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Simulating household energy behavior diffusion using spatial microsimulation and econometric models

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ABSTRACT

Analyzing household energy behaviors from a spatial perspective is crucial for both policymakers and network operators. However, conducting spatial analysis at a fine scale presents significant challenges, primarily due to data scarcity. This article demonstrates the potential of integrating spatial microsimulation and spatial econometric models to address this issue. Specifically, we construct a static spatial microsimulation model to create a synthetic population for the entire Netherlands, simulating neighborhood-level spatial distributions of household energy behaviors. The results indicate significant neighborhood-level spatial heterogeneity in the adoption of energy behaviors. Subsequently, this simulated output is used as input for spatial econometric models to analyze the neighborhood-level spatial determinants of household energy behavior adoption. We identify the roles of both spatial endogenous effects and neighborhood-specific characteristics in contributing to the observed spatial variations in household energy behaviors.

1. Introduction

Residential energy use accounted for 20.3 % of global final energy consumption in 2022 (IEA, 2024). In the European Union (EU27), this share is even higher at 25.8 %, with only 22.6 % of residential energy consumption derived from renewable sources—just over half of the 42.5 % target set for 2030 (Eurostat, 2024). Efforts to understand household energy behaviors and develop strategies for decarbonization in the residential sector have garnered significant attention (Belaïd, 2024; Dietz, Gardner, Gilligan, Stern, & Vandenbergh, 2009). Among these efforts, studies in the geography of sustainability transitions emphasize the importance of analyzing household energy behaviors from a spatial perspective to address policy and infrastructure challenges (Bridge, Bouzarovski, Bradshaw, & Eyre, 2013; Coenen, Benneworth, & Truffer, 2012; Köhler et al., 2019). Spatial insights reveal regional variations in energy behavior and the place-specific factors driving them, enabling targeted interventions and equitable resource allocation. Additionally, understanding the geographic distribution of energy supply and demand supports grid optimization and decentralized energy integration, enhancing system efficiency and stability (Denholm et al., 2021; Zhang, Ballas, & Liu, 2024).

Many studies on household energy behavior modeling emphasize the importance of place-specific characteristics and spatial interaction effects. However, the reliance on low-resolution spatial data of most studies introduces two significant shortcomings. First, aggregated data at coarse spatial scales fail to capture local variations and contextual differences within smaller units, as data homogenization over large areas obscures spatial heterogeneity and localized dynamics (Irwin, 2021; Kosugi, Shimoda, & Tashiro, 2019; Tao, Hayashi, Shiraki, Huang, & Dem, 2024). Second, accurately modeling spatial interactions requires accounting for individual travel and interaction patterns, which typically occur at finer spatial scales. High-resolution spatial data are crucial for capturing these localized interactions since social dynamics and cross-border activities largely unfold within small geographic areas, such as neighborhoods, rather than larger units like municipalities (Salat et al., 2023; Zhang, Ballas, & Liu, 2023).

A few studies demonstrate household energy behavior modeling at finer spatial scales but often with limitations. For example, Kucher, Lacombe, and Davidson (2021), Nyangon and Byrne (2021), and Kosugi et al. (2019) focus on single cities, neglecting cross-border effects that are particularly relevant for households near regional or national boundaries. Others examine only specific household energy behaviors,

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narrowing their scope to determinants unique to those behaviors (Derkenbaeva, Hofstede, van Leeuwen, & Vega, 2023; Hesselink & Chappin, 2019). Li, Wang, and Zhang (2023) and Babutsidze and Chai (2018) emphasize that household energy behaviors differ in complexity, with actions like habit adjustments, equipment upgrades, and housing retrofits being influenced by different sets of factors. To date, there remains a lack of studies that simultaneously address place-specific factors, spatial interactions, and multiple household energy behaviors using high-resolution spatial data at a nationwide scale.

In practice, many empirical studies are constrained to coarse-grained spatial scales primarily due to the unavailability of high-resolution spatial information for agent-based data (Peplinski, Mayes, & Sanders, 2025; Wu, Heppenstall, Meier, Purshouse, & Lomax, 2022). Data on consumer energy consumption and household energy behaviors are often sourced from surveys or energy providers (Tuccillo et al., 2023; Zhang et al., 2018). However, privacy restrictions and security concerns frequently limit access to detailed geographic information (Ballas, Rossiter, Thomas, Clarke, & Dorling, 2005; Garcia-Gabilondo, Shibuya, & Sekimoto, 2024). Consequently, while rich explanatory variables, such as socio-demographic characteristics, are available at finer spatial scales through national censuses, these variables are frequently aggregated to coarser spatial units to align with the limited resolution of agent-based data during modeling (Hörl & Balac, 2021). A major challenge lies in combining agent-based information at coarse spatial resolutions with aggregate summary data available at high spatial resolutions (Wiki, Marek, Sibley, & Exeter, 2023; Zhou, Li, Basu, & Ferreira, 2022).

This paper addresses the limitations of low-resolution spatial data in existing studies by pursuing two main objectives. First, we develop a spatial microsimulation model that combines two publicly available datasets to generate a synthesized small area population microdata set in the Netherlands. This process estimates the probability of individuals residing in specific neighborhoods based on their demographic and socioeconomic characteristics. The resulting synthetic database provides fine-scale geographic information and simulated household energy behaviors, which are further aggregated at the neighborhood level. Second, these spatial microsimulation results are used as inputs for spatial econometric models, where the simulated household energy behaviors act as dependent variables, and neighborhood-level census data serve as independent variables. The spatial econometric models account not only for the influence of neighborhood-specific factors but also for spatial interaction effects, capturing how energy behaviors in one neighborhood are influenced by those in neighboring areas. Fig. 1 illustrates the workflow for simulating household energy behaviors using spatial microsimulation and spatial econometric models.

We use the Netherlands, an EU member state, as a case study for several reasons. First, both the EU and the Netherlands face significant challenges with aging residential building stocks. As of 2023, 61 % of EU residential buildings were constructed before 1980 (HBF, 2023). In the Netherlands, this figure is higher, at around 70 % (CBS, 2023), which is notably higher than in other developed countries such as the United States (50 %) (USCB, 2023), Australia (50 %) (ABS, 2023), and Japan (40 %) (MLIT, 2023). These older homes, built prior to the widespread adoption of energy efficiency standards, require extensive retrofitting measures, including insulation, double glazing, and heating system upgrades. These older homes often lack energy efficiency standards and require retrofitting, such as insulation and heating system upgrades. Additionally, the Netherlands is highly reliant on natural gas for residential energy (66.2 % in 2022, the highest in the EU27, where the average is 30.89 %), with renewables accounting for only 7.94 % (Eurostat, 2024). These circumstances highlight the pressing need to decarbonize the residential sector in both the EU and the Netherlands.

Furthermore, the EU leads global efforts to address climate change and improve energy efficiency in the residential sector through ambitious policies. The *European Green Deal* aims to make the EU the first climate-neutral continent by 2050, with a milestone of reducing net greenhouse gas emissions by at least 55 % by 2030 compared to 1990 levels. The *Revised Energy Performance of Buildings Directive* mandates a 60 % reduction in building sector emissions by 2030 relative to 2015 and requires Member States to improve the average energy performance of their residential building stock by 16 % by 2030 and 20–22 % by 2035. Additionally, the *Renovation Wave Initiative* sets out a comprehensive plan to at least double the annual energy renovation rate of buildings by 2030 and accelerate deep renovations. The Netherlands exemplifies proactive implementation of these policies through programs like the *Incentive Scheme for Sustainable Energy and Energy Saving*, and the *Home Energy Saving Grant Scheme*, aiming at driving large-scale adoption of household energy measures.

In addition, the availability of comprehensive data makes the Netherlands an ideal case for this study. The Netherlands Housing Survey (WoOn) 2021, conducted by the Central Bureau of Statistics (CBS) and the Ministry of the Interior and Kingdom Relations (BZK), provides detailed nationwide information on household energy behaviors (BZK & CBS, 2022). This triennial survey includes responses from 46,658 individuals, covering energy measures undertaken between 2017 and 2021, such as home insulation, solar panel installations, and heating system upgrades. Moreover, the Netherlands offers nationwide consistency in factors like electricity rates, regulations on household energy efficiency measures, and climatic conditions like solar radiation, which helps minimize regional disparities and reduces potential estimation biases.

Our results indicate significant spatial endogenous effects, with certain neighborhood-specific factors emerging as key drivers of household energy behavior adoption. We contribute to the understanding of household energy behaviors from a spatial perspective in three ways. First, we develop a spatial microsimulation model to tackle the critical challenge of lacking high-resolution spatial data for understanding the spatial distribution of household energy behaviors. By integrating high-resolution geographic information from census data with detailed household-level attributes from survey data, our model enables a more precise analysis of patterns and variations in energy behaviors at granular spatial scales. Second, we broaden the scope of analysis by examining a wider range of household energy behaviors, including insulation, solar panel installations, heating upgrades, and double-glazing retrofits. This contrasts with most existing studies, which tend to focus on singular behaviors, such as hybrid-electric vehicles (Morton, Anable, Yeboah, & Cottrill, 2018; Pan, Uddin, & Lim, 2024; Shi & Goulias, 2024; Yang, Liu, Yang, & Lu, 2023), solar PV systems (Irwin, 2021; Pronti & Zoboli, 2024), and micro-generation technologies (Steadman, Bennato, & Giulietti, 2023). Third, we advance the modeling of determinants and spatial interaction effects in household energy behaviors by integrating the high-resolution spatial data generated

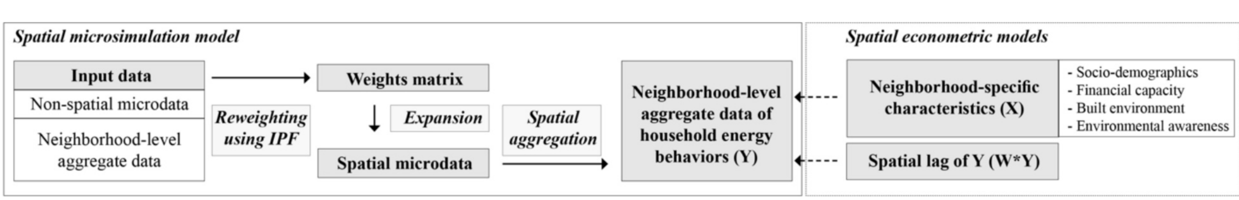

Fig. 1. Workflow of simulating household energy behaviors using spatial microsimulation and spatial econometric models.

through spatial microsimulation into spatial econometric models. Our analysis covers 14,080 Dutch neighborhoods, each spanning an average area of approximately 2.38 km^2 and housing around 1,207 inhabitants. This fine-grained data enables more accurate estimation of place-specific characteristics and spatial interaction effects.

The paper is organized as follows: Section 2 reviews the literature, Section 3 describes the empirical setting and data, Section 4 presents the results, and Section 5 discusses the findings. Finally, conclusions and policy implications are provided in Section 6.

2. Relevant literature

2.1. Determinants of household energy behavior adoption

Household energy behaviors refer to the actions and decisions households make that affect their energy consumption and efficiency (Nielsen et al., 2024; Wolske, Gillingham, & Schultz, 2020). These behaviors are typically classified into three types based on their complexity and commitment: habit adjustments, equipment upgrades, and housing retrofits (Black, Stern, & Elworth, 1985; Li et al., 2023; Parker, Rowlands, & Scott, 2003; Trotta, 2018; Urban & Ščasný, 2012). Habit adjustments, such as reducing standby power usage or adjusting thermostats, involve minimal costs and effort (Flavin & Nakagawa, 2008). Equipment upgrades include purchasing energy-efficient appliances or technologies like hybrid-electric vehicles, requiring moderate financial investment but offering greater savings (Biswas, Fuentes, McCord, Rackley, & Antonopoulos, 2024). Housing retrofits, including installing solar panels or upgrading insulation, demand significant financial and time commitments yet deliver the most substantial and long-lasting energy reductions (Giandomenico, Papineau, & Rivers, 2022).

Empirical studies on household energy behavior adoption often examine *socio-demographic characteristics, financial capacity, built environment features*, and *spatial interaction effects*. *Socio-demographic characteristics* significantly influence decision-making, though findings are mixed. For example, older generations may face barriers like unfamiliarity with technology but benefit from financial stability for retrofits and feel stronger obligations to adopt sustainable practices (Ameli & Brandt, 2015; Busic-Sontic & Fuerst, 2018; Trotta, 2018; Willis, Scarpa, Gilroy, & Hamza, 2011). Conversely, younger households often favor behaviors like adopting solar PV systems due to their openness to new technologies and focus on long-term benefits (Nair, Gustavsson, & Mahapatra, 2010). *Educational level* is another widely recognized determinant of energy behavior adoption. Higher education enhances environmental awareness and understanding of energy-efficient solutions (Alem, Beyene, Köhlin, & Mekonnen, 2016), enabling informed decision-making (Mills & Schleich, 2012). Educated individuals are also more aware of government incentives, technological advancements, and cost-saving opportunities (Acheampong & Cugurullo, 2019). *Migration background* can also influence energy behavior adoption, as cultural differences shape living habits and preferences for energy-saving measures (Winkler & Matarrita-Cascante, 2020). Furthermore, migrants, particularly new migrants, often face limited access to resources and knowledge about energy-efficient practices, government incentives, or available technologies, which can hinder their ability to adopt sustainable energy behaviors (Head, Klocker, & Aguirre-Bielschowsky, 2019). *Household type* also matters, with larger households having higher energy demands, making efficiency upgrades appealing (Van der Kam, Meelen, Van Sark, & Alkemade, 2018). Ellsworth-Krebs (2020) adds that larger or detached homes, often associated with multi-person households, provide the necessary space for adopting certain measures.

As for *financial capacity*, there is evidence that *high-income households* are more likely to adopt energy-efficient measures due to their ability to afford substantial upfront costs and greater financial flexibility, enabling early adoption of innovative technologies (Dharshing, 2017; Umit, Poortinga, Jokinen, & Pohjolainen, 2019; Urban & Ščasný, 2012). Conversely, low-income households face financial barriers that limit their ability to invest in retrofits or renewable energy measures, particularly those with high initial costs (Brown, Sorrell, & Kivimaa, 2019; Chandrashekeran, de Bruyn, Sullivan, & Bryant, 2024). Some studies suggest that accumulated wealth, rather than marginally higher income, plays a greater role in adoption decisions (Balta-Ozkan, Yildirim, & Connor, 2015; Graziano & Gillingham, 2015). Additionally, Ruokamo, Laukkanen, Karhinen, Kopsakangas-Savolainen, and Svento (2023) argue that high-income households may deprioritize cost-saving behaviors, as reducing energy expenses is less critical for them. *Property value* has also been consistently found to correlate positively with energy-efficient investments. Kwan (2012) notes that owners of high-value homes often possess greater equity stakes, which can be leveraged as collateral for financing such upgrades. Moreover, homeowners may view energy-efficient improvements as valuable investments that enhance property value (Zhang, Liu, & Ballas, 2023).

Regarding the *built environment*, some studies highlight the role of *population and housing density* in influencing household energy behavior adoption. In densely populated areas, the visibility of energy-efficient measures, like solar PV systems, can drive adoption through social influence and spillovers (Alipour, Salim, Stewart, & Sahin, 2020; Briguglio & Formosa, 2017). Such areas often benefit from shared infrastructure, enabling measures like insulation or heat pumps (Adil & Ko, 2016). However, high-density urban settings may face challenges, such as limited space in multi-story buildings, hindering structural upgrades (Kucher et al., 2021). *Building features* also play a significant role. Mangold, Österbring, Wallbaum, Thuvander, and Femenias (2016) argue that older homes often require retrofitting measures to address inefficiencies stemming from outdated construction standards and materials. Additionally, *detached houses*, with more space and autonomy, are well-suited for large-scale energy measures compared to shared or multi-unit properties (Balta-Ozkan et al., 2015; Hu et al., 2023). Many studies also highlight the role of *homeownership*, arguing that homeowners are more likely to undertake costly upgrades for long-term savings and property value increases (Briguglio & Formosa, 2017; Sommerfeld, Buys, Mengersen, & Vine, 2017). Conversely, renters often lack the authority or incentive to make such changes (Ebrahimigharehbaghi, Qian, Meijer, & Visscher, 2019).

Additionally, *environmental awareness*, reflecting individuals' understanding of the environmental impact of their actions, is often associated with increased motivation for pro-environmental behaviors. Conrad and Hilchey (2011) argue that heightened environmental awareness fosters a sense of responsibility, encouraging individuals to adopt energy-efficient measures to mitigate environmental harm. This awareness not only influences individual lifestyle choices but also promotes environmentally conscious behaviors that collectively reduce their carbon footprint (Broska, 2021).

2.2. Modeling spatial interaction effects

Beyond place-specific characteristics, research increasingly emphasizes the role of spatial interaction effects in household energy behavior adoption. Existing studies can be categorized into three approaches. First, many focus on individual energy behaviors, such as hybrid-electric vehicles (Morton et al., 2018; Pan et al., 2024; Shi & Goulias, 2024; Yang et al., 2023), solar PV systems (Irwin, 2021; Pronti & Zoboli, 2024), and micro-generation technologies (Steadman et al., 2023). Second, a limited number of studies compare spatial interaction effects across behaviors. For instance, Babutsidze and Chai (2018) examine 15 greenhouse gas mitigation practices (e.g., recycling, carpooling) and find behavior-specific spatial effects, especially in visible green behaviors. Third, other studies focus on cumulative energy behavior outcomes, using metrics like energy consumption and demand (Nyangon & Byrne, 2021; Wolske et al., 2020).

A central rationale for the observed spatial interaction effects is the dissemination of information within social networks. This is particularly important for new technologies like solar PV systems, where consumers often lack market knowledge or prior experience (Dubé, Hitsch, & Jindal, 2014; Rai & Henry, 2016). In such cases, social interactions mediate the flow of information, shaping individuals' access to knowledge about these technologies and potentially influencing normative perceptions of costs, benefits, and the likelihood of adoption (Babutsidze & Cowan, 2014; Constantino et al., 2022; Henry & Vollan, 2014; Nielsen et al., 2024; Nyborg et al., 2016).

Methodologically, a crucial aspect of modeling spatial interaction effects lies in identifying and quantifying spatial interactions. Some studies use spatial banding methods or predefined spatial boundaries to define peer groups at the micro level (Irwin, 2021; Zhang, Ballas, & Liu, 2023). Others adopt spatial econometric techniques to analyze interactions at aggregate levels, such as zip codes or municipalities. The interdependence among spatial units is typically defined using spatial weights matrices, which measure the intensity of spatial relationships based on geographic proximity. For example, Yang et al. (2023) identify significant spatial correlations in battery electric vehicle adoption across 422 Norwegian municipalities using a first-order queen contiguity matrix. Park and Yun (2022) apply a spatial error model to analyze residential electricity consumption in 225 Korean municipalities, revealing spatial endogenous effects. Nyangon and Byrne (2021) use a spatial Durbin error model to study adoption trends for residential energy-efficiency measures at the ZIP code level in New York state, while Shi and Goulias (2024) employ a spatial error model to predict zero-emission vehicle sales at the census tract level in California.

Current research on household energy behavior modeling emphasizes the importance of place-specific determinants and spatial interaction effects. However, the lack of high-resolution spatial data limits most studies to coarse-grained spatial analyses, reducing their ability to capture localized variations and model spatial interactions accurately. To address this, we propose developing a spatial microsimulation model to generate population data and simulate the spatial distribution of household energy behaviors at a fine spatial scale.

2.3. Spatial microsimulation

Microsimulation, originally developed by economists, generates synthetic populations that replicate target populations across characteristics like age, household composition, and employment (Pfeffermann, 2002; Tanton, 2014; Tanton, Vidyattama, Nepal, & McNamara, 2011). Spatial microsimulation incorporates geographic dimensions, allocating synthetic populations to specific locations to reflect real-world demographics (Ballas & Clarke, 2009; Chan & Sayre, 2024; Farrell, Morrissey, & O'Donoghue, 2012). Recent applications demonstrate the utility of spatial microsimulation in generating fine-grained data across various contexts. For instance, Lin (2024) develops synthetic population data in the US at the census block group level, including variables like housing type, age, and race. Wu et al. (2022) simulate residential and job location dynamics in Singapore at the household and building levels. Salat et al. (2023) model social interactions at the MSOA level in the UK, while Wiki et al. (2023) examine well-being at the Statistical Area 2 level in Aotearoa New Zealand. Höhn et al. (2024) estimate quality-adjusted life expectancy across British local authorities, and Broomhead, Ballas, and Baker (2023) simulate dental public health outcomes at the LSOA level in Sheffield to assess national policy impacts. In sustainability transition studies, Chingcuanco and Miller (2012) generate a synthetic population for the Greater Toronto–Hamilton Area to estimate residential space heating demand, while Zhang et al. (2018) estimate neighborhood-level residential energy consumption in Atlanta, US.

While spatial microsimulation models are commonly used to create synthetic populations and simulate target variables, their integration with other modeling approaches remains limited (Ballas, Broomhead, & Jones, 2019). For instance, Cajka, Cooley, and Wheaton (2010) combine synthetic population data with agent-based models to simulate epidemic spread in the US, while Merler, Ajelli, Fumanelli, and Vespignani (2013) integrate stochastic microsimulation with agent-based modeling to study flu outbreaks in the Netherlands. More recently, Derkenbaeva et al. (2023) use spatial microsimulation to address survey data gaps in Amsterdam and incorporate the results into agent-based models to estimate homeowners' energy efficiency decisions. Bhattacharjee, Pabst, Szendrei, and Hewings (2024) provide a rare example of integrating spatial microsimulation with spatial econometrics to analyze the impacts of macroeconomic shocks like COVID-19 and Brexit on UK households across 12 ITL1 regions. By using dynamic microsimulation informed by regional and national macroeconomic projections, they generate spatially detailed consumption and labor data, which are then utilized in a spatial econometric model to assess inter-regional spillovers and the socio-economic effects of policy interventions. Despite diverse contexts, these studies share a common goal: addressing the limitations of low-resolution spatial data by using spatial microsimulation methods to generate synthetic individual-level data enriched with fine-grained geographic information.

This study builds on the concepts of previous research by employing a spatial microsimulation model to generate population microdata, addressing the shortcomings in modeling household energy behavior caused by the lack of high-resolution spatial data. This approach allows for the simulation of neighborhood-level heterogeneity in household energy behavior adoption. With this detailed data, we integrate neighborhood-level aggregate data from census sources to capture neighborhood-specific characteristics and use spatial weights matrices from spatial econometrics to model spatial interaction effects.

3. Methods and data

3.1. Spatial scale

We use the neighborhood level as the spatial unit for this study. This scale includes 14,080 neighborhoods, averaging 2.38 km^2 in size and 1,207 residents. The fine-grained resolution enables precise capture of spatial characteristics, avoiding the detail loss common with coarser data. Additionally, we emphasize the significance of interpersonal communications during cross-border activities for shaping household energy behaviors. According to the Dutch Travel Survey 2021, the average daily non-vehicle travel distance for Dutch residents was 8.1 km (CBS, 2022). Therefore, the neighborhood-level spatial dimension is well-suited to capture cross-border human interactions.

3.2. Spatial microsimulation model

3.2.1. Data

The spatial microsimulation model utilizes two data types: spatial aggregate data and non-spatial microdata. Spatial aggregate data, typically derived from censuses, provide accurate statistical summaries at the neighborhood level with extensive geographic coverage. However, they lack the detailed insights found in survey-based datasets, especially on emerging topics like household energy behaviors. This limitation arises because censuses primarily focus on core demographic and socioeconomic variables, while collecting detailed energy behavior data is often cost-prohibitive and time-intensive (Ballas et al., 2005). Non-spatial microdata, typically derived from surveys, provide detailed information on variables like household energy behaviors but often lack geographical identifiers due to privacy restrictions. Spatial microsimulation addresses this gap by integrating microdata with aggregate census data. By matching shared population characteristics, this technique estimates the likelihood of individuals or households with specific traits residing in particular neighborhoods, thereby producing a synthetic population dataset that combines detailed survey data with geographic specificity.

For this study, neighborhood-level aggregate data are sourced from CBS, while the WoOn 2021 dataset, the most recent available microdata, serves as the primary source of survey data (BZK & CBS, 2022). WoOn is a triennial, individual-level survey conducted by CBS and BZK, providing detailed information on demographics, socioeconomic status, housing characteristics, neighborhood attributes, housing tenure, and household energy behaviors. The 2021 survey includes responses from 46,658 individuals. CBS aggregate data and WoOn 2021 are well-suited for this analysis for several reasons. First, CBS, as the national authority for statistical data, ensures high reliability and accuracy in its collection, editing, and publication processes. The availability of high-resolution spatial data at the neighborhood level enables the capture of place-specific characteristics, which are essential for modeling spatial determinants of household energy behaviors. Second, WoOn 2021 provides detailed insights into a range of household energy behaviors, offering a broader and more detailed perspective compared to surveys conducted by energy providers, which often have limited geographical coverage or focus narrowly on specific behaviors. With its representative sample of the Dutch population (BZK & CBS, 2022), WoOn 2021 supports the generation of synthetic populations through spatial microsimulation that mirror real-world demographics, socioeconomic conditions, and energy behaviors. Finally, the integration of CBS aggregate data and WoOn 2021 is particularly advantageous for spatial microsimulation because both datasets are conducted, collected, and published by the same institution. This consistency ensures methodological alignment between aggregate and microdata, enhancing the accuracy of constraint variables and improving the spatial allocation of agents to different neighborhoods.

The primary variables of interest in this study are household energy behaviors. Respondents reported whether they had undertaken any of the following energy-saving measures between 2017 and 2021: installing double glazing (6,923 affirmative responses), insulating houses (including exterior walls, interior walls, or floors; 5,690 responses), installing residential solar panels (6,070 responses), installing heat pumps (447 responses), and renewing central heating boilers (11,601 responses). While the first two behaviors fall under housing retrofits, the latter three are categorized as equipment upgrades. These measures highlight a focus on investment-intensive measures rather than low-cost habit adjustments. We aggregate the affirmative responses at the Dutch NUTS3 level, the most detailed spatial scale from WoOn 2021. Fig. 2 illustrates the spatial distribution of household energy behavior, revealing significant regional variations. The responses range from Delfzijl with 64, to Utrecht with 3,595, followed by Rijnmond with 2,009 and Noord-Overijssel with 1,864. Additional details on these behaviors and other variables from WoOn 2021 are summarized in Table 1.

In spatial microsimulation, constraint variables are essential for aligning individual-level data with aggregate data to generate synthetic populations. These variables constrain the microsimulation process, ensuring that the synthetic population reflects the known aggregate characteristics of the population at the chosen spatial scale (Edwards & Clarke, 2009). The selection of constraint variables often follows several theoretical and practical criteria (Ballas, Clarke, Dorling, & Rossiter, 2007). First, they must be available in both survey and census datasets. Second, they should theoretically influence the target variables. Third, they must demonstrate strong and statistically significant correlations with the target variables. Finally, they should capture key sociodemographic characteristics of the population, reflecting diversity and serving as indicators of socioeconomic status at the spatial scale. To ensure theoretical relevance (criterion 2), we review determinants of household energy behaviors in Section 2.1. For statistical robustness (criterion 3), we follow Panori, Ballas, and Psycharis (2017) and Lovelace, Ballas, and Watson (2014) by conducting preliminary correlation analyses between potential constraint variables and the target variables within the WoOn 2021 dataset. Based on these criteria, we select six constraint variables: *age, educational level, migration background, household composition, income level, and housing values*. Table 2 provides detailed information on these variables, including their categories or bin breaks and theoretical considerations.

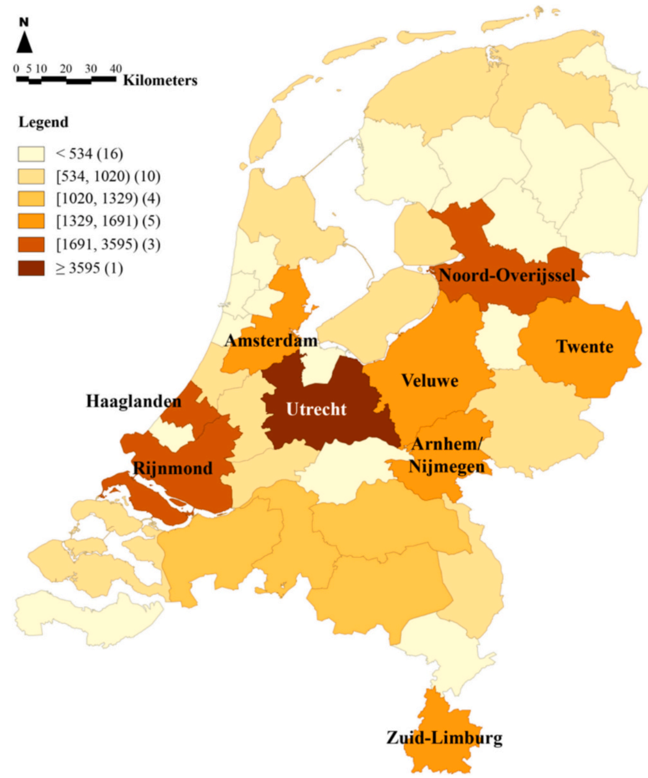

Fig. 2. Spatial distribution of total counts of household energy behaviors at the Dutch NUTS3 level. Source: WoOn 2021.

Nevertheless, several potential biases in the WoOn 2021 survey responses might influence the results. First, the exclusion of pre-2017 behaviors may underrepresent neighborhoods with long-standing commitments to energy efficiency. WoOn 2021 focuses exclusively on energy behaviors undertaken between 2017 and 2021, omitting earlier actions. For example, solar panel installations began increasing significantly as early as 2010 due to subsidy programs in the Netherlands. Consequently, neighborhoods that were early adopters might appear to have lower adoption rates, leading to potentially inaccurate conclusions about their energy behavior patterns. Second, a cumulative reporting bias may arise when respondents overgeneralize their actions, attributing pre-2017 measures to the survey period. For instance, a household that started retrofitting insulation in 2015 but continued incremental improvements after 2017 might report all their actions as occurring within the survey timeframe. Such overreporting can inflate adoption rates for behaviors that are often implemented gradually over time.

Third, the COVID-19 pandemic might introduce variability in household decision-making during the survey period. Mobility restrictions and supply chain disruptions likely delayed energy-efficient installations for some households. Conversely, increased time spent at home may have heightened awareness of energy consumption, motivating others to undertake energy-saving measures such as insulation upgrades. These mixed effects complicate the attribution of trends to specific spatial determinants or broader societal shifts. Finally, biases related to housing associations (VvEs) may influence responses in neighborhoods with prevalent shared ownership structures. In the WoOn 2021 dataset, 93 % of owner-occupied apartments are part of buildings with an active VvE, and 86 % of these associations have formal maintenance plans. In the Netherlands, VvEs typically manage decisions affecting shared spaces, such as installing solar panels or EV charging points. Residents in VvE-managed properties might misattribute collective actions to personal efforts or underreport them, viewing such measures as the association's responsibility. This discrepancy is particularly relevant in densely populated urban areas, where VvEs are

Table 1
Descriptive statistics of variables retrieved from WoOn 2021 ($n = 40{,}658$).

Variables	Description	Mean	Std. Dev.	Min	Max
Household energy behavior	Count of household energy behaviors	0.733	1.005	0	6
Installing double glazing (Dummy)	Number of affirmative responses: 6,923				
Insulating houses (Dummy)	Number of affirmative responses: 5,690				
Installing residential solar panels (Dummy)	Number of affirmative responses: 6,070				
Installing heat (Dummy)	Number of affirmative responses: 477				
Renewing central heating boilers (Dummy)	Number of affirmative responses: 11,601				
Age	Age of respondents (years)	49.150	17.685	20	70
Annual income (Euros)	Annual household income (in euros)	39,251.3	34,008	0	1,197,865
Housing values (1,000 euros)	Housing value (in 1,000 euros)	312.595	197.091	9,165	9,476,000
Educational level (Categories)	Number of respondents by educational level: - Below secondary school: 11,800 - Secondary school: 18,357 - Above secondary school: 16,389				
Migration background (Categories)	Number of respondents by background: - Dutch: 41,960 - Western migrants: 2,109 - Other migrants: 2,589				
Household composition (Dummy)	Number of respondents by household type: - Single-person households: 13,409 - Multi-person households with children: 24,162 - Multi-person households without children: 9,087				

Table 2
Description of constraint variables and theoretical considerations.

Variables	Categories/ bin breaks	Theoretical considerations
Age	(0–14], (14–24], (24–44], (44–64], (64–100]	- Older generations often have financial stability for retrofits but may face barriers such as unfamiliarity with technologies. - Younger generations are more open to new technologies and prioritize long-term benefits.
Educational level	Under secondary school, Secondary school, Above secondary school	- Higher education levels enhance environmental awareness and knowledge of energy-efficient solutions. - Educated individuals are more likely to access government incentives and evaluate long-term benefits.
Migration background	Dutch, Western migrants, Other migrants	- Cultural differences influence living habits and preferences for energy-saving measures. - Migrants, particularly new ones, may face barriers such as limited resources and awareness.
Household composition	Single-person households, Multi-person households with children, Multi-person households without children	- Larger households have higher energy demands, making energy upgrades more appealing. - Detached homes, often associated with larger households, are better suited for retrofits.
Income level (Euros)	(0−20,000], (20,000-40,000], Above 40,000	- High-income households can afford costly energy-efficient measures and retrofits. - Low-income households face financial constraints, limiting adoption.
Housing values (1,000 Euros)	(0,150], (150,200], (200,250], (250,300], (300,400], (400,500], Above 500	- High-value homes support retrofits due to greater equity and opportunities to enhance property value.

Note: Curved brackets indicate that the endpoint is not included, while square brackets indicate that the endpoint is included.

common, potentially skewing comparisons with individually managed households.

3.2.2. Methods

Spatial microsimulation methods typically employ probabilistic or deterministic sample reweighting techniques to generate synthetic population microdata for small geographic areas (Ballas & Clarke, 2009). The probabilistic approach employs a combinatorial search to select individuals from survey microdata that best align with aggregate data, replicating the small-area population (Tanton, 2014). This method relies on random number generators, introducing variability across model runs and demanding substantial computational resources. Conversely, the deterministic approach, often implemented via Iterative Proportional Fitting (IPF), offers a structured alternative. Originally designed for adjusting contingency tables, IPF iteratively adjusts survey data to match marginal control distributions (Ballas et al., 2005; Lovelace et al., 2014). Individuals whose characteristics align more closely with neighborhood demographics and socioeconomic features receive higher weights, indicating a greater likelihood of appearing in these neighborhoods. Compared to probabilistic models, IPF-based methods provide consistent results across model runs, lower computational complexity, and faster execution (Dumont & Lovelace, 2016; Lovelace & Ballas, 2013). For these reasons, we adopt an IPF-based deterministic approach using the R package *ipfp* (Lovelace & Dumont, 2017). This method iteratively adjusts individual weights to match marginal control totals from census data, following the formula:

$$w(i,z,t+1) = w(i,z,t)^{*}\frac{cons\_t(z,c,ind(i,c))}{\sum_{j=1}^{n_{ind}} w(j,z,t)^{*} I(ind(j,c) = ind(i,c))} \quad (1)$$

where $ind(i,c)$ is the category of individual i for the variable c. The $cons\_t(z,c,v)$ represents constraining count data based on census, which is the number of individuals corresponding to the marginal for the neighborhood $z \in Z$ in the variable $c \in C$ for the category $v \in V$. The indicator function $I(ind(j,c) = ind(i,c))$ has a value of 1 if the condition is true and 0 otherwise. This process ensures selecting only those individuals j in the set I that share the same category as the individual i for the given variable c. The weight matrix $w(i,z,t)$ corresponds to the weight of individual i in the neighborhood z during the step t.

The spatial microsimulation produces synthetic microdata for the entire Dutch population, detailing the number of energy behaviors adopted by each individual (i.e., the target variable), along with constraint variables and neighborhood-level geographical information.

From these results, the simulated household energy behavior adoption rate for each neighborhood is calculated by dividing the total number of simulated energy behaviors in the neighborhood by its corresponding total population. This process is illustrated in the Fig. 3.

3.3. Spatial econometric model

To model spatial endogenous effects, we adopt a specific-to-general testing approach to identify the most suitable spatial model (Anselin, 2013). This process begins with estimating a non-spatial linear regression using Ordinary Least Squares (OLS), which assumes no dependence of the dependent variable on those in neighboring neighborhoods. From the baseline OLS model, we apply classic and robust Lagrange Multiplier (LM) tests to determine whether the model should be extended to a Spatial Autoregressive (SAR) model, incorporating a spatially lagged dependent variable, or a Spatial Error Model (SEM), accounting for spatial interaction effects in the error term. The OLS, SAR, and SEM models are defined as follows:

$$OLS: Y_a = \phi + X_a\beta + u_a, \tag{2}$$

$$SAR: Y_a = \phi + \lambda \sum_{b=1}^{N} W_{ab}Y_b + X_a\beta + u_a, \tag{3}$$

$$SEM: Y_a = \phi + X_a\beta + u_a, u_a = \rho \sum_{b=1}^{N} W_{ab}u_b + \epsilon_a, \tag{4}$$

where Y_a represents the dependent variable - the simulated household energy behavior adoption rate in neighborhood a. X_a is a vector of independent variables for neighborhood a, including *socio-demographic characteristics, financial capacity, environmental awareness,* and *built environment* factors identified as significant spatial determinants in prior studies. ϕ is the intercept. λ captures the endogenous interaction effect, representing the influence of the dependent variable in one neighborhood Y_a on the dependent variables in neighboring units Y_b. ρ is the spatial autocorrelation coefficient in the error term. W_{ab} represents the $(a,b)^{th}$ element of the N x N spatial weights matrix W. The spatial weights matrix W in our study is non-negative and symmetric, representing the spatial interdependence among the 14,080 neighborhoods analyzed.

The spatial weights matrix W constructed in this study is based on several assumptions that should be considered during interpretation. A

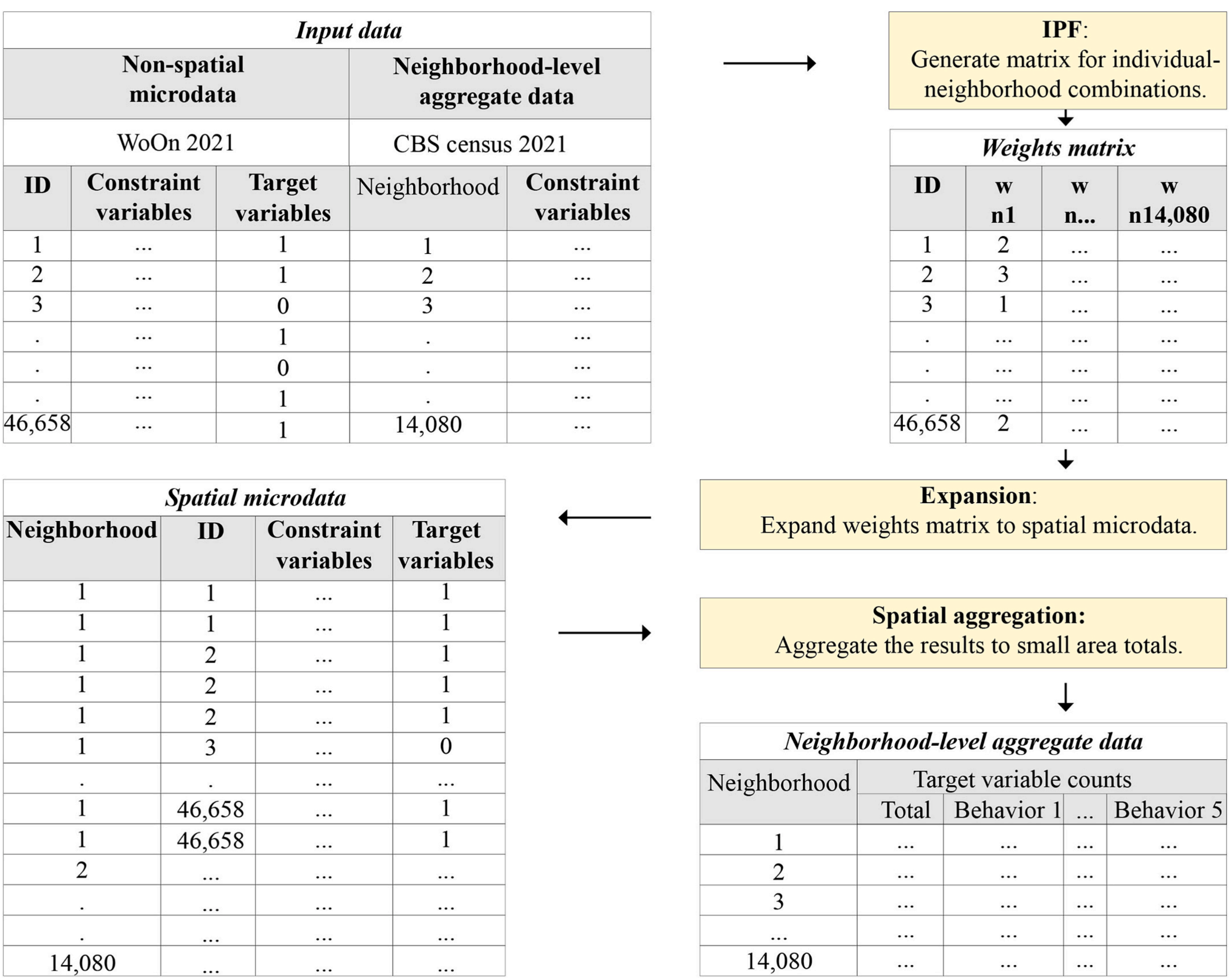

Fig. 3. Workflow of the spatial microsimulation model for generating neighborhood-level aggregate data on household energy behaviors.

primary assumption is that non-motorized travel fosters greater observational learning and social interactions compared to motorized travel (Tolsma, Van der Meer, & Gesthuizen, 2009). According to the Dutch Travel Survey 2021, the average non-motorized travel distance is approximately 8.1 km, corresponding to a radius of 4 km (CBS, 2022). Based on this, we adopt a 4 km cut-off distance matrix to define spatial relationships, assuming that neighborhoods within this radius are likely to engage in social interactions and exchange information about household energy behaviors. However, this approach leaves 21 rural neighborhoods unconnected, as their centroid distances to the nearest neighboring centroids exceed 4 km. To address this limitation, we incorporate a first-order queen contiguity matrix, which accounts for spatial adjacency irrespective of distance. The use of the contiguity matrix for rural areas relies on the assumption that rural residents typically travel longer distances and maintain stronger informal social ties, mitigating the effects of geographical isolation (Nation, Fortney, & Wandersman, 2010). This hybrid approach ensures that all neighborhoods, including those in rural or sparsely populated areas, are included in the analysis.

Moreover, the spatial weights matrix assumes uniform influence among all neighbors within the 4 km radius and first-order queen contiguity, treating these relationships as equal. While this simplification facilitates modeling, it may fail to account for variations in interaction strength that could arise from factors such as physical barriers, cultural differences, or variations in social networks. Additionally, the matrix presumes bidirectional interactions, meaning that if neighborhood *a* influences neighborhood *b*, then *b* exerts an equal influence on *a*. While computationally efficient, this assumption may not accurately reflect asymmetrical dynamics that arise from disparities in socioeconomic conditions, resource access, or neighborhood attributes, where influence might flow predominantly in one direction. While acknowledging that these assumptions may limit the ability to fully capture the complexity of spatial interactions, they remain essential for simplifying the modeling process and ensuring analytical feasibility. Formally, the spatial weights matrix element W_{ab} is defined as:

$$W_{ab} = \begin{cases} 1, & \text{if linked to } b, \text{or } 0 \leq d_{ab} \leq 4\ km \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

Table 3 provides descriptive statistics for the variables utilized in the regression models.

Table 3
Descriptive statistics of variables used for spatial econometric models (n = 14,080).

Variables	Description	Mean	Std. Dev.	Min	Max
Simulated household energy behavior adoption rates	Average energy behaviors adopted per household in neighborhood	0.110	0.140	0	2.318
Socio-demographics					
Ages	Percentage of pop^n aged 26–45 (%)	21.418	10.508	0	100
	Percentage of pop^n aged 46–65 (%)	29.185	10.742	0	100
	Percentage of pop^n aged over 65 (%)	20.246	11.718	0	100
Education	Percentage of pop^n with high education (%)	22.661	11.705	0	79.245
Household type	Percentage of multi-person households (%)	66.900	19.947	0	100
Financial capacity					
Income	Percentage of pop^n receiving income (%)	69.526	28.262	0	100
Property value	Average property value (1,000 euros)	311.391	156.719	0	2,133
Environmental awareness					
Electricity consumption	Average annual electricity use (kWh)	3,212.036	1,066.211	0	7,611
Built environment		6.370	2.587	0	10.785
Log population density	Natural logarithm of population density				
Home ownership	Percentage of owner-occupied houses (%)	65.367	25.806	0	100
House age	Percentage of houses built before 2000 (%)	72.890	33.978	0	100
House structure	Percentage of detached houses (%)	68.289	35.157	0	100

4. Results

4.1. Spatial microsimulation results

This section presents the results of the spatial microsimulation model, focusing on the simulated spatial distribution of total household energy behaviors. While individual behaviors are also simulated, their spatial distributions are detailed in maps provided in Appendix A.

Fig. 4 presents the simulated spatial distribution of household energy behavior adoption rates across 14,080 neighborhoods in the Netherlands. Darker colors indicate higher adoption rates in the neighborhood, while lighter colors represent lower adoption rates. Significant spatial heterogeneity can be observed in adoption rates across the country. Urban areas exhibit the highest adoption rates, particularly in metropolitan regions within the Randstad, including Rotterdam, The Hague, Amsterdam, Utrecht, Zaandam, and Almere. This trend is also evident in cities outside the Randstad, such as Eindhoven, Breda, and Den Bosch in North Brabant, as well as Maastricht in South Limburg. Additionally, cities like Groningen in the north and Nijmegen in the east display relatively high adoption rates compared to their surrounding areas. In contrast, rural and less densely populated areas demonstrate lower adoption rates, with fewer dark-colored neighborhoods visible on the map.

CBS categorizes neighborhoods into five urbanity levels based on address density: very highly urbanized (>2,500 addresses/km^2), highly urbanized (1,500–2,500 addresses/km^2), moderately urbanized (1,000–1,500 addresses/km^2), less urban (500–1,000 addresses/km^2), and not urbanized (<500 addresses/km^2). Fig. 5 illustrates the simulated distribution of household energy behavior adoption across these urbanity levels. The histogram (shaded bars) represents the percentage of neighborhoods within specific adoption ranges, while the kernel density plot (blue line) provides a smoothed distribution for each urbanity level.

The x-axis represents the simulated total number of household energy behaviors per neighborhood, and the y-axis shows the percentage of neighborhoods corresponding to each range of values. The results reveal distinct variations in adoption rates across urbanities. Urbanized neighborhoods, particularly those classified as very highly and highly urbanized, display broader adoption distributions with longer tails, indicating a wide range of adoption counts. Conversely, less urbanized and not urbanized neighborhoods show narrower distributions, with peaks concentrated near lower adoption counts, reflecting their

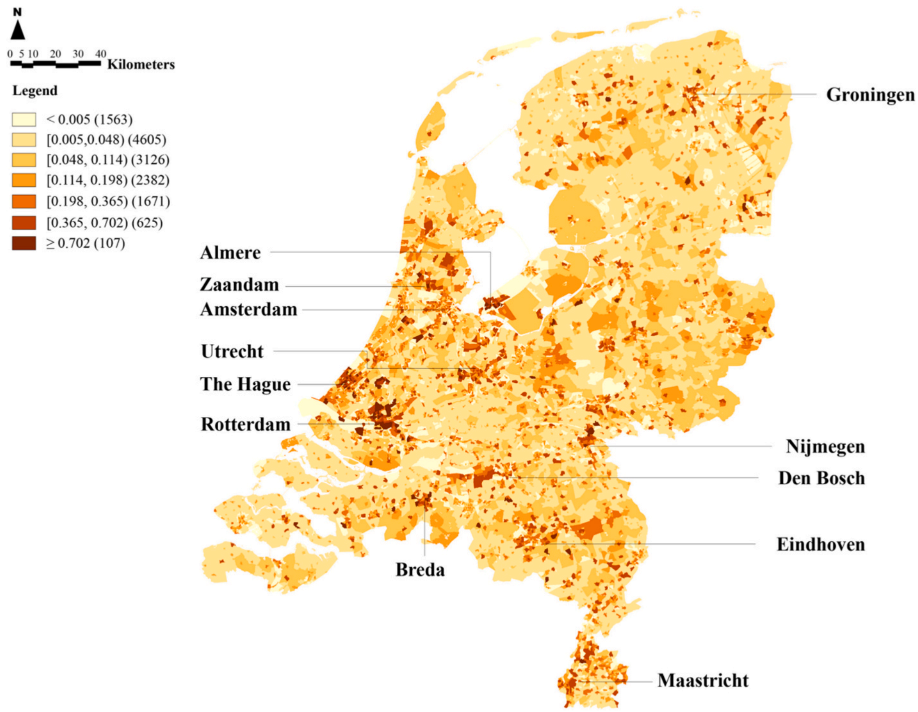

Fig. 4. Simulated spatial distribution of household energy behavior adoption rates across 14, 080 neighborhoods.

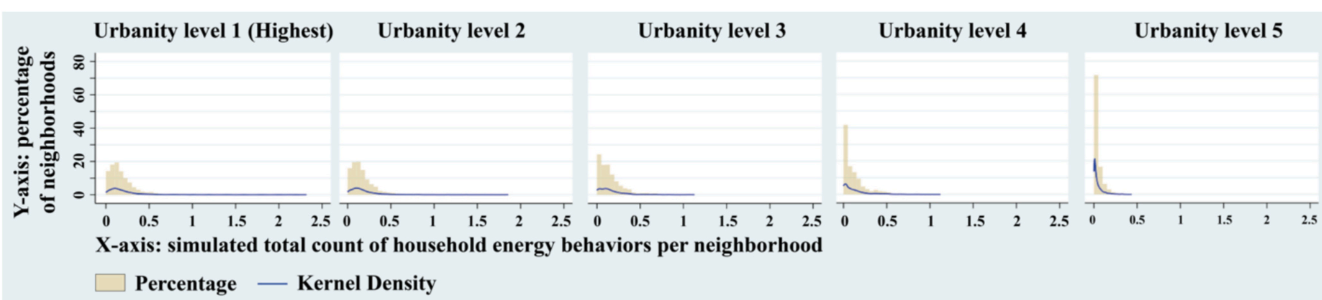

Fig. 5. Simulated distribution of household energy behavior adoption by urbanity level.

relatively lower average adoption rates. These findings align with previous studies that emphasize higher adoption rates of household energy behaviors in areas with greater population density (Babutsidze & Chai, 2018; Beattie, Han, & La Nauze, 2019). High-density neighborhoods provide greater opportunities for observation, social interactions, and information transmission, fostering behavioral visibility and environmental behavioral spillovers. These dynamics increase the likelihood of individuals adopting energy-efficient behaviors by observing and learning from peers.

Fig. 4 also highlights the spatial clustering of household energy behavior adoption rates, with neighborhoods of similar adoption rates grouping together. For example, the Randstad area, including Rotterdam, The Hague, Amsterdam, and Utrecht, contains many high-adoption neighborhoods, while Drenthe predominantly exhibits low-adoption neighborhoods. To quantify this clustering, Global Moran's I is calculated using the spatial weights matrix, yielding a positive and statistically significant value of 0.196 ($p = 0.000$), confirming spatial autocorrelation. High-adoption neighborhoods tend to cluster near other high-adoption areas, and low-adoption neighborhoods similarly group together. To further explore localized spatial patterns, Local Moran's I (LISA) analysis is performed to identify specific clusters of similar adoption rates. The results, shown in Fig. 6, reveal distinct spatial patterns: low-low clusters dominate the northern regions, while high-high clusters are concentrated in major urban centers such as Rotterdam, The Hague, Amsterdam, and Utrecht.

4.2. Spatial econometric regression results

This section presents the outcomes of the spatial econometric regression analysis. The first column of Table 4 summarizes the results of the non-spatial OLS model alongside spatial diagnostics. All classic and robust Lagrange Multiplier (LM) tests yield statistically significant

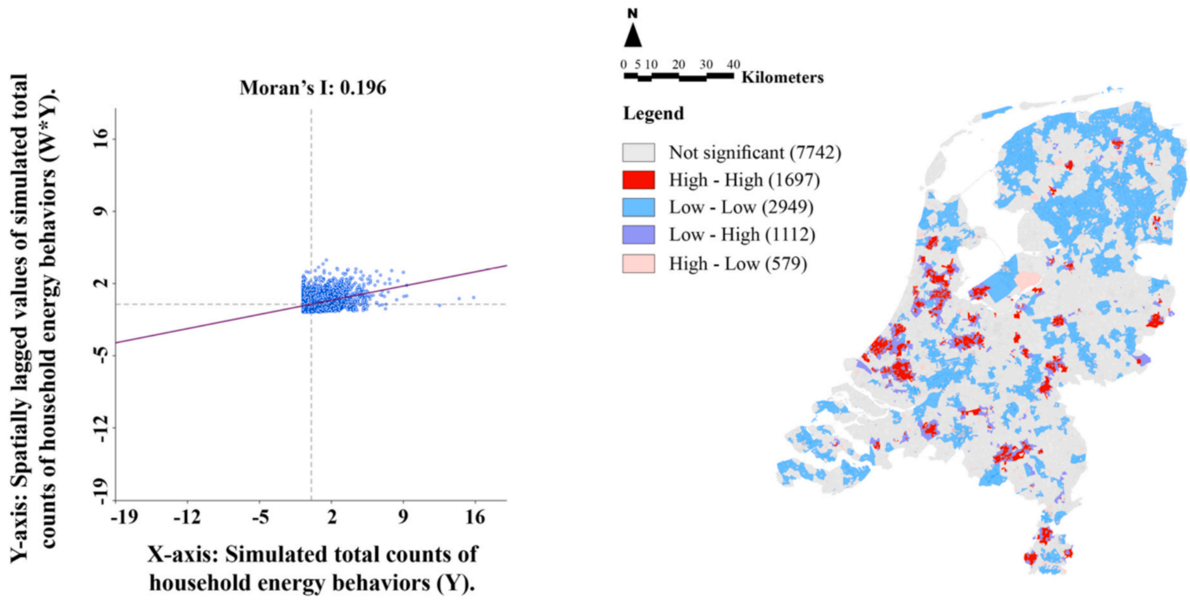

Fig. 6. Moran's I test and LISA cluster map.

results (LM lag = 2,117.727***, LM error = 4,439.246***, Robust LM lag = 36.540***, Robust LM error = 2,358.068***), indicating the presence of spatial dependence. Consequently, the null hypothesis of no spatial dependence is rejected, confirming that the OLS model is inadequate for capturing the spatial structure inherent in the data. Consequently, to account for this spatial dependence, two alternative spatial models i.e. SAR and SEM are considered. Given this study's emphasis on spatial endogenous effects, the SAR model is selected for further analysis in the discussion session, with its results presented in the second column of Table 4.

5. Discussion

5.1. Spatial endogenous effects

The autoregressive parameter ($\lambda = 0.494$***) indicates significant spatial autocorrelation, confirming spatial endogenous effects at the neighborhood level on household energy behavior adoption rates. This suggests that energy-efficient practices in one neighborhood can boost adoption in surrounding areas. This result aligns with prior studies. For example, Zhang, Liu, and Ballas (2023) report a comparable value of 0.407 for solar PV installations based on 13,208 Dutch neighborhood samples, while Kucher et al. (2021) document an estimate of 0.410 using data from 111 mid-Atlantic counties in the US. Similarly, Müller and Trutnevyte (2020) report a value of 0.45 across 143 Swiss districts. Higher estimates are documented by Schaffer and Brun (2015) and Dharshing (2017), who identify values of 0.65 and 0.76, respectively, using cross-sectional data and panel data from 402 German counties.

The spatially endogenous nature of energy behaviors is well-documented in the literature. First, behavioral economics highlights that consumer decisions about energy technologies are influenced not only by economic considerations but also by non-economic factors, such as prior experiences, expectations, and trust-based information networks (Rai & Henry, 2016). Limited knowledge and experience with emerging energy technologies can hinder decision-making processes, as individuals often lack sufficient information to make fully informed choices (Frederiks, Stenner, & Hobman, 2015). In such scenarios, learning from early adopters becomes crucial. Interactions with early adopters can supplement knowledge, shape perceptions, and influence expectations and behaviors. Geographic proximity facilitates these interactions through mechanisms such as word-of-mouth communication and observational learning, which help explain the spatial clustering of energy technology adoption (Liu, Qi, & Xu, 2023; Meyners, Barrot, Becker, & Goldenberg, 2017).

Second, concerns about social status also drive spatially endogenous effects. Social status is often shaped by the predispositions and actions of one's peer group, which serve as signals reflecting shared norms and expectations (Messick, 1999). To maintain their group identity and achieve social conformity, individuals tend to align their behaviors with a unified standard of conduct within their community (Contractor & DeChurch, 2014; Hogg & Reid, 2006). Third, descriptive social norms play an important role in reinforcing these effects. People tend to emulate the behaviors of the majority within their social environment to avoid disapproval or criticism. Even small deviations from established norms can jeopardize social status and invite strong criticism or accusations of non-conformity (Ioannides & Topa, 2010). These norms create a reinforcing cycle where visible energy-efficient practices in a neighborhood encourage others to adopt similar behaviors, amplifying the spatial clustering of energy behaviors.

5.2. Neighborhood-specific characteristics

The analysis identifies several neighborhood-specific characteristics that positively and significantly influence the adoption of household energy behaviors. First, *population density* ($\beta = 0.022$***) significantly influences household energy behavior adoption, aligning with previous studies (Briguglio & Formosa, 2017; Graziano, Fiaschetti, & Atkinson-Palombo, 2019; Müller & Trutnevyte, 2020; Schaffer & Brun, 2015). As highlighted in the descriptive analysis, urban areas consistently exhibit higher adoption rates than rural regions. This disparity is largely driven by the dynamics of behavioral visibility and information transmission associated with densely populated settings (Babutsidze & Chai, 2018; Beattie et al., 2019). In such areas, individuals have more opportunities to observe and interact with others, facilitating the flow of information and the exchange of experiences. These social interactions amplify behavioral spillover effects, where residents are more likely to adopt energy-efficient practices after observing similar actions in their community (Consiglio, De Angelis, & Costabile, 2018). However, this finding contrasts with studies reporting a negative relationship between population density and household energy behavior adoption (Balta-

Table 4
Estimation results ($n = 14,080$).

Variables		OLS	SAR	SEM
		β	β	β
Intercept		0.002	−0.044	0.008
Socio-demographics				
Ages	Percentage of pop^n aged 26–45 (%)	−0.033**	−0.041***	−0.042***
	Percentage of pop^n aged 46–65 (%)	−0.044 ***	−0.036***	−0.036***
	Percentage of pop^n aged over 65 (%)	−0.063***	−0.042***	−0.051***
Education	Percentage of pop^n with high education (%)	0.016	0.029***	0.0005
Household type	Percentage of multi-person households (%)	0.040***	0.043***	0.048***
Financial capacity				
Income	Percentage of pop^n receiving income (%)	0.0002***	0.0002***	6.71844e-0.5
Log property value	Natural logarithm of average property value (1,000 euros)	0.006***	0.003***	0.005***
Environmental awareness				
Log electricity consumption	Natural logarithm of average annual electricity use (kWh)	−0.010***	−0.009***	−0.012***
Built environment				
Log population density	Natural logarithm of population density	0.024***	0.022***	0.030***
Home ownership	Percentage of owner-occupied houses (%)	−0.0003***	−0.0002***	−0.0003***
House age	Percentage of houses built before 2000 (%)	0.010***	0.006*	0.009***
House structure	Percentage of detached houses (%)	−0.016***	0.006	−0.012***
Rho			0.494***	
LAMBDA				0.651***
Log Likelihood		14,002	14,673.9	15,029.704
R^2		0.343	0.413	0.451
Akaike Information Criterion (AIC)		−27,978	−29,319.8	−30,033.4
Moran's I		0.195***		
LM lag		2117.727***		
LM error		4439.246***		
Robust LM lag		36.540***		
Robust LM error		2358.068***		

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Ozkan et al., 2015; Kucher et al., 2021) These studies argue that densely populated areas, often dominated by less-detached dwellings, pose challenges for renewable energy technology integration, such as limited rooftop availability and construction constraints. In the Netherlands, this discrepancy may stem from the high proportion of detached houses, which account for 79 % of residential buildings—ranked second highest in the EU27 (Eurostat, 2023).

Educational levels ($\beta = 0.029$***) show a significant positive effect, where a 1 % increase in the share of the educated population corresponds to a 2.9 % increase in household energy behavior adoption rates within the same neighborhood. This finding aligns with existing studies, such as Niemeyer (2010) and Dharshing (2017), which highlight the positive influence of educational attainment on energy behavior adoption. Alem et al. (2016) and Mills and Schleich (2012) argue that Education enhances environmental awareness and knowledge of energy-efficient solutions, equipping individuals to better evaluate the long-term benefits of energy-saving measures and make informed decisions regarding their adoption. Furthermore, educated individuals are often more aware of government incentives, technological advancements, and the cost-saving potential of energy-efficient upgrades (Acheampong & Cugurullo, 2019). Consequently, they tend to exhibit higher levels of environmental consciousness and possess a more comprehensive understanding of options related to energy conservation and alternative energy sources (Saari, Damberg, Frömbling, & Ringle, 2021).

A higher *percentage of multi-person households* is associated with significantly greater adoption rates of energy-efficient practices. The positive estimate ($\beta = 0.043$***) indicates that a 1 % increase in the share of multi-person households is associated with an average 4.3 % increase in household energy behavior adoption within the same neighborhood. This finding corroborates prior studies by Bashiri and Alizadeh (2018) and Van der Kam et al. (2018) and Best, Burke, and Nishitateno (2019). We similarly attribute this trend to two factors. First, multi-person households often face higher energy expenses due to the cumulative energy consumption of multiple occupants, creating a stronger incentive to adopt cost-saving technologies (Balcombe, Rigby, & Azapagic, 2013). Second, these households benefit from pooled financial resources, making it easier to afford upfront investments in energy-efficient technologies. The shared decision-making dynamics within multi-person households may further encourage these investments, as joint financial responsibilities can make long-term energy savings more appealing (Huebner, Shipworth, Hamilton, Chalabi, & Oreszczyn, 2016).

Income is positively associated with household energy behavior adoption ($\beta = 0.0002$***), consistent with studies showing that high-income households are more likely to adopt energy-efficient measures (Dharshing, 2017; Umit et al., 2019). This tendency can be attributed to several factors. High-income households often have the financial capacity to manage the substantial upfront costs associated with energy-efficient technologies, such as solar PV installations and home retrofits (Best, Nepal, & Saba, 2021; Nielsen, Nicholas, Creutzig, Dietz, & Stern, 2021). Additionally, their greater financial flexibility and risk tolerance enable them to adopt innovative technologies earlier, gaining long-term benefits despite initial costs (Urban & Ščasný, 2012). Moreover, high-income households are better positioned to bear the significant initial expenses of energy-efficient upgrades and have the resilience to wait for returns on these investments over time (Crago, Grazier, & Breger, 2023; Lekavičius, Bobinaitė, Galinis, & Pažėraitė, 2020). Conversely, lower-income households may encounter substantial financial challenges that limit their ability to invest in energy retrofits or renewable energy measures, particularly those with high upfront costs, where affordability becomes a significant barrier (Brown et al., 2019; Chandrashekeran et al., 2024).

Additionally, *property value* ($\beta = 0.003$***) exerts a positive and significant influence on energy behavior adoption. This finding aligns with evidence in the literature suggesting that homeowners of higher-value properties are more likely to invest in energy-efficient upgrades due to the dual market benefits, including enhanced property valuation and improved marketability (Best, Esplin, Hammerle, Nepal, & Reynolds, 2023; Jakob, 2006). For instance, Fuerst, McAllister, Nanda, and

Wyatt (2016) provide evidence from Wales, the UK, showing that homes with high energy performance certificate ratings appreciate in value more rapidly, offering clear financial incentives for energy efficiency improvements. Similarly, Lan, Gou, and Yang (2020), using housing data from Southport in Queensland, Australia, demonstrate that energy-efficient homes historically sell faster than their less-efficient counterparts. More recently, Carroll, Denny, Lyons, and Petrov (2024) provide evidence from the Irish nationwide housing market, showing that energy-efficient properties not only sell faster but also benefit from cost-effective energy labels that significantly reduce the time-to-sell.

Furthermore, our findings indicate that neighborhoods with a higher *percentage of old houses* (built before 2000) tend to have higher adoption rates of household energy behaviors. The estimate ($\beta = 0.006^{*}$) suggests that a 1 % increase in the share of houses built before 2000 is associated with a 0.6 % increase in the neighborhood's household energy behavior adoption rate. This positive correlation aligns with findings in previous studies (e.g., Vega, van Leeuwen, & van Twillert, 2022) and reflects multiple contributing factors. First, older houses are often less energy-efficient due to the construction technologies and materials available at the time of their development. These houses typically lack advanced insulation, double glazing, and modern heating systems, making retrofitting essential for improving energy efficiency. In contrast, newer homes often incorporate energy-saving features, reducing the immediate need for upgrades (Hamilton, 2021). Second, older homes are more likely to qualify for policy incentives and subsidies aimed at retrofitting and energy renovations, such as the *Sustainable Energy Investment Subsidy* in the Netherlands, which provides financial support for adopting energy-efficient technologies in older properties. Moreover, outdated systems in older homes often result in higher energy consumption, making the potential cost savings from energy-efficient upgrades particularly attractive to their owners. This economic incentive motivates households in these neighborhoods to adopt energy-saving behaviors and technologies (Wilson, Crane, & Chryssochoidis, 2015; Wilson, Pettifor, & Chryssochoidis, 2018).

In contrast, *annual electricity uses,* and *the percentage of owner-occupied houses* are identified as negatively influencing the adoption of household energy behaviors. The negative correlation between *electricity consumption* ($\beta = -0.009^{***}$) and household energy behavior adoption aligns with findings in some studies (e.g., Zhang, Ballas, & Liu, 2023) while diverging from others that report a positive effect of energy demand. For example, Balta-Ozkan, Yildirim, Connor, Truckell, and Hart (2021) suggest that households with higher energy demands may be more motivated to adopt energy-saving measures to achieve self-sufficiency. A possible explanation is that households with higher electricity consumption may exhibit lower environmental awareness, reducing their motivation to adopt energy-efficient behaviors (Broska, 2021; Conrad & Hilchey, 2011; Li, Zhang, Zhang, Ji, & Lucey, 2021). Supporting this, Smiley, Chen, and Shao (2022) use green vote share data in Copenhagen, Denmark, as a proxy for environmental awareness and find a strong positive correlation between environmental awareness and pro-environmental behaviors. Similarly, Van der Kam et al. (2018) use Dutch data, and Dharshing (2017) analyze German green voter data, both demonstrating that higher environmental awareness significantly influences the adoption of energy-saving measures.

Surprisingly, our findings indicate that neighborhoods with a higher *percentage of owner-occupied homes* have lower rates of energy behavior adoption ($\beta = -0.0002^{***}$), contrary to much of the literature, which typically identifies a positive relationship (e.g., Briguglio & Formosa, 2017; Schaffer & Brun, 2015; Vega et al., 2022). Homeownership is generally linked to long-term investments like solar PV systems, as homeowners benefit from sustained property value improvements (Rochlitz & Hagist, 2024). The negative association observed in our study could be attributed to several factors. One potential explanation relates to the temporal scope of the survey data, which spans respondents' behaviors from 2017 to 2021. Many homeowners may have already adopted energy-saving measures before this period, resulting in lower observed adoption rates during the survey timeframe. Another significant factor is the impact of recent housing policies in the Netherlands that emphasize green metrics for rental properties. For example, the nationwide Housing Valuation System (Woningwaarderingsstelsel, WWS) directly links energy efficiency to rental prices by assigning additional points to properties with better energy performance, such as higher Energy Performance Certificate ratings. These points contribute to the calculation of the maximum allowable rent, providing landlords with a clear financial incentive to invest in sustainable upgrades. This incentivizes landlords to invest in energy-saving measures to enhance their property's energy performance. Moreover, in regulated rental sectors, where rent control caps the maximum rent based on the WWS score, achieving higher energy efficiency ratings can have significant financial implications. Properties that accumulate sufficient points through energy-efficient improvements can surpass the rent control thresholds, allowing landlords to transition their properties into the free-market rental sector. In this sector, rents are not capped, enabling landlords to charge higher prices and realize greater returns on their investments in energy performance upgrades.

6. Conclusion

Current studies in household energy behavior modeling often rely on low-resolution spatial data, limiting their ability to capture place-specific characteristics and model spatial interactions. This constraint is primarily due to the lack of data with detailed geographic information. To address this challenge, we integrate two widely used spatial analysis models to examine household energy behavior adoption at a fine geographic scale, covering 14,080 neighborhoods in the Netherlands. First, we develop a static spatial microsimulation model to generate synthetic population microdata, incorporating socio-economic characteristics and energy behavior outcomes for the entire country. These micro datasets are then spatially aggregated at the neighborhood level and serve as input for spatial econometric models. This approach allows us to analyze neighborhood-level spatial determinants of energy behavior adoption while simultaneously accounting for localized factors and spatial interactions at a significantly finer spatial scale.

We present two key empirical findings. First, we identify notable *spatial endogenous effects* in the adoption of household energy behaviors among spatially proximate neighborhoods. This suggests that the adoption of energy-efficient practices in one neighborhood can potentially boost energy behaviors in surrounding neighborhoods. Second, when accounting for *spatial endogenous effects*, several neighborhood-specific characteristics are positively associated with household energy behavior adoption. Specifically, neighborhoods with higher *population densities*, a higher *percentage of highly educated individuals*, a higher *percentage of multi-person households*, a higher *percentage of individuals receiving income*, higher *property values*, and a higher *percentage of older houses in the neighborhood housing stock* tend to show higher rates of energy behavior adoption. Conversely, our results indicate that the adoption of energy behaviors is negatively associated with *annual electricity use* and the *percentage of owner-occupied houses in the neighborhood housing stock*.

Our findings reveal important implications for policymakers and network operators from a spatial perspective. First, we highlight the necessity of accounting for place-specific characteristics and the diverse nature of populations when designing policy interventions aimed at promoting energy-efficient behaviors. A one-size-fits-all approach is unlikely to succeed given the heterogeneity of local conditions. Instead, interventions should be tailored to the unique attributes of individual neighborhoods, leveraging the factors we identify as significant drivers of household energy behaviors. Taking the positive role of population density in household energy behavior adoption as an example. High-density areas are particularly suitable for shared infrastructure projects, such as community solar installations, district heating systems, or shared EV charging stations, which can make energy-efficient technologies more accessible and cost-effective. Additionally, densely populated neighborhoods are ideal for centralized energy advice centers or community energy hubs, which can provide tailored guidance, workshops, and resources to support adoption. Pilot programs can also be implemented in these areas to test innovative energy solutions, such as smart grids or energy storage systems, with the potential to scale successful initiatives citywide or nationally. For instance, *Copenhagen's district heating system* provides centralized heating to over 98 % of the city's buildings by utilizing surplus energy from waste incineration plants, biomass facilities, and industrial heat, leveraging its dense urban network. Similarly, *Rotterdam's Green Roof Initiative* capitalizes on high-density urban areas by installing energy-efficient green roofs, enhancing insulation and stormwater management while fostering visible community participation.

In addition to enhancing efforts in neighborhoods with high adoption rates, policymakers should identify and address barriers in high-potential areas, such as those with high population density but low adoption rates. Identifying and mitigating these barriers is critical for unlocking latent potential. For example, the *UK's Energy Company Obligation* program targets low-income and fuel-poor households, particularly in urban areas where adoption has lagged despite significant potential. Through surveys and consultations, policymakers identify challenges such as financial constraints, lack of information, or limited access to technologies. The program offers tailored solutions, including subsidies, low-interest loans, and tax incentives to reduce the upfront costs of energy-efficient measures. Localized outreach campaigns, mobile advice centers, and partnerships with community organizations further enhance awareness and accessibility, creating a pathway for increased adoption in these underserved areas.

Third, our findings highlight significant spatial endogenous effects in household energy behaviors. This indicates that policies put into place to encourage household energy behaviors in one place may generate additional adoptions in surrounding areas stemming solely from these spatial endogenous effects. From a policy perspective, enhancing the visibility of household energy behaviors and creating knowledge-sharing platforms are effective strategies to foster imitative green behaviors across communities. For example, *housing energy labeling schemes* in many European countries prominently display energy efficiency ratings, establishing behavioral norms among households. These labels not only raise awareness but also serve as benchmarks, creating a ripple effect where highly rated properties inspire broader adoption of energy-efficient practices and investments. Another notable initiative is *Amsterdam's Energy Atlas*, an interactive tool that visualizes sustainable energy practices across the city to stimulate their adoption. The atlas provides detailed information on energy consumption, renewable energy production, and potential opportunities for improvement. For instance, it highlights neighborhoods with solar panel installations, energy-efficient retrofits, and other green initiatives. By making this data publicly accessible, the Energy Atlas raises awareness about local energy behaviors and inspires households and communities to adopt similar measures, fostering a city-wide transition to sustainability.

Additionally, fostering social interactions through partnerships among stakeholders, such as environmental organizations, energy companies, charities, and local authorities, can significantly amplify knowledge dissemination and the adoption of energy-efficient practices. An example is the *Solarcity Berlin Program* in Germany, which brings together more than 22 entities in a collaborative network and combines grassroots engagement with structured initiatives to accelerate solar PV adoption. The program organizes community workshops, information campaigns, and conferences to educate residents about solar technology, installation processes, and financing options. These events often feature live installations on community buildings, offering tangible demonstrations of solar panel effectiveness and simplicity. To further inspire participation, the initiative implements local demonstration projects like public exhibitions and competitions, showcasing practical applications of solar technology and fostering enthusiasm within the communities. The program also promotes peer-to-peer knowledge sharing through neighborhood meetings and online forums, enabling residents to exchange firsthand experiences and practical advice. Similarly, the *Power of Neighbors* initiative in the Netherlands fosters collaboration among residents to promote energy-saving actions. The initiative empowers communities to organize collective projects, such as group purchases of solar panels and insulation materials, thereby reducing costs and maximizing impact. It also provides robust support, including expert consultations, tailored guidance on energy-efficient technologies, and access to customized resources.

For network operators, our methodologies offer a framework to simulate the spatial distribution of energy-efficient measures at granular scales. This simulation provides valuable insights into potential fluctuations in energy supply and demand, particularly in areas with high adoption of renewable and distributed energy sources. These insights allow operators to make informed, data-driven decisions to design and optimize energy infrastructure. For instance, strategically placing inverter-based grids or implementing other adaptive technologies can enhance system stability by enabling better control of critical parameters such as frequency, rotor angle, and demand flows. These measures ensure that the grid can accommodate fluctuations in renewable energy output while maintaining reliability and efficiency. Moreover, the granular understanding gained through this approach facilitates the deployment of demand-side management strategies, such as incentivizing load shifting during peak production times or integrating energy storage solutions in high-demand areas. These interventions can help mitigate mismatches between energy production and consumption, reducing the risk of overloading the grid or wasting excess renewable energy.

The approach presented in this study is effective for modeling spatial heterogeneity and cross-border interactions at fine spatial scales. It is adaptable to diverse contexts, provided suitable constraint variables linking survey and census data are available. Our study focuses on the Netherlands, where minimal nationwide variation in electricity rates, solar radiation, and subsidy schemes enables an analysis of spatial endogenous effects of behavior adoption while simplifying the modeling process by excluding spillover effects from these factors. This method can also be applied in other countries in Europe with comparable data sets as well as larger countries such as China and the United States to simulate both direct and spatial spillover effects of regional disparities in policies, incentives, and climate on household behaviors at fine spatial scales. Moreover, this approach can also be considered for application to specific regions characterized by strong community dynamics but limited data availability, as long as there is a minimum level of social survey microdata and small area data to conduct spatial microsimulation. Examples include informal settlements like favelas in Brazil and slums in South Africa and India. Beyond household energy behaviors, this methodology is well-suited for scenarios where individuals rely heavily on social networks for decision-making due to limited prior experience or knowledge. Relevant applications include adopting broadband technologies and digital literacy programs, engaging in health-related behaviors such as vaccination campaigns, and choosing sustainable transportation options like shared mobility services and public transit usage.

Naturally, our study has several limitations. A key limitation is the sample size used for spatial microsimulation, a common challenge in the field. This study relied on data from 34,222 recorded energy behaviors from 46,659 individuals to simulate the entire Dutch population. Larger sample sizes, as demonstrated in previous studies, generally produce more accurate population representations. Future research could enhance accuracy by using a larger input sample and incorporating a broader range of constraint variables to better link survey and census data, further refining the synthetic population. A second limitation involves the spatial econometric model, which did not account for regional variations in policy incentives, electricity tariffs, and solar radiation—factors known to significantly influence household energy behavior adoption. Incorporating these variables in future models could yield a more nuanced understanding of the determinants of energy-efficient behaviors. The third limitation stems from constraints in the WoOn 2021 survey data, which captures energy behaviors only from 2018 to 2021 and, as a cross-sectional survey, does not track the same respondents over time. As a result, our study cannot account for behaviors implemented before 2018. However, the methodologies presented here could be applied to older datasets, enabling researchers to incorporate the time dimension and analyze whether spatial patterns, such as adoption hotspots, evolve over time.

CRediT authorship contribution statement

Jianhua Zhang: Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Loes Bouman:** Supervision, Methodology, Data curation, Conceptualization. **Dimitris Ballas:** Writing – review & editing, Supervision, Resources, Methodology, Conceptualization. **Xiaolong Liu:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Simulated spatial distribution of five household energy behaviors across 14,080 neighborhoods

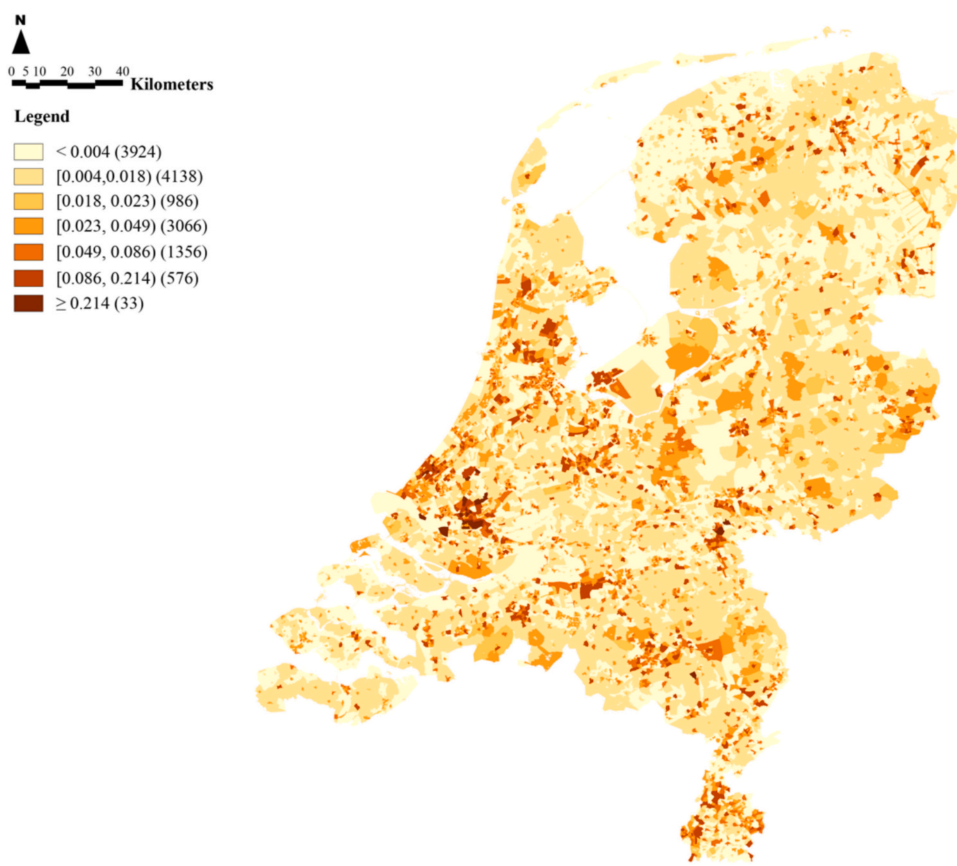

Fig. 7. Simulated spatial distribution of double glazing installation rates across 14,080 neighborhoods.

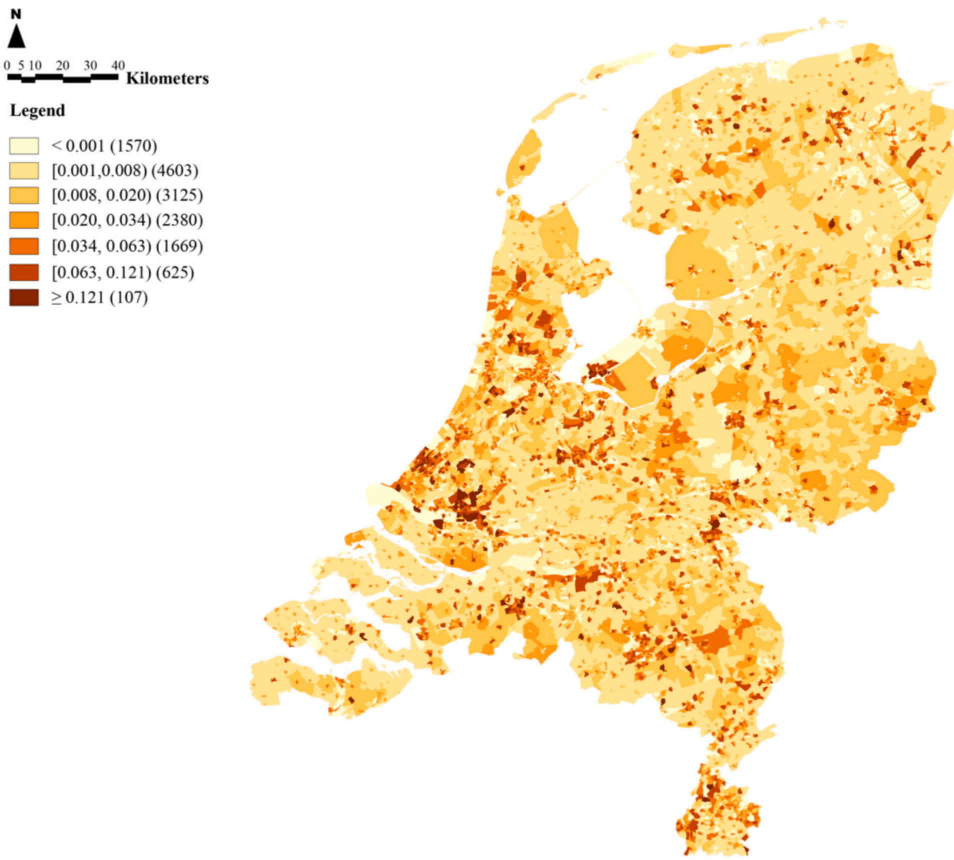

Fig. 8. Simulated spatial distribution of house insulation rates across 14,080 neighborhoods.

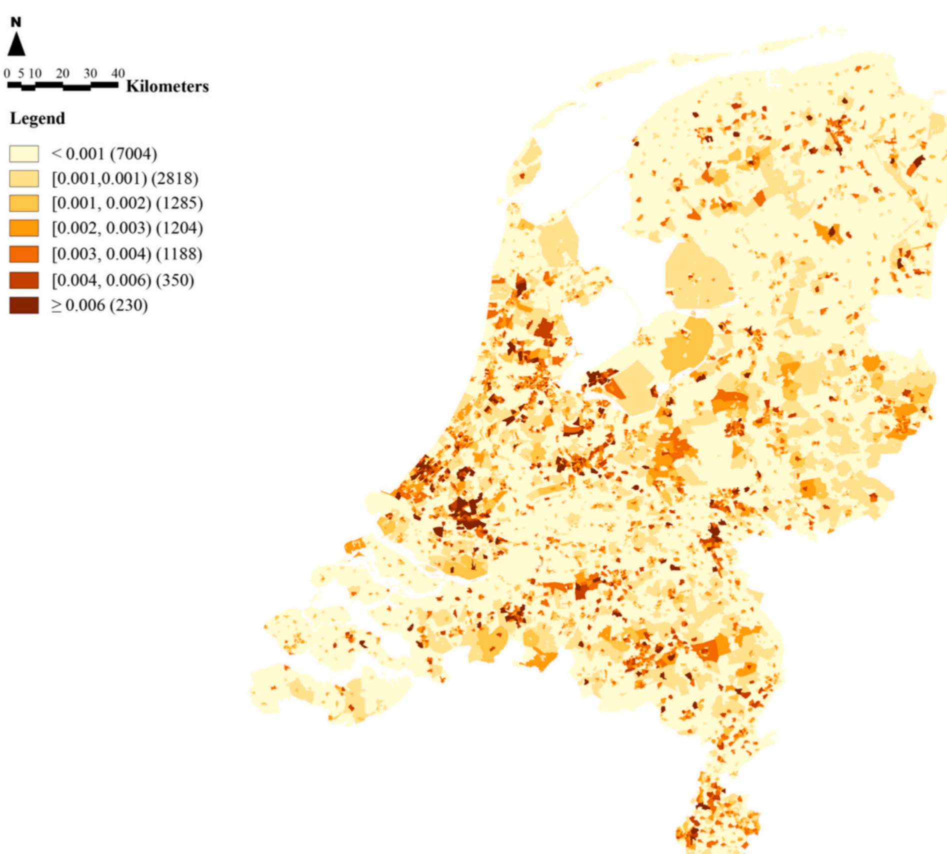

Fig. 9. Simulated spatial distribution of residential solar panel installation rates across 14,080 neighborhoods.

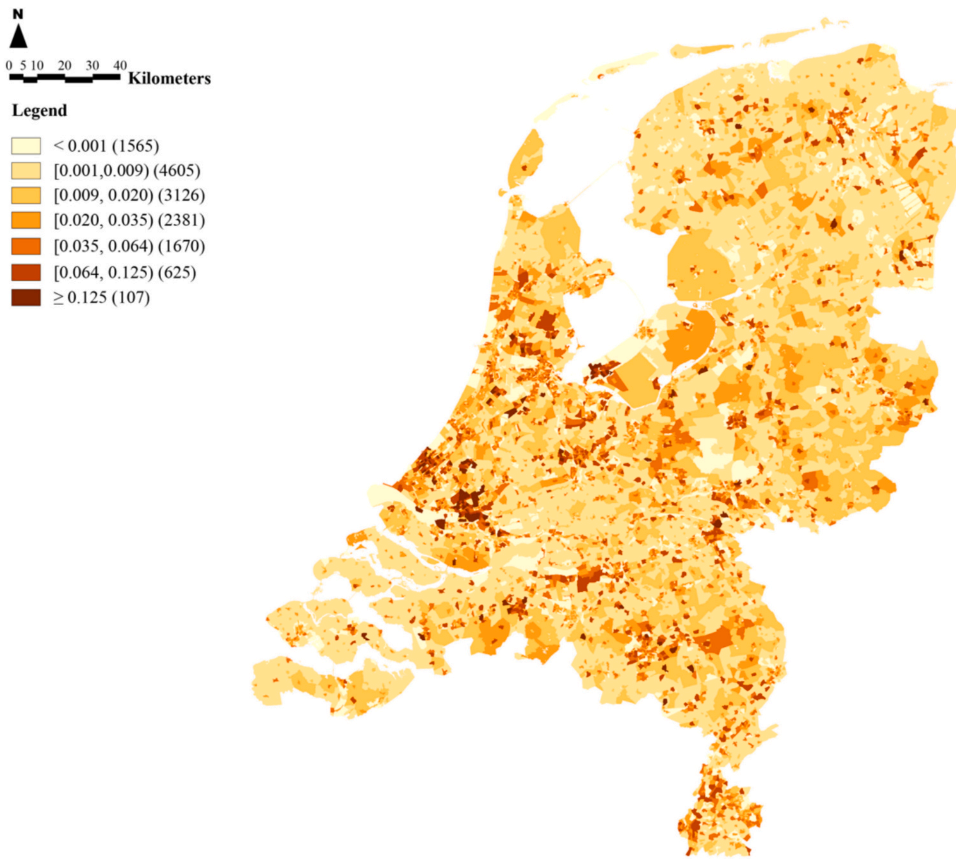

Fig. 10. Simulated spatial distribution of heat pump installation rates across 14,080 neighborhoods.

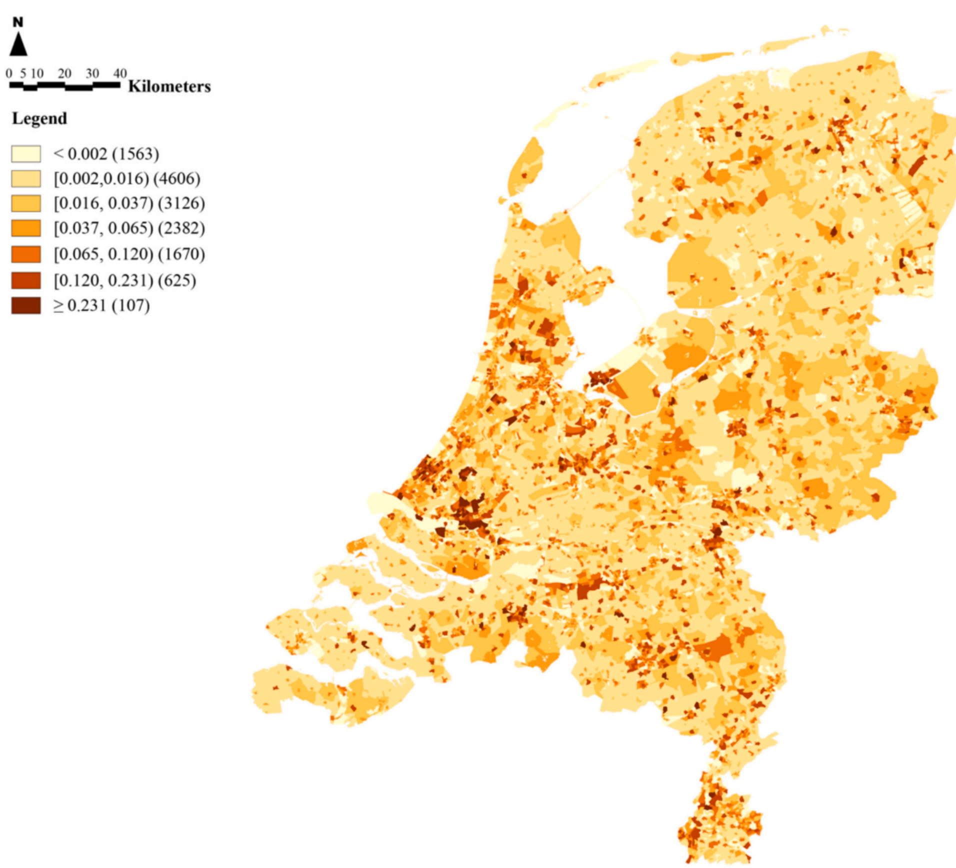

Fig. 11. Simulated spatial distribution of central heating boiler renewal rates across 14,080 neighborhoods.

Data availability

Data will be made available on request.

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