{N}\frac{x_i}{\mu}log\left(\frac{x_i}{\mu}\right), \tag{1}$$

where:

$$\mu = \frac{1}{N}\sum_{i=1}^{N}x_i \tag{2}$$

We used Moran's I statistic to test for spatial dependence. As with all spatial autocorrelation tests, Moran's I begins with the null hypothesis that there is no systematic spatial dependence in the sample (i.e., a null hypothesis of spatial randomness). The formula for Moran's I (see Equation (3)) is as follows [42]:

$$I = \frac{N}{\sum_{i=1}^{N}\sum_{j=1}^{N}D_{ij}}\frac{\sum_{i=1}^{N}\sum_{j=1}^{N}(x_i-\overline{x})(x_j-\overline{x})D_{ij}}{\sum_{i=1}^{N}(x_i-\overline{x})^2}, \tag{3}$$

where N is the number of area units, x_i and x_j are the values of the variable to be examined in each area unit, $\overline{x}$ is the arithmetic mean of the examined indicator, and D_{ij} is the adjacency matrix. We applied queen adjacency, meaning that polygons that share either a vertex or an edge were considered adjacent. Under the null hypothesis, the expected value of Moran's I is given by $E(I) = -1/(N-1)$.

To assess statistical significance, we relied on a permutation approach. For each region and year, we generated 999 random permutations of the observed values to obtain a reference distribution of Moran's I under spatial randomness and computed pseudo-p values accordingly. Moran's I ranges between -1 and +1: values close to +1 indicate strong positive spatial autocorrelation, values close to -1 indicate strong negative spatial autocorrelation, and values around 0 indicate no detectable spatial autocorrelation [43].

Table 2 reports the Theil T index and Moran's I statistic for the absolute number of household-scale solar PV systems across Hungarian districts in the three NUTS1 regions and for the country as a whole over 2019–2024. In all years, Moran's I is positive at the national level, while regional patterns differ across macro-regions. Central Hungary shows positive spatial autocorrelation throughout the period, whereas the Great Plain and North and Transdanubia display negative Moran's I values. Taken together, these results provide clear evidence that the absolute distribution of household-scale PV systems is not spatially random: at the national level and in Central Hungary, districts with many (few) installations tend to cluster, while in the Great Plain and North and Transdanubia, negative Moran's I values indicate more dispersed patterns.

While the magnitude of Moran's I varies across regions and years, it consistently exceeds the expected value under conditions of spatial randomness. In particular, spatial dependence tends to be strongest in Central Hungary, somewhat weaker in Transdanubia, and lowest in the Great Plain and North, mirroring the regional differences in the intensity and timing of solar PV deployment. We do not reinterpret statistically significant negative values of Moran's I as artifacts arising from small observations; such cases are instead treated as evidence of significant negative spatial autocorrelation. In our empirical results for 2019–2024, however, the estimated Theil T index values are positive in all regions and years.

Table 2. Theil T and Moran's I indicators of the district number of household-scale solar PV systems in the NUTS1 regions of Hungary (2019–2024).

Regions	2019	2020	2021	2022	2023	2024
			Theil T			
Central Hungary	0.166	0.170	0.180	0.181	0.180	0.180
Great Plain and North	0.175	0.170	0.184	0.192	0.200	0.194
Transdanubia	0.151	0.144	0.148	0.156	0.163	0.157
Hungary	0.170	0.164	0.175	0.183	0.190	0.186
			Moran's I			
Central Hungary	0.276	0.274	0.268	0.268	0.260	0.259
Great Plain and North	−0.030	−0.034	−0.039	−0.043	−0.042	−0.039
Transdanubia	−0.106	−0.108	−0.109	−0.102	−0.096	−0.100
Hungary	0.049	0.033	0.044	0.055	0.070	0.073

Source: Authors' calculations.

These findings suggest that, at the national level and particularly in Central Hungary, the expansion of household-scale PV systems in 2019–2024 became increasingly uneven and spatially clustered, while in the Great Plain and North and in Transdanubia the negative Moran's I values point to more dispersed configurations. Inequality in the absolute number of systems across districts grew, and neighboring districts tended to exhibit similar levels of adoption. In the case of the Global Moran's I value by region, this indicates that in Central Hungary, although the value decreases slightly, a stable positive autocorrelation persists, while in the other two regions, a steadily decreasing negative autocorrelation can be observed.

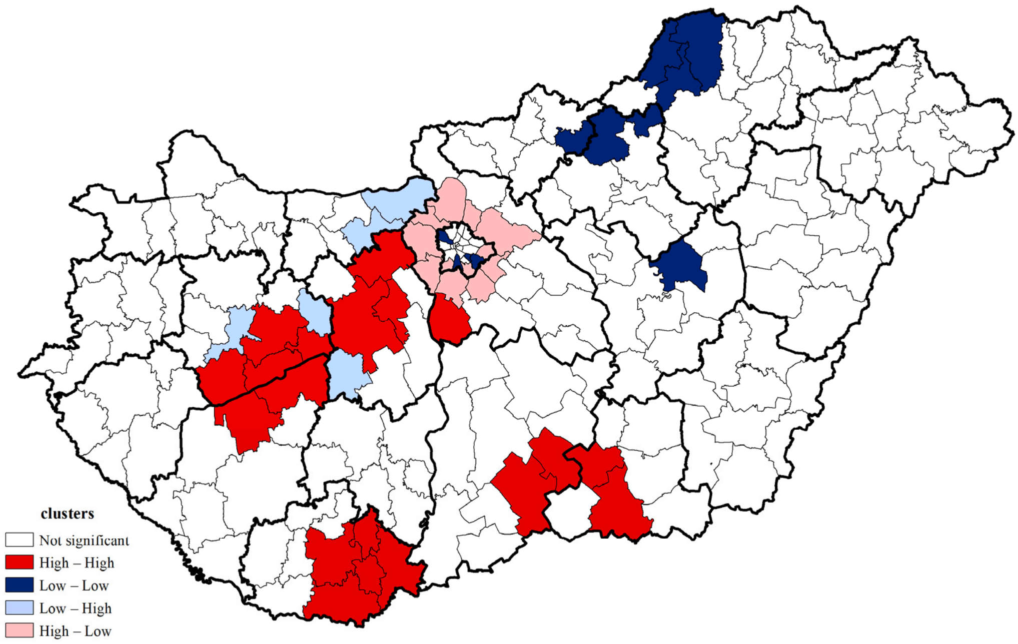
However, because these results are based on absolute counts rather than a normalized intensity measure, they may partly reflect differences in district size. We therefore interpret the 2019–2024 Moran's I statistics primarily as evidence of clustered absolute expansion, while substantive conclusions about adoption intensity are restricted to the 2024 analysis based on *solar PV systems per 100 households* presented below. Here, we note that although the use of the relative indicator (%) would have been justified in the study, data on the number of households were available only for 2022, not annually, as the data come from the census. In addition, our decision to use absolute counts is justified because the number of households represented by the specific indicator does not change substantially from year to year, so the true temporal change is reflected in the absolute data.

In case of Moran's I calculations the number of permutations is 999, and the pseudo p-value is 0.00100.

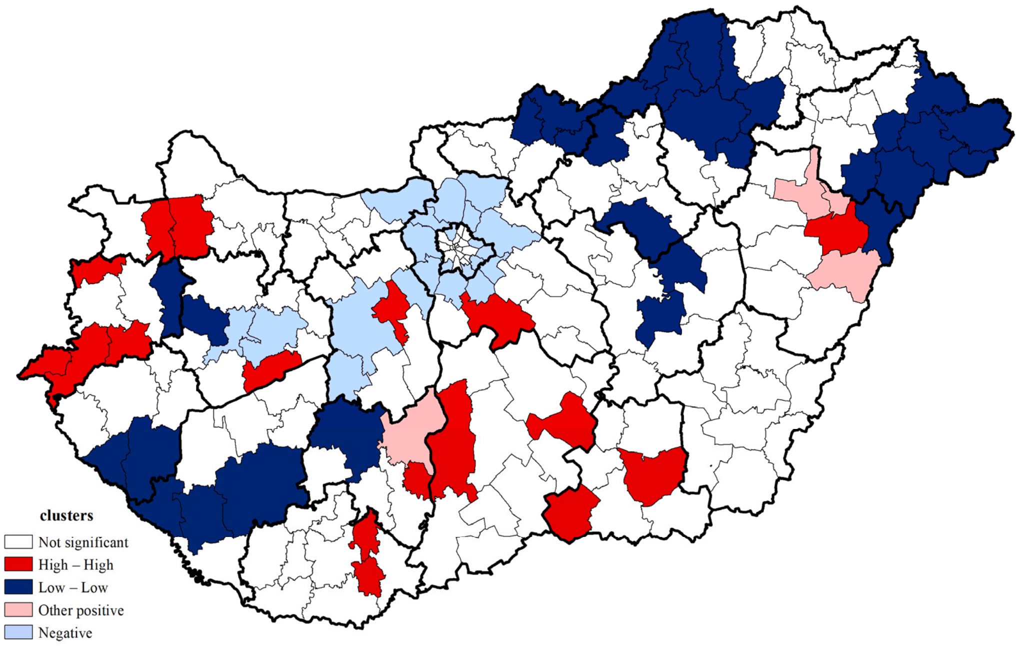
Figure 4 (Map A) shows the Local Moran's I map of *household-scale solar PV systems per 100 households*. As the background to and practical application of the method have already been described in several of our studies [44,45] and are widespread in the literature (see, for example, [46–48]), we will not describe these further. However, we present the Local Geary statistic in detail due to its novelty (see [49]).

First outlined in [50] and further developed in [51], the Local Geary statistic is a measure of local spatial autocorrelation. Like its global counterpart, the emphasis is on squared differences, or rather, on variances. In other words, small values of the statistic indicate positive spatial autocorrelation, while large values indicate negative spatial autocorrelation. The ref. [52] c-statistic for spatial autocorrelation takes the following form (see Equation (4)):

$$c = \frac{\sum_i \sum_j w_{ij}\left(x_i - x_j\right)^2 / 2S_0}{\sum_i (x_i - \overline{x})^2 / (n-1)}, \tag{4}$$



(**a**) Local Moran's I (Map A)



(**b**) Local Geary (Map B)

Figure 4. Spatial clusters of the proportion of household-scale solar PV systems per 100 households at the district level, 2024.

where x_i and x_j are the values of the studied phenomenon in area units, $\overline{x}$ is the average of the studied phenomenon, n is the number of area units, w_{ij} is the adjacency matrix, $S_0 = \sum_i \sum_j w_{ij}$, and the x in the numerator does not need to be in standardized form due to the squared difference. Under the null hypothesis of spatial randomness, the mean of the statistic is 1. Significant values less than 1 indicate positive spatial autocorrelation, and values greater than 1 indicate negative spatial autocorrelation.

After checking the parts of the expression that do not change with i, the local version of the statistic can be given as follows, using the usual notation (Equation (5)) (for technical details, see [50,51]):

$$LG_i = \sum_j w_{ij} \left(x_i - x_j\right)^2 \tag{5}$$

This statistic is the weighted sum of the squared distances in the attribute space of the geographical neighbors of observation *i*. Since Local Geary uses a different criterion for measuring attribute similarity, it can detect patterns that Local Moran's I cannot, and vice versa.

The basic statistics for our calculations are as follows:

Local Moran's I: Number of permutations 999, significance $p = 0.05$, number of significant districts 47.

Local Geary: Number of permutations 999, significance $p = 0.05$, number of significant districts 74. We note that, to ensure the robustness of our results, the tests were conducted using additional spatial weight matrices beyond the queen contiguity approach presented here. Statistical significance was adjusted for multiple testing using the False Discovery Rate (FDR) correction.

Based on the Local Moran's I statistic, the high–high cluster (where high values are surrounded by nearby high values) comprises 19 districts (see Figure 3, Map A). These districts are mainly located in Fejér County, around Lake Balaton, and in Baranya, Pest, and Csongrád-Csanád counties. The low–low cluster (low values surrounded by nearby low values; 11 districts) mainly comprises districts in Budapest, the border district in north-eastern Hungary, and one district in Jász-Nagykun-Szolnok County. The districts of Ajka, Enying, Esztergom, Tatabánya, and Várpalota have lower values than their neighbors. Conversely, higher values are seen in the two Budapest districts and the agglomeration districts than in their neighbors.

The spatial picture drawn by Local Geary differs somewhat from those identified previously (Figure 4, Map B). The high–high cluster is somewhat more restricted, comprising 17 districts. Only the districts of Bóly, Balatonfüred, Gárdony, and Pécsvárad appear in this cluster in both local autocorrelation tests. Thirty-one districts belong to the low–low cluster, more than double the number identified using the Local Moran's I.

Based on the results of both tests, the following districts belong to the low–low cluster: Bátonyterenye, Edelény, Kazincbarcika, Kunhegyes, Pétervására, and Putnok. The low–low cluster resulting from Local Geary is much more extensive, including peripheral districts in both north-eastern and south-western Hungary. When using this method, districts in the other positive category can be considered positive outliers, i.e., districts that differ positively from their surroundings. Examples include Derecske, Hajdúböszörmény, Hajdúhadháza and Paks. Those that differ negatively from their environment include the three districts of Budapest, a significant part of the Budapest agglomeration, and the districts of Ajka, Veszprém, Enying, and Esztergom.

3.3. Explaining the Spatial Distribution of Household-Scale Solar PV Systems per 100 Households

In continuation of our study, we again calculated the heterogeneity and dependency indices, this time focusing on the number of *household-scale solar PV systems per 100 households*. In the latter case, we also calculated the Moran I index, while in the former case, we calculated the Theil L index (Equation (6)) [53].

$$T_L = \frac{1}{N}\sum_{i=1}^{N} log\left(\frac{x_i}{\mu}\right), \tag{6}$$

where μ is the average of household-scale solar PV systems per 100 households.

In terms of heterogeneity, the highest values are seen in the Great Plain and North, and in terms of dependency, in Central Hungary. In both cases, the lowest values are seen in Transdanubia (Table 3).

Table 3. Theil L and Moran I indicators of the number of household-scale solar PV systems per 100 households in the NUTS1 regions of Hungary (2024).

Macro Regions (NUTS-1)	Theil *L*	Moran *I*
Central Hungary	0.142	0.542
Great Plain and North	0.244	0.405
Transdanubia	0.022	0.316
Hungary	0.056	0.460

Source: Authors' calculation.

In case of Moran's I calculations, the number of permutations is 999, and the pseudo *p*-value is 0.00100.

The subsequent analysis sought to explain the number of *household-scale solar PV systems per 100 households* using a spatial econometric model.

Previously, we found spatial dependence regarding the number of household-scale solar PV systems. However, when we examined the spatial dependence of *household-scale solar PV systems per 100 households*, the values we obtained were much higher than those for the spatial distribution of absolute values (Moran's I = 0.460). Therefore, geographical location more strongly affects the relationships in models estimating the specific values of *household-scale solar PV systems per 100 households*. Consequently, traditional econometric estimates are likely to be biased.

When selecting the indicators to include in the study, we considered the results of the reviewed literature (Table 1) and began with the list of variables (Table 4) previously identified as significant. The selected indicators cover six areas: the economic and social characteristics of households in settlements; the built environment; energy characteristics; environmental conditions affecting investment and returns; and the characteristics of settlement structures.

Before starting the study, we hypothesized that the ratio of *household-scale solar PV systems per 100 households* would be fundamentally explained by income; that is, the higher the per capita income (which forms the basis for personal income tax), the higher the former ratio. Further, although education may be somewhat related to income, we also considered it important to examine its effect. We hypothesized that the larger the share of people with a high school diploma, the higher the proportion of household-scale solar PV systems.

We considered the type of building an important factor, hypothesizing that the higher the proportion of newly built dwellings (after 2000), the higher the ratio of household-scale solar PV systems. We hypothesized that the type of housing greatly influences the proportion of *household-scale solar PV systems per 100 households*; that is, where the share of single-family homes (defined as homes with a floor area of 100 square meters or more) is higher, the proportion of *household-scale solar PV systems per 100 households* is also higher. We also assumed that being connected to pipeline natural gas and per-consumer electricity consumption would positively affect the proportion of *household-scale solar PV systems per 100 households*.

Further, we examined the impact of climate on the installation of household-scale solar PV systems, accounting for global radiation. We hypothesized that in districts with relatively high levels of global radiation, residents would be more motivated to moderate their fossil fuel consumption, resulting in a higher proportion of *household-scale solar PV systems per 100 households*. Lastly, we accounted for district population and population density, assuming that higher values of these indicators would correspond to a higher proportion of *household-scale solar PV systems per 100 households*. We also considered the built-up area of the districts, assuming that the smaller the inner area of the settlements relative to the administrative area, the higher the proportion of *household-scale solar PV systems per 100* households.

Table 4. Indicators.

Group of Indicators	Indicator	Year
Economic characteristics	Per capita income forming the basis for personal income tax	2024
Social characteristics	Proportion of people with a high school diploma or higher education degree	2022
Built environment	Ratio of dwellings built since 2000 to occupied dwellings	2022
	Proportion of dwellings with a floor area of 100 square meters or larger	2022
Energy characteristics	Number of households connected to pipeline natural gas	2024
	Electricity consumption per household	2024
Environmental conditions	Annual amount of global radiation	2024
Characteristics of settlement structure	Ratio of the inner area of the settlements of districts to the administrative area	2024
	Population of districts	2024
	Population density of districts	2024

Source: Authors' construction.

However, our preliminary calculations only partially confirmed our hypotheses. Some indicators showed no significant effect, such as per capita income, global radiation, and the proportion of households connected to piped natural gas. Of these, we considered the most significant finding to be that increases in income do not affect the proportion of solar panels that have been installed. This also corroborates the findings of [16]. In other cases, however, we found that including additional variables increased multicollinearity in the model since most of their explanatory power is already captured by other indicators. Accordingly, we rejected their inclusion.

Ultimately, we opted to retain five explanatory variables in our model: the proportion of individuals with a high school diploma or higher education and dwellings with a floor area of 100 square meters or more; the share of the inner area of settlements within districts relative to the administrative area; the ratio of dwellings constructed since 2000 relative to occupied dwellings; and population, in thousands. As will be seen later, we used data from 2022 and 2024 (we sought to use the most recent data in all cases). Our dependent variable is from 2024, while the explanatory variables come from the most recent census, or 2022 data.

The fit of the multivariate linear regression model was moderately strong (adjusted $R^2 = 0.663$), and all five indicators were significantly related to the explanatory variable. The proportion of solar panels can be characterized as either spatially separated or clustered (see Global Moran's I results). We therefore deemed it necessary to examine the spatial dependence further. This was confirmed by the significant results of the Global Moran's I test, Lagrange multiplier diagnostics, and residual spatial autocorrelation tests, indicating that our indicators exhibit spatial dependence. Therefore, it was necessary to create a spatial model that accounts for these characteristics.

3.4. Spatial Models

The concept of lag is used when performing spatial analyses. The general spatial lag model can be written as follows (Equation (7)):

$$y = \rho W y + \beta X + \varepsilon, \tag{7}$$

where y is the vector of values of the outcome variable, ρ is the coefficient of the outcome variable lagged in space (i.e., the spatial autoregression parameter), W is the row-standardized weight matrix, β is the parameter vector of exogenous explanatory variables, X is the matrix of exogenous explanatory variables, and ε is the vector of values of the error term [37,54].

Another common form of spatial econometric modeling is the spatial error-autocorrelation model (SEM). The general formula for this model is illustrated by the following equations (Equations (8) and (9)):

$$y = \beta X + \varepsilon \tag{8}$$

and

$$\varepsilon = \lambda W_{\varepsilon} + \xi, \tag{9}$$

where ε is the vector of autoregressive error terms; λ is the spatially lagged parameter coefficient of the autoregressive error terms; and ξ is the vector of independent, identically distributed error terms with zero expected value (Equation (9)) [37]. Spatial dependence may be indicated if λ is significant, since in this case the interactions between spatial units close to each other appear in the values of the error term.

There is also a combined spatial econometric model that incorporates both spatial lag and spatial error autocorrelation.

Our calculations were performed with GeoDaSpace (Version 1.2) using a queen-contiguity-based neighborhood structure. (We also implemented the modeling with several types of adjacency matrices (e.g., rook and second- and third-degree queen adjacency, etc.), but the fit of the model deteriorated in each case.) We used White's standard errors to account for heteroscedasticity. The multicollinearity condition number of our model is 23.1, in line with commonly used rules of thumb, a condition number of around 20–30 indicates moderate but acceptable multicollinearity, suggesting that our estimates are not unduly inflated by linear dependencies among regressors. The Lagrange multiplier test was significant for the spatial error model, so we estimated the model accordingly.

Compared to traditional OLS, the explanatory power of the spatial models improved, with an adjusted R^2 of 0.844. Compared to the OLS model, the spatial error specification substantially improved model fit: the adjusted R^2 increased from 0.663 to 0.844, and the Akaike and Schwarz information criteria both decreased (Table 5). The estimated spatial error coefficient is large and highly significant (λ = 0.852, $p < 0.001$), indicating strong residual spatial dependence in the model. In other words, unobserved factors that raise the share of household-scale PV systems per 100 households in one district tend to be positively correlated with similar unobserved factors in neighboring districts, even after controlling for the included covariates and the chosen queen-contiguity weight matrix.

The magnitude and significance of λ should not be interpreted as evidence of non-normal errors or nonlinear relationships between the dependent and explanatory variables. Instead, λ captures the extent to which spatially structured unobserved heterogeneity remains in the residuals. Departures from normality and potential nonlinearity need to be assessed using specific diagnostic tests and alternative functional forms. In our case, the Jarque–Bera and heteroskedasticity diagnostics for the OLS model (reported in Appendix B) suggest that the residuals deviate from homoscedastic normality, which—together with the significant Moran's I and Lagrange Multiplier tests for the residuals—motivated the use of a spatial error model to obtain more reliable inference.

Table 5. Results of applied models.

Indicators	OLS	Spatial Error
Constants	−3.138 ***	−6.398 ***
Ratio of dwellings built since 2000 to occupied dwellings	0.245 ***	0.190 ***
Proportion of people with a high school diploma or higher education degree	0.182 ***	0.182 ***
Proportion of dwellings with a floor area of 100 square meters or larger	0.105 ***	0.183 ***
Population, thousand	−0.021 ***	−0.160 ***
Proportion of the inner area of settlements in districts to administrative area	−0.105 ***	−0.045 ***
Lambda		0.852 ***
Adjusted R^2	0.663	0.844

Note: OLS: Ordinary Least Squares; *** $p < 0.001$. Source: Authors' calculations.

After estimating the spatial error model, the residual Moran's I falls substantially and becomes statistically insignificant (I = 0.0033, $p = 0.4080$, z-value: 0.1958, number of permutations: 999), indicating that most of the residual spatial autocorrelation has been absorbed by the spatial error term. This supports the interpretation that PV adoption intensity is influenced not only by the observed socio-economic and built-environment characteristics of districts but also by unobserved spatially correlated factors such as local policy implementation, institutional capacity, or social norms.

There may be several reasons for this. First, the range of regressor variables involved is small and inadequate. It is also possible that the spatial weight matrix we used is inappropriate; however, we attempted to address this by performing the test with a different weight matrix, but the outcome remained unchanged. We believe that the explanation is that, as of 31 October 2022, the possibility of feeding into the public grid was temporarily suspended in Hungary by government decree [55]. This suspension was lifted on 1 January 2024 by [56]. However, this did not apply to household-scale power plants implemented in response to applications submitted before 31 October 2022.

The moratorium may have significantly affected the spatial distribution, and it can be assumed that inhabitants of settlements behaved similarly to their neighbors in response to the feed-in stoppage. This is consistent with ref. [57]'s view on the imitative behavior of economic actors, which provides a reasonable explanation for the development of the specific spatial pattern.

The second-largest impact on the dependent variable is the share of dwellings built since 2000 among occupied dwellings; namely, a high share of relatively new dwellings is also associated with a high share of *household-scale solar PV systems per 100 households*. Next in terms of impact is the proportion of dwellings with a floor area of at least 100 square meters. The high proportion of large dwellings, essentially family homes, results in an increase in the number of *household-scale solar PV systems per 100 households*. Fourth is the proportion of people with a high school diploma or higher education, which has a positive effect. Therefore, we conclude that the increase in the proportion of *household-scale solar PV systems per 100 households* is associated with higher education. Built-up area is also important: the larger the proportion of the inner area of settlements compared to the administrative area, the smaller the proportion of *household-scale solar PV systems per 100 households*. Finally, population growth is accompanied by a decrease in the proportion of *household-scale solar PV systems per 100 households*, but this plays the smallest role.

Figure A1 maps the number of *household-scale solar PV systems per 100 households*; Figure A2 shows the model's estimated values; and Figure A3 shows the model's residuals (all Figures in Appendix A). Appendix B presents the model diagnostics. In both the

OLS and spatial error specifications, we include the same set of five explanatory variables (Table 4), and the variable names in Table 5 and Appendix B correspond exactly to those in the replication dataset.

4. Discussion and Conclusions

The number of household-scale solar PV systems increased rapidly after 2010. The study described here aimed to map, quantify, and explain the territorial distribution of household-scale solar PV systems across Hungary's districts in 2024. The assembled empirical evidence demonstrates that household-scale solar PV adoption in Hungary has become mainstream. Between 2019 and 2024, the number of household-scale solar PV systems increased from 59,106 to 296,231 units, representing a fivefold increase (approximately 501%), with private households accounting for about 255,691 of these systems by 2024. National PV capacity also expanded significantly, reaching 7551 MW in 2024, of which roughly 2690 MW is household-scale. As a result, more than 6.4% of occupied dwellings are now prosumers. These developments position Hungary among the most rapidly evolving solar markets in Europe and render the observed spatial patterns both policy-relevant and operationally significant.

In the updated 2024 version of its National Energy and Climate Plan, Hungary has set the objective of increasing the share of renewable energy in gross final energy consumption to at least 30% by 2030 [23]. In addition, it acknowledges that energy-efficiency upgrades are required in 2.6 million residential properties, as the average energy performance of the domestic housing stock falls into the category "FF." If these targets are met, the plan anticipates 20% energy savings by 2030 and a 60% reduction in emissions by 2040. To achieve the latter, particular emphasis is placed on replacing existing biomass (conventional) stoves and promoting heating systems based on renewable energy sources.

Spatial aspects, including regional disparities, are only limitedly reflected in energy policy. However, these considerations are essential for understanding how households and settlements move up the energy ladder—that is, how they transition from lower-quality energy carriers to cleaner, more modern energy sources along with the associated technological solutions. A more pronounced geographical perspective on the energy transition could support its successful implementation. In our interpretation, this would imply the use of differentiated policy approaches and measures across clusters and/or geographical areas. Ref. [58] argues for a spatially sensitive and decentralized energy policy that recognizes territorial inequalities in energy use and energy poverty. In line with the conclusions of [59], we also see the solution in deliberative energy planning (and policymaking), which involves the active participation of local residents in the modernization of heating systems. Particular attention should be paid to the spatial linkages of regions where modern, renewable-based heating solutions are more widespread (i.e., where technological diffusion has been more successful). Our results contribute to identifying these regions in Hungary.

In our study, we examined the spatial characteristics of solar PV systems. We find that the majority of these household-scale systems are located in Budapest and its surrounding areas, in the districts of county-level cities and around Lake Balaton. Three districts stand out according to the number of households with solar systems, all of which are important holiday areas: Bóly, Gárdony, and Mórahalom. Moran's I statistic confirms positive spatial autocorrelation in the number of household-scale solar PV systems, while the Theil T index highlights increased heterogeneity.

Global Moran's I and local LISA tests indicate clear positive spatial autocorrelation: districts with numerous installations tend to cluster, as do those with few systems. Based on Local Moran's I, the high–high cluster encompasses 19 districts. These districts are mainly located in Fejér County, around Lake Balaton, and in Baranya County, Pest County, and

Csongrád-Csanád County. The low–low cluster (11 districts) mainly comprises districts in Budapest, the border district in north-east Hungary, and one district in Jász-Nagykun-Szolnok County.

The spatial picture drawn by Local Geary is somewhat different. The high–high cluster includes 17 districts. Only the districts of Bóly, Balatonfüred, Gárdony, and Pécsvárad are present in both clusters. Thirty-one districts belong to the low–low cluster. Based on both tests, the low–low cluster includes the following districts: Bátonyterenye, Edelény, Kazincbarcika, Kunhegyes, Pétervásár, and Putnok. However, the low–low cluster resulting from the application of Local Geary is much more extensive, covering not only north-eastern Hungary but also peripheral south-western districts.

In the second part of our analysis, we focused on *household-scale solar PV systems per 100 households*. The Moran I statistic confirms spatial dependence, consistent with previous studies [17,28,30–32] (Table 1). When we move from maps to multivariate spatial econometrics (a spatial error model tailored to the distribution of systems per 100 households), the spatial error term is the dominant explanatory factor—stronger than conventional socioeconomic predictors such as local income. Based on the spatial error autocorrelation model, the proportion of *household-scale solar PV systems per 100 households* is most influenced by the construction period, the size of occupied properties, residents' education level in the district, and the built-up area and population. Notably, per capita income and insolation (global radiation) were not significant once spatial structure and building characteristics were accounted for. This finding contradicts the research of [17,28–31]. The large and significant spatial error coefficient indicates that PV adoption intensity is shaped by spatially correlated unobserved factors beyond the included covariates. These may be related to local permitting conditions, the temporary feed-in moratorium, or other geographically structured institutional and social influences, although identifying these mechanisms more precisely would require further analysis.

The rapid expansion of household solar observed up to 2023 occurred within a policy environment characterized by highly favorable compensation and support schemes. The elimination of net metering for new installations from 8 September 2023 and the shift toward gross metering with very low feed-in compensation substantially increased the payback period (approximately 7 years under net metering compared to around 15 years under gross metering). Given the strong spatial dependence and local network effects we identified, regulatory changes are likely to affect not only the national growth rate but also the spatial distribution of installations. Areas with robust peer effects and established local financing or installer networks may sustain growth longer than peripheral districts where adoption has depended more on financial incentives. Consequently, policy changes interact with spatial path-dependence to produce divergent regional outcomes.

For addressing this phenomenon, centralized, uniform policy instruments are likely to be inefficient. The identified clusters suggest the relevance of distinguishing between three policy categories: (a) high-uptake, innovation-rich districts where market instruments and grid integration support should be prioritized; (b) transition districts with medium uptake, where targeted information campaigns, group purchasing, and low-interest financing can leverage peer effects; and (c) peripheral, low-uptake districts where subsidies combined with renovation and social-welfare measures are necessary to prevent increasing inequalities. Given the strength of neighbor effects, public investment in local demonstration projects, community energy facilitators, and installer networks can reduce information and coordination costs and convert latent interest into actual installations. In contexts where apartment-block ownership and tenancy complicate rooftop access, municipal or cooperative models warrant explicit support.

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The clustering of distributed generation results in concentrated injection points that exert varying effects on distribution networks. Grid reinforcement, smart-meter deployment, and localized storage or demand-response capacity should be prioritized in areas where “high–high” clusters are projected to expand. Without compensatory measures, the benefits of prosumption (cost savings, resilience) will accrue disproportionately to residents in detached homes and to better-educated populations. Social tariffs, targeted grants for low-income households, and combined retrofit and PV programs should be considered to prevent the deepening of regional and household inequality.

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Data Availability Statement: All core data and results that can be shared openly have been deposited in a Zenodo repository (https://doi.org/10.5281/zenodo.19626336 (accessed on 7 June 2026)). This repository contains the cleaned district-level dataset used in the final econometric models (including the dependent variable, all explanatory variables listed in Table 4, and district identifiers), as well as an accompanying results file containing district-level model predictions and residuals. These materials allow independent researchers to reconstruct the main regression analyses and to verify the quantitative results reported in the paper. However, full replication of every step of the spatial analysis cannot be completely guaranteed, as this would require sharing numerous contextual elements and auxiliary inputs.

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

Appendix A

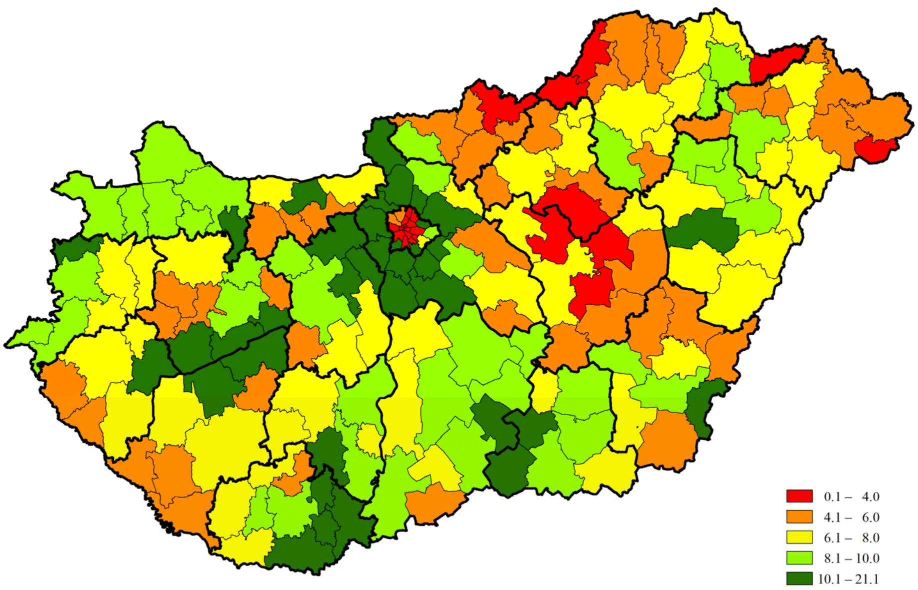

Figure A1. Number of household-scale solar PV systems per 100 households (2024).

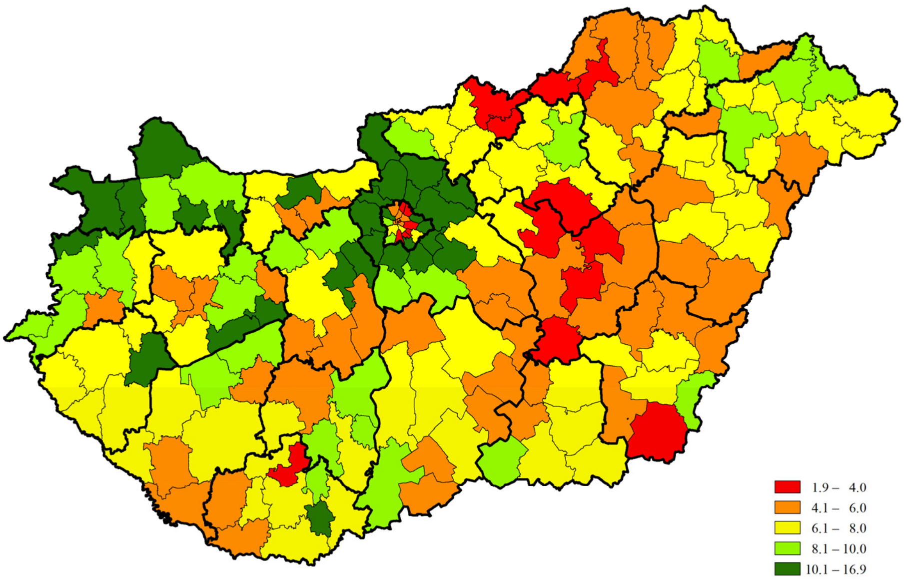

Figure A2. Values of the spatial error model estimating the number of household-scale solar PV systems per 100 households (2024).

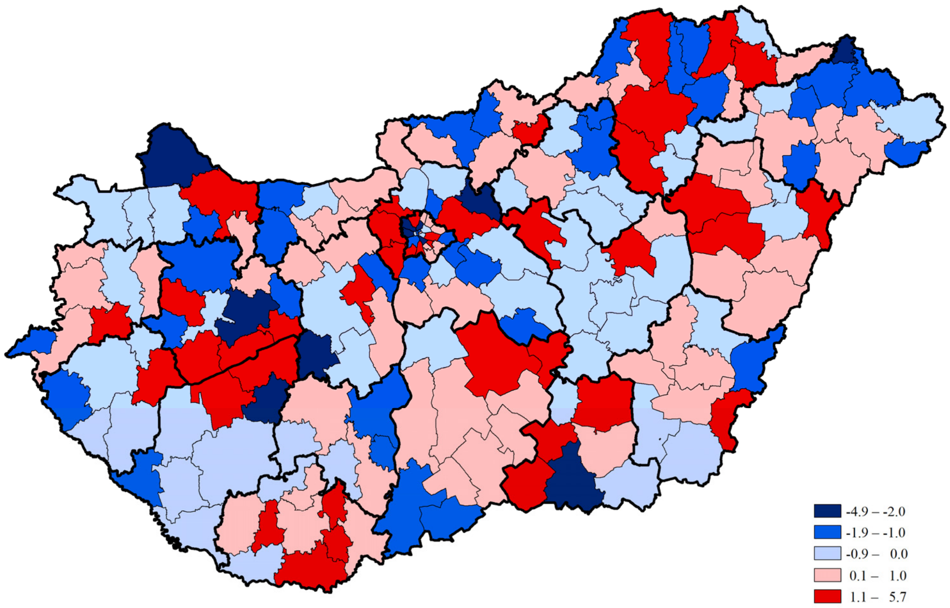

Figure A3. Residuals of the spatial error model estimating the number of household-scale solar PV systems per 100 households (2024).

Appendix B. Model Diagnostics

Summary of output: Ordinary Least Squares estimation
Dependent Variable: Household-scale solar PV systems per 100 households
Number of Observations: 197
Mean dependent var: 7.39182 Number of Variables: 6
S.D. dependent var: 3.6059 Degrees of Freedom: 191
R-squared: 0.671616 F-statistic: 78.1271
Adjusted R-squared: 0.663019 Prob(F-statistic): 2.52234×10^{-44}
Sum squared residual: 841.155 Log likelihood: -422.511
Sigma-square: 4.40395 Akaike info criterion: 857.022
S.E. of regression: 2.09856 Schwarz criterion: 876.721
Sigma-square ML: 4.26982

S.E of regression ML: 2.06636

Variable	Coefficient	Std.Error	z-Value	Probability
Constant	−3.138	1.166	−2.691	0.008
Ratio of dwellings built since 2000 to occupied dwellings	0.245	0.029	8.557	0.000
Proportion of people with a high school diploma or higher education degree	0.182	0.027	6.796	0.000
Population, thousand	−0.021	0.005	−3.989	0.000
Proportion of dwellings with a floor area of 100 square meters or larger	0.105	0.023	4.652	0.000
Ratio of the inner area of settlements in districts to the administrative area	−0.105	0.011	−9.665	0.000

Multicollinearity condition number: 23.146267			
Test on normality of errors			
Test	DF	VALUE	PROB
Jarque–Bera	2	75.4142	0.00000
Diagnostics for heteroskedasticity			
Randomcoefficients			
Test	DF	VALUE	PROB
Breusch–Pagan test	5	34.0431	0.00000
Koenker–Bassett test	5	16.5248	0.00550
Diagnostics for spatial dependence			
Test	MI/DF	VALUE	PROB
Moran's I (error)	0.439	10,607	0.000
Lagrange Multiplier (lag)	1	63,120	0.000
Robust LM (lag)	1	1376	0.241
Lagrange Multiplier (error)	1	98,587	0.000
Robust LM (error)	1	36,844	0.000
Lagrange Multiplier (SARMA)	2	95,963	0.000

Summary of output: Spatial error model—Maximum Likelihood estimation
Spatial Weight: Queen contiguity
Dependent Variable: Household-scale solar PV systems per 100 households
Number of Observations: 197
Mean dependent var: 7.391824 Number of Variables: 6
S.D. dependent var: 3.605901 Degrees of Freedom: 191
Lag coeff. (Lambda): 0.852110

R-squared: 0.844219	R-squared (BUSE): –
Sq. Correlation: –	Log likelihood: −369.621321
Sigma-square: 2.02555	Akaike info criterion: 751.243
S.E of regression: 1.42322	Schwarz criterion: 770.942

Variable	**Coefficient**	**Std.Error**	**z-Value**	**Probability**
Constant	−6.398	1.208	−5.295	0.000
Ratio of dwellings built since 2000 to occupied dwellings	0.190	0.023	8.163	0.000
Proportion of people with a high school diploma or higher education degree	0.182	0.021	8.683	0.000
Proportion of dwellings with a floor area of 100 square meters or larger	0.183	0.019	9.705	0.000
Population, thousand	−0.016	0.004	−4.401	0.000
Ratio of the inner area of settlements in districts to the administrative area	−0.045	0.015	−3.071	0.002
LAMBDA	0.852	0.039	21.685	0.000

Diagnostics for heteroskedasticity			
Random coefficients			
Test	DF	VALUE	PROB
Breusch–Pagan test	5	31.6068	0.00001

Diagnostics for spatial dependence			
Spatial error dependence for weight matrix: Queen contiguity			
Test	DF	VALUE	PROB
Likelihood Ratio Test	1	105.7789	0.00000

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