Beyond City Average: Spatial Analysis to Support Energy-Saving Interventions in Urban Planning

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Abstract. Actions to handle the threats posed by climate change-related events and energy crisis are becoming increasingly needed. The transition from fossil fuels-based development to a more sustainable one has been prioritised in global agendas. The energy-saving issue is the foundation of the social and economic model of transformation for the near future and the turning point for sustainable, smart and energy resilient urbanisation. Thus, integrating energy-saving solutions with urban planning remains a challenge. This study aims at bridging this gap by investigating the relationship between urban characteristics and residential energy consumption using statistics and spatial analysis. Starting from deepening the results of a first GIS-based analysis applied to Naples (Italy) and the methodology behind them, this contribution aims at exploring how to support policy-makers in decision processes by implementing novel representation techniques. This study reveals how urban context dynamically impacts household energy usage, with a focus on green urban areas, by using Geographically Weighted Regression (GWR) and depicting the non-stationary estimation coefficients derived from the investigation. This knowledge could enable local decision-makers to maximize the efficiency of energy-saving actions in building more resilient and sustainable cities by customizing them for particular metropolitan locations.

Keywords: Energy-Saving · Urban Planning · GIS

1 Introduction and Scientific Background

Regardless of the source, energy is a key factor for urban development and, hence, urban areas substantially influence global energy demand and energy-related emissions. In the light of the increasing impact of climate change-related phenomena and the need to boost a transition towards more sustainable models, energy saving is becoming a major concern for urban scientists, stakeholders and planners.

It is worth noting that cities consume about 75% of global primary energy and emit between 50% and 60% of total greenhouse gases [1]. This trend peaks at approximately 80% when also the indirect emissions generated by urban inhabitants are included [2].

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As far as the European scenario, cities take up only 4% of the EU land area yet are home to 75% of citizens, and this number is expected to rise to approximately 84% by 2050 [3].

Cities, as complex macrosystems, consume a significant amount of energy across various sectors, including buildings, transportation, and industry. Buildings are major energy consumers throughout their life cycle, from material extraction and construction to ongoing maintenance and daily operations like heating, cooling, and lighting [4]. Urban sprawl further exacerbates energy demands by increasing commute distances and hindering the effectiveness of public transport systems, leading to greater reliance on private vehicles [5, 6]. Sprawling cities also contribute to the formation of the urban heat island phenomenon: due to the heat absorption of concrete and asphalt, and lack of green spaces, urbanized areas can get significantly warmer than surroundings. Therefore, urban heat islands generally raise the demand for air conditioning, generating a vicious cycle [7]. These are just a few examples of how cities are challenged by an increasingly complex energy management, due to rapid urbanisation.

Climate change adds urgency, demanding practical solutions to make cities resilient against extreme weather events. Moreover, disruptions in power or fuel supply due to increasingly frequent extreme weather events cascade across infrastructure sectors, impacting businesses, essential services as well as the immediate response of urban system to manage emergencies.

The IPCC's Sixth Assessment Report [8] underscores the link between a city's energy performance and its ability to withstand climate extremes like floods, heat waves, and droughts. The report also warns of escalating risks posed by climate change and states that investments are crucial to accelerate the shift to renewables and away from fossil fuels, mitigating greenhouse gas emissions and bolstering overall energy system resilience. The current energy crisis has further exacerbated the need for cities to curb energy use and finally boost the transition to renewable sources [9, 10].

Despite their vulnerabilities, cities may play a crucial role in turning the current development model, based on an unsustainable fossil fuel dependence into a lower energy footprint and renewable energy use. This shift tackles pollution, greenhouse gas emissions, and potential damage from climate events. This confluence of factors necessitates integrating energy concerns into urban development strategies. However, translating these goals into action remains challenging. Even the latest Conferences of the Parties (COPs), designed to implement the Paris Agreement through practical measures, are struggling to find effective solutions.

Despite these challenges, positive developments have been recorded recently. Recovery plans, developed in response to the Covid-19 pandemic's economic crisis, increasingly emphasise environmental sustainability and energy saving in urban planning tools. In Italy, government incentives like the Ecobonus program (currently in dismission) have promoted energy efficiency and building quality improvements. However, these initiatives lack a focus on collective efforts to enhance the quality of broader urban areas. Given the close connection of the energy challenge to climate resilience, a more comprehensive urban approach should be preferred.

To effectively address these combined challenges, urban planning, building regulations, and other policies need to be integrated to enable a deep and cost-effective decarbonization of all urban activities. Historically, the lack of integration between energy and urban planning has resulted in misalignment between urban development and energy conservation efforts.

To bridge this gap, energy planning must be incorporated into the iterative cycle of urban and territorial transformations. This fosters the development of more comprehensive and effective strategies for reducing energy consumption.

Scientific advancements in recent decades have yielded models to investigate, simulate and, most frequently, to predict energy consumption at the city level. These models fall into two broad categories: top-down and bottom-up [11–13]. Top-down models take a macroscopic view of cities, analyzing historical energy data to understand consumption patterns and their relationship with urban features, considering the effects of technology, socioeconomics, and time. Conversely, bottom-up models examine energy use at the individual building level before extrapolating the data to larger regions. This approach relies heavily on detailed data to analyse individual user consumption. Both approaches are usually designed to predict energy demand in urban areas. Both types of models are mainly used to predict urban energy demand.

This contribution presents the first results of a research specifically targeting the decision-making processes of urban planning by building a solid ground-based knowledge framework, aiming to support local authorities in identifying key areas for intervention to reduce energy consumption. Hence, a GIS-based methodology has been designed in order to delve deeper into the relationships between a city's energy footprint and its urban features.

This research breaks new ground by expanding the investigation from individual buildings to the entire urban environment. This shift in scale necessitates the development of new models capable of interpreting the complex relationships between energy consumption and urban features.

The outcomes of the methodology will help local decision-makers identify areas requiring interventions to reduce energy consumption. Moreover, insights gained into the relationships between energy footprint and urban features will inform the development of more effective urban planning strategies.

The methodology, whose first steps are described in the following paragraph, has been designed with real-world implementation in mind, aiming to integrate energy planning seamlessly with urban and land-use planning processes. The model, built on a Geographic Information System (GIS) platform, will primarily rely on open-source data from resources like ISTAT (Italian Statistical Institute) census tracts. This design choice allows urban technicians and policymakers to easily replicate the model in different areas. In order to test the preliminary steps of the methodology, a case-study approach was adopted and the city of Naples was selected as significant application to validate the methodology results.

This contribution sums the first results of a joint research activity carried out within two research project: NEST[1] - Network for Energy Sustainable Transition and "Definition of a guidelines handbook to implement climate neutrality by improving ecosystem service effectiveness in rural and urban areas"[2].

The contribution is organised as follows: after this introduction, which summed some key elements of the main research question, the developed methodology is presented; in the third paragraph, the results of the application of the methodology to the city of Naples are presented; finally, the last paragraph highlights the main findings as well as areas of improvements for further development of the research.

2 Materials and Method

Recognizing the established connection between urban energy consumption and urban features [14, 15], this contribution presents the early stages of the development of a methodology to identify and weight the most significant urban features. The methodology presented in this section will be the ground of a decision-support tool aimed at identifying strategies and interventions for defining a set of actions and interventions in urban areas to reduce energy consumption. The classification of urban areas based on their features (physical, functional, geomorphological, environmental, climatic and socio-economic) represents the final output of the methodology; such classification will be useful to identify the required interventions of physical transformation, for each kind of urban area, to reduce energy consumption.

The methodology has been designed to be performed in GIS environment, in order to be integrated into urban planning decision processes. In particular, the methodology employs an array of GIS-based statistical and spatial analyses to interpret which urban features significantly affect urban energy consumption and where dependencies among variables are more significant. Hence, the results may explain where these relationships are useful for decision-makers in energy planning.

In this contribution, the first two steps of the methodology will be investigated through an application-based approach: (i) data collection and preparation and (ii) spatial statistical analyses.

The first phase concerns the collection of data and preparation of the dataset. First, urban characteristics and corresponding variables that have the greatest impact on energy consumption have to be identified. Scientific literature suggests taking into account several characteristics of urban environment that can be grouped according to the urban subsystem they relate to:

[1] NEST is a project funded under the National Recovery and Resilience Plan (NRRP), Mission 4 Component 2 Investment 1.3 - Call for tender No. 1561 of 11.10.2022 of Ministero dell'Università e della Ricerca (MUR); funded by the Euro-pean Union –NextGenerationEU.

[2] "Definition of a guidelines handbook to implement climate neutrality by improving ecosystem service effectiveness in rural and urban areas" (CUP E53D23018970001) is a project funded by EU in the NextGenerationEU Plan through the Italian "Bando Prin 2022-D.D. 1409 del 14-09-2022".

– Physical characteristics. Information such as the number of buildings, residential and not residential, construction type, and surface area, is important to understand the key features of the urban fabric and built environment;
– Socio-economic condition. The social and economic circumstances of a city may have an impact on energy usage. Therefore, we have chosen to collect data on variables such as the number of residents, age ranges and employment status. Since economic data per each census tracts are not available, proxy variables have been introduced, such as the education level (given as the percentage of people that accomplished different educational goals).

Twenty one indicators, falling in both groups were selected for analyses. More details on indicators are given in Table 1. To these variables must be added the energy consumption data. Hence, the dataset will also include residential energy consumption given as kWh consumed annually by urban residents.

Since the methodology has been designed to support effective energy saving-oriented urban planning practice, data will be collected using opensource dataset. Moreover, data will be associated to census tracts, which are the minimum territorial reference area for this study. The output of this first phase is a set of arrays, for each territorial unit, collecting data about dependent variable y (energy consumption) and independent variable x_i (concerning urban features for each territorial unit i).

The second step concerns statistical and spatial analyses to obtain a model defining the strength (magnitude of closeness) and the kind (positive or negative) of relationships between the dependent variable (residential electric energy consumption) and independent variables (concerning urban physical and socio-economic environment). Geographically weighted regression (GWR) analyses were chosen to investigate spatial heterogeneities and relationships between energy usage and urban environment features. Since GWR was first proposed by Brunsdon et al. [16], it is being increasingly used in spatial analyses of social, environmental and urban data. The main idea beneath the GWR method is that whole map (constant-coefficient) linear regression models (LRM), such as those estimated by ordinary least squares (OLS) may produce unreasonable conclusions about the stationarity of the regression coefficients under investigation, assuming that regression relationships are the same, no matter where you measure them within the study area. Hence, GWR can be defined as follow:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=i}^{m} \beta_k(u_i, v_i) x_{ik} + e_i \tag{1}$$

where (u_i, v_i) are the spatial coordinates of the observations *i* (the centroids of territorial units), and $\beta_k(u_i, v_i)$ are the coefficients estimated at those locations which describe the kind of relationship (positive or negative) between dependent (y_i) and independent variables (x_{ik}). $\beta_0(u_i, v_i)$ are the intercept terms, while the set of e_i is the random error term, which obeys an independent normal distribution with zero mean and variance σ^2. The calibration process of $\beta_k(u_i, v_i)$ is based on kernel distance-decay functions and their bandwidths. In GWR, bandwidth plays a crucial role as it refers to a distance metric or the number of nearest neighbors used for each local regression equation. It essentially defines the spatial scale of influence for estimating the relationship between variables at a specific location. Automated routines exist to determine an optimal bandwidth for

calibrating GWR coefficients, such as the Akaike information criterion (AIC). In general, the result of larger bandwidth is that the GWR model tends toward a whole-map LRM.

The second stage of the methodology is therefore a flow of statistical and spatial analyses.

First, an autocorrelation analysis will be performed. Using the Global Moran's I Statistics and given a set of features and an associated attribute, the autocorrelation analysis calculates Pearson correlation coefficients and p-values to indicate whether the null hypotheses can be rejected. In this case, the null hypothesis states that the values of the features are spatially uncorrelated. The degree of correlation between variables is a crucial factor to consider before conducting the two spatial analyses, to avoid data redundance and multi-collinearity. The output of this step is a first set of indicators, selected from the original sample by excluding those whose Pearson correlation coefficient exceeds 0.700. Such result is the input of the second step, which consists of performing a first GWR. In order to perform a GWR, the opensource software GWR4 developed and programmed by Professor Tomoki Nakaya of the Department of Geography, Ritsumeikan University, Kyoto, Japan [17]. Our methodology implies for the selection of bandwidth the golden section search based on AICc (Akaike Information Criterion corrected for small sample sizes), which is a relatively efficient way to narrow down the search for the optimal bandwidth.

To further refine the model and focus on the most statistically significant relationships, we employed an iterative approach. After running the initial GWR analysis, choropleth maps will be created to visualise the spatial variations in the coefficients $\beta_k(u_i, v_i)$ of each independent variable. Variables with coefficients exhibiting very low significance (below 90% confidence level for more than 80% of the case study area) from the subsequent GWR model. This step helped to improve the overall model robustness by focusing on the most relevant spatial relationships influencing the dependent variable. Variables with coefficients exhibiting consistently low statistical significance (e.g., below 90% confidence level for a substantial portion, such as 80%, of the study area) will be excluded from the subsequent GWR model. This approach enhances the overall model robustness by focusing on the most statistically significant spatial relationships influencing the dependent variable. Thus, for our research questions where understanding all potential relationships is crucial, even those with weaker statistical support, a lower significance coverage threshold might be considered. This approach was preferred at this stage of the research for a more comprehensive exploration of the spatial dynamics, although the resulting model may be less robust and require careful interpretation due to the inclusion of potentially less reliable relationships. In order to support interpretations, maps and statistical charts will be developed, employing data classification schemes informed by the (nonspatial) data distribution, diverging colour schemes, and bivariate choropleth mapping, in order to highlight whether the relationships between dependent and independent variables are significant and, where they are, whether they are positive or negative [18]. These thematic maps utilize color shading to represent the values of a specific variable across different geographical units, such as census tracts in our case. In our study, choropleth maps were created to depict the local β_k values estimated by the GWR model at each location. Darker or more intense colors on the map indicate areas where the model explains a larger portion of the variation in

energy consumption (higher significance level), while lighter colors represent areas with a weaker model fit.

It's important to acknowledge that alternative spatial regression techniques exist, such as Spatial Autoregressive Models (SAR). SAR models account for spatial autocorrelation, where the dependent variable at one location is influenced by the values of the dependent variable in neighboring locations. However, unlike GWR, SAR models assume a constant relationship between variables across space. In our research question, we were particularly interested in exploring how these relationships might vary geographically. Therefore, GWR, with its ability to capture local variations, was a more suitable choice for investigating the nuanced spatial dynamics influencing energy consumption in urban environment.

Figure 1 below represents the whole methodology workflow, whose first two steps (Data collection and preparation and Spatial and statistical analyses) have been described in this paragraph.

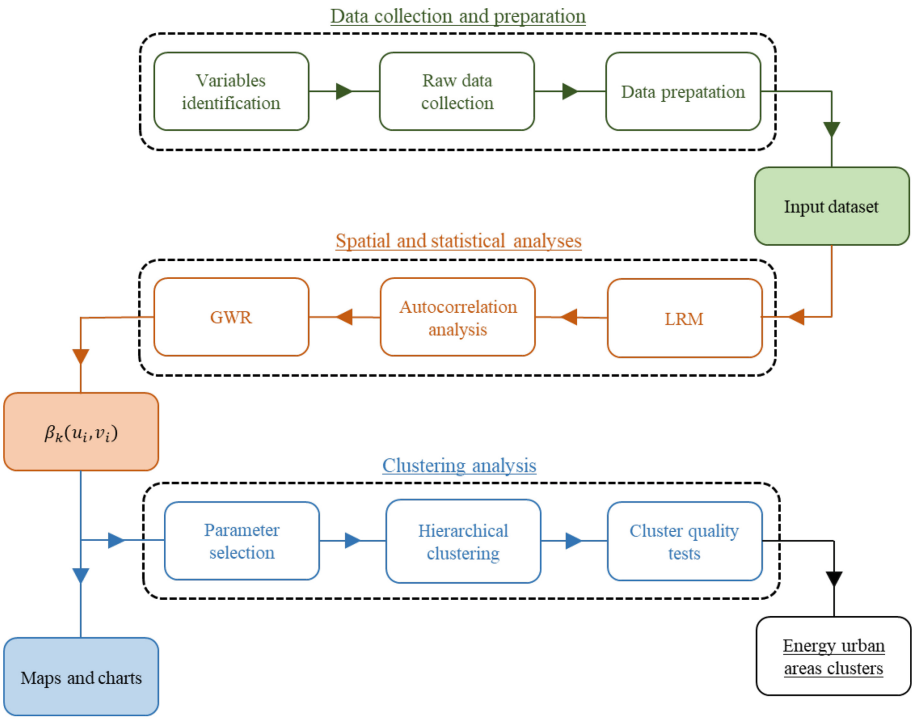


Fig. 1. Methodology workflow.

The following paragraph describes the application of the methodology to the city of Naples and its main results.

3 Application Results

The methodology described in the previous paragraph has been applied to a significant case study in order to be tested. Naples is the third largest Italian city in terms of population, about 909,000 citizens (2022), while it is the most densely populated among major cities. Despite its cultural richness, Naples faces significant challenges regarding energy consumption. The dense urban core, with its older buildings and potentially less energy-efficient infrastructure, is likely to have higher energy demands. Figure 2 below shows how annual electricity consumption per inhabitant varies across the city of Naples. Additionally, economic disparities across different districts might influence energy use patterns. This complex urban environment necessitates a holistic understanding of energy consumption patterns. A one-size-fits-all approach wouldn't be effective. By employing a spatially explicit technique like GWR, we can capture the variations in energy consumption across different districts and develop targeted urban planning and energy management strategies for a more sustainable city.

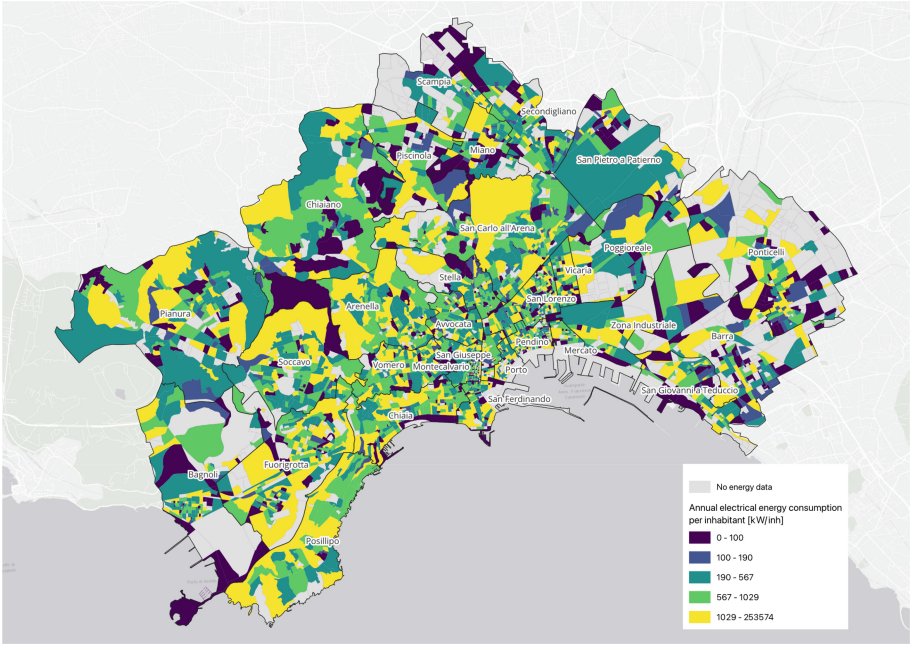


Fig. 2. Annual residential electricity consumption per inhabitant per census tract.

The initial dataset of independent variables was constructed using exclusively open-source data sources to ensure the methodology's replicability across different territorial contexts. Specifically, data was obtained from ISTAT (Italian National Institute of Statistics), Corine Land Cover (CLC), and Città Metropolitana di Napoli (Metropolitan City of Naples). For what concerns energy usage, the annual electrical consumption per census tracts was obtained by Italian revenue Agency (Agenzia delle Entrate). Raw data were then processed in order to be associated to each census tract within the study area.

The second step, concerning spatial statistical analyses, started with a bivariate autocorrelation analysis. We employed Pearson's correlation coefficient to identify and exclude highly correlated independent variables. Variables with a correlation coefficient exceeding 0.70 were removed to mitigate multicollinearity.

Table 1 below presents the selected indicators for the study, along with their descriptions and some initial statistical analyses. The second and third columns, respectively, show the percentage of territorial units where each variable exhibits a significance level exceeding 90%. The third column also highlights indicators with a Pearson correlation coefficient greater than the pre-defined threshold, indicating potential multicollinearity and exclusion from further analysis.

After excluding highly correlated indicators, the initial GWR model based on 16 variables yielded an average local R2 of 0.26. Our primary objective at this stage is to explore the spatial relationships between energy consumption and urban features in greater detail. To achieve this, we examined the significance level of each remaining indicator. We focused on those with a 90% significance level coverage falling below 20% of the entire study area.

To gain deeper insights into the geographically varying relationships between energy consumption and urban features, we employed choropleth maps. The visual representation provided valuable insights for understanding how the strength of the relationships between energy consumption and urban features varies spatially across Naples. Areas with consistently high significance values on the choropleth map might indicate urban features exerting a stronger influence on energy consumption patterns in those locations. Thanks to bivariate colour shading, the direction of the relationship (positive or negative) was also highlighted. These spatial variations, identified through choropleth maps, informed the subsequent exclusion of indicators with limited explanatory power across a significant portion of the study area. This iterative process ultimately led to the development of a more robust GWR model with a stronger explanatory power for understanding the spatial relationships between urban features and energy consumption in Naples.

This iterative process involved excluding additional indicators beyond just addressing multicollinearity. It aimed to identify the variables that most effectively explain the spatial variations in energy consumption. Consequently, a second GWR model was developed using only seven indicators (including the dependent variable). This refined model achieved a higher average local R2 of 0.35, and all remaining indicators exhibited a 90% significance level coverage exceeding 20% of the study area. This suggests a statistically more robust model with a stronger explanatory power.

To visualize the impact of key urban features on energy consumption, we utilized choropleth maps. This contribution focuses specifically on the relationship between the density of urban green areas and energy use.

Table 1 reveals a significant association (greater than 90%) in slightly over 27% of the census tracts analyzed. Interestingly, Image 1 differs from previous choropleth maps exploring energy consumption and other indicators. It shows a wider distribution of census tracts with statistically significant relationships, and these relationships can be either positive or negative.

Table 1. Synthesis of employed independent indicators and some results from statistical analyses.

Indicator	Description	Autocorrelation	GWR 1	GWR 2
		Pearson > 0.70	% 90 significance coverage	
D_P_tot	Density of total population		28,70	64,61
D_rooms	Density of rooms per census tract	x	x	x
I_ut_occ	Ratio between volume of occupied buildings and territorial surface per census tract	x	x	x
P_0_19	Ratio between population aged 0–19 and total population		0,56	x
P_20_64	Ratio between population aged 20–64 and total population		1,51	x
P_over65	Ratio between population aged over 65 and total population		3,53	x
P_grad	Ratio between university graduated population and total population		26,00	20,85
P_high	Ratio between population with high school diploma and total population		29,26	28,51
P_mand	Ratio between population with mandatory school diploma and total population		1,02	x
P_illit	Ratio between illiterate population and total population aged over 6		4,91	x
P_work	Ratio between population in workforce (aged over 15) and total population	x	x	x
P_empl	Ratio between employed population and total population	x	x	x
I_empl	Ratio between employed population and population in workforce	x	x	x
P_unempl	Ratio between unemployed population and total population		11,42	x
I_unempl	Ratio between unemployed population and population in workforce		13,56	x
D_tot_build	Density of building per census tract		70,95	25,09
D_tot_build_res	Density of residential building per census tract		0,00	x

(*continued*)

Table 1. (*continued*)

Indicator	Description	Autocorrelation	GWR 1	GWR 2
		Pearson > 0.70	% 90 significance coverage	
D_notres	Density of not residential building per census tracts		0,00	x
D_mas_buil	Density of masonry buildings	x	x	x
D_con_build	Density of concrete buildings		12,84	24,85
D_sur_green	Density of green areas (ratio between green surfaces and census tract territorial surfaces)		24,23	27,55

The colors on the map (Fig. 3) represent the combination of two information: the red scale, the level of significance of the relationship, while the blue scale how beta coefficient values, estimated by the GWR model, vary their direction, from negative to positive, in the study area. Darker colors likely indicate a positive relationship between green spaces and energy consumption. In these areas, higher green space density might be associated with higher energy use. Lighter colors likely indicate a negative relationship. In these areas, higher green space density might be associated with lower energy consumption.

The map also highlights where energy residential consumption data are missing. Our analysis of green space density and energy consumption in Naples revealed a surprising trend. While initially expecting a negative correlation (green space reducing energy use), approximately 50% of census tracts with a statistically significant relationship (>90% significance level) exhibited a positive association. In simpler terms, these green spaces seem to contribute to higher annual electricity consumption.

This positive relationship is particularly pronounced in peripheral areas, specifically the northeastern and western districts of Naples. These areas tend to have larger, denser green spaces compared to the city center. However, the data also suggests that green spaces are not detrimental to energy savings everywhere, also according to scientific literature on the topic [19–23]. Especially in highly urbanized neighborhoods, both central (Chiaia, Vomero and Posillipo) and peripheral (San Giovanni, Miano and Arenella), green spaces have a significant negative impact on energy consumption. Table 2 provides insightful information for each city neighborhood.

It details the percentage of territorial units where the link between green space distribution and electricity consumption is statistically significant at a 90% confidence level. Additionally, the table shows how the β coefficients vary across these neighborhoods, ranging from negative to positive values.

This result represents the very first attempt to delve deep into the relationships between energy consumption and urban features, and to develop an automated methodology to be integrated into a decision-support tool. While this initial exploration, mainly focused on the extension and distribution of green urban areas, serves as a foundation, it also highlights the potential for further refinement.

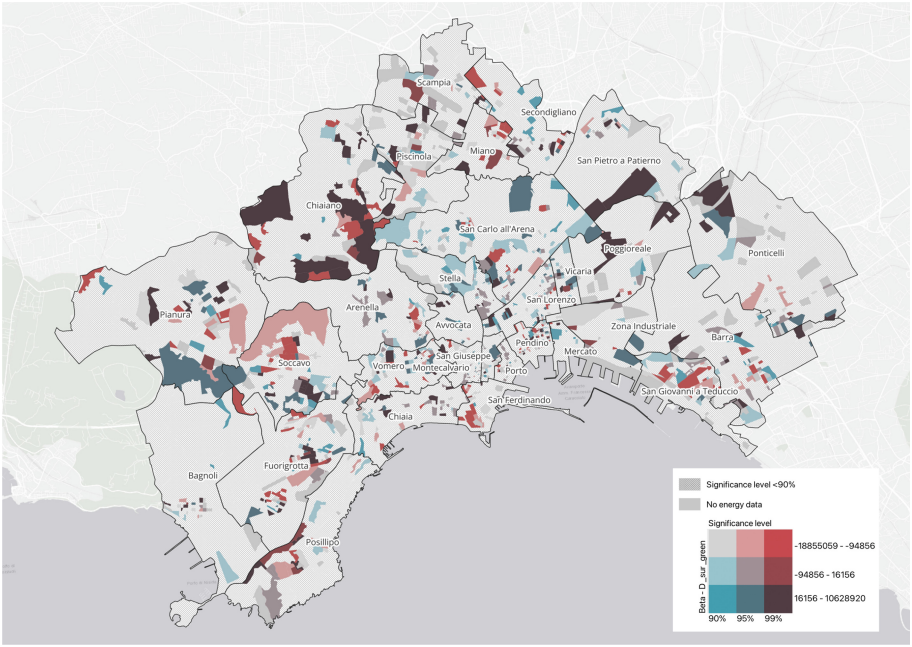


Fig. 3. Choropleth map of main results of GWR model to explain the relationship between density of green urban areas and energy consumption.

Table 2. Main results per neighbourhood.

Neighbourhood	D_sur_green [ha/ha]	90 significance coverage [%]	Units where $\beta > 0$ [%]	Units where $\beta < 0$ [%]
Arenella	0.225	18.78	32.35	67.65
Avvocata	0.052	11.72	66.67	33.33
Bagnoli	0.146	20.27	40.00	60.00
Barra	0.018	27.09	36.36	63.64
Chiaia	0.097	20.71	31.43	68.57
Chiaiano	0.233	44.55	55.10	44.90
Fuorigrotta	0.141	29.96	46.48	53.52
Mercato	0.000	12.07	71.43	28.57
Miano	0.028	30.77	7.14	92.86
Montecalvario	0.115	17.21	33.33	66.67
Pendino	0.000	39.57	40.66	59.34

(*continued*)

Table 2. (*continued*)

Neighbourhood	D_sur_green [ha/ha]	90 significance coverage [%]	Units where $\beta > 0$ [%]	Units where $\beta < 0$ [%]
Pianura	0.216	29.59	42.00	58.00
Piscinola	0.062	41.05	41.03	58.97
Poggioreale	0.134	32.29	58.06	41.94
Ponticelli	0.035	23.29	54.90	45.10
Porto	0.000	30.77	25.00	75.00
Posillipo	0.164	29.55	26.92	73.08
San Carlo all'Arena	0.304	28.41	66.67	33.33
San Ferdinando	0.042	21.43	8.33	91.67
San Giovanni a Teduccio	0.023	37.14	28.21	71.79
San Giuseppe	0.000	28.57	54.55	45.45
San Lorenzo	0.003	25.17	55.26	44.74
San Pietro a Patierno	0.011	32.89	56.00	44.00
Scampia	0.064	33.33	41.94	58.06
Secondigliano	0.069	20.99	41.18	58.82
Soccavo	0.075	38.78	61.40	38.60
Stella	0.244	34.38	75.00	25.00
Vicaria	0.000	25.71	88.89	11.11
Vomero	0.079	27.78	46.67	53.33
Zona Industriale	0.000	28.89	23.08	76.92

4 Discussion and Conclusions

This contribution presents the initial stages of a methodology for classifying urban areas based on their energy consumption patterns and key features. We applied the first two steps of the methodology to the city of Naples, Italy.

Physical characteristics, socio-economic conditions, and relevant proxy variables were defined to holistically depict urban environment. In order to allow the replicability of the methodology, only open-source datasets were consulted for the data collection of preparation step. Statistical analyses, including spatial autocorrelation assessment and Geographically Weighted Regression (GWR), were employed to identify significant relationships between energy consumption and various urban features. The initial GWR model provided insights into the spatial variations of these relationships across Naples. Further refinement through the exclusion of highly correlated variables and those with low spatial significance allowed for the development of a more robust model with a

stronger explanatory power. Choropleth maps were then generated to visualize these variations, effectively depicting how the strength and direction (positive or negative) of the relationships between energy consumption and urban features differ geographically throughout the city.

For this contribution, urban green areas and how they are related to energy demand in cities have been the focus of the research. The results of the application to Naples show that their effect on electricity consumption vary significantly within the city, both in terms of magnitude and direction. In particular, results showed that a negative effect on the total electricity consumption in cities is exacerbated in the northeastern and western districts of Naples, where larger green spaces are located, compared to the city center. On the other hand, in highly urbanised neighborhoods, both central (Chiaia, Vomero and Posillipo) and peripheral (San Giovanni, Miano and Arenella), green spaces have a significant negative direction on energy consumption (contributing at reducing energy consumption).

However, it is important to acknowledge some limitations of the current research. The first concerns open-source data availability. Future iterations could explore incorporating additional data sources, potentially requiring procedure to update data in real-time. A second concern is about the robustness of the model. While the refined GWR model achieved a higher average local R2, there is still room for improvement. Future steps could explore additional explanatory variables or investigate the influence of spatial factors not yet considered.

This initial exploration paves the way for the next stages of the methodology. These will involve, first, the classification of urban areas in Naples based on their shared features and energy use patterns. Secondly, the methodology will include the development of a decision-support tool that can be used by urban planners and policymakers to identify targeted interventions for reducing energy consumption in different districts of the city. Finally, in order to delve into the influence of green areas on energy consumption, further variables will be investigated to take into account the cooling effect they produce in urban areas.

By understanding the spatial relationships between urban features and energy consumption, this methodology can contribute to the development of more sustainable and energy-efficient urban environments.

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