Energy Model for Space Heating in Mendoza, Argentina

Developing a Top-down Statistical Urban Building Energy Model for Space Heating in Mendoza, Argentina

Guglielmina Mutani
Department of Energy, R3C
Politecnico di Torino
Torino, Italy
guglielmina.mutani@polito.it

Mahmoud Ghanipour
Interuniversity Department of Regional and Urban Studies and Planning
Politecnico di Torino
Torino, Italy
MahmoudGhanipour@gmail.com

Ghazale Zabetitarghi
Interuniversity Department of Regional and Urban Studies and Planning
Politecnico di Torino
Torino, Italy
Zabeti.Ghazale1994@gmail.com

Mariela Edith Arboit
Institute of human, social, and environmental sciences
National council of scientific and technical research
Mendoza, Argentina
marboit@mendoza-conicet.gob.ar

***Abstract*—Energy represents a fundamental requirement for the development process, while buildings are becoming essential consumers in urban landscapes. Given the global need to optimize energy use, urban planners and decision-makers are placing increasing emphasis on energy efficiency in urban planning. The focus of this project is on developing predictive energy consumption models that are tailored to different building characteristics and thus offer differentiated insights into energy dynamics. Using a data-centric approach, the study draws on a comprehensive dataset of building characteristics and weather information, with a focus on residential space heating and domestic hot water consumption. The key to this research is the use of district-level gas consumption data as the dependent variable for modeling purposes. Given the different scales of other datasets, a top-down modeling technique was used. In addition, to strengthen the robustness of the analysis and improve understanding of energy consumption patterns, dependent variables were normalized based on factors that have the greatest influence on gas consumption. These factors include urban altitude, population density, number of families, building area, and volume. Another critical aspect of this study concerns the various independent variables that reflect the quality and characteristics of buildings in Mendoza City. Given the heterogeneous nature of the districts, efforts have been made to delineate homogeneous districts with similar consumption patterns through K-means clustering. Examining the relationship between dependent and independent variables required the use of correlation analysis and then applying multi-linear regression to create the model.**

Keywords—Urban building energy models, multi-linear regression, statistical top-down model, space heating, domestic hot water, Geographic Information System, urban planning

I. INTRODUCTION

Today, rapid growth in urbanization and population, driven by economic demands, has led to a significant increase in energy consumption [1]. Combined with the impacts of extreme climate change, this requires a targeted approach to energy planning as part of sustainable development [2]. Such planning is essential for increasing productivity, saving energy, and promoting renewable energy sources, thus shaping urban areas as sustainable entities [3]. At the heart of this process is the need to identify energy consumption patterns and develop predictive models, particularly in the residential sector, which provide a basis for evaluating potential efficiency measures and promoting informed urban development strategies [4]. This study aims to address these needs by developing a top-down urban energy statistical model for Mendoza, Argentina. Using statistical data and computational analysis, the model predicts energy consumption patterns for space heating and domestic hot water in residential buildings according to their different characteristics. By comparing these predictions with real data, the study aims to provide valuable insights into the city's energy landscape and discover priority areas for intervention providing city planners with informed perspectives for future development efforts.

II. LITERATURE REVIEW

A. Global challenges issue and its response

The world's heavy reliance on fossil fuels is unsustainable, posing environmental threats like droughts, floods, biodiversity loss, and climate change. Governments are addressing energy consumption concerns for development goals with rapid urbanization [5]. Annual meetings align urban development goals with environmental sustainability, guided by SDGs. These discussions guide urban planners, emphasizing present needs without compromising future generations' ability to meet their needs [6,7].

B. Urban, building, energy planning

Urban energy demand is increasing, necessitating a holistic approach to planning and management. Buildings, responsible for 27% of greenhouse gas emissions and 30% of global energy consumption, require optimization for sustainable development goals and reduced emissions. Traditional energy planning primarily targets individual building efficiency, focusing on space heating and domestic hot water, which account for 43% and 19% of private and residential energy consumption respectively. However, transitioning from building-scale to urban-scale energy planning requires strategic decision-making to strengthen resilience, reduce carbon emissions, and promote sustainable practices, balancing economic, environmental, and social considerations. [1,8]

C. Urban scale energy models and statistical methods

Urban building energy models (UBEMs) are emerging as crucial tools for effective energy management in urban environments, providing a comprehensive understanding of energy consumption patterns taking into account the spatial variable [9]. UBEMs estimate energy requirements based on urban context, climate conditions, urban heat island effects, building characteristics, occupancy patterns, and social characteristics. They can be categorized as top-down or bottom-up approaches, each suited for specific needs [10]. UBEMs are crucial for understanding, optimizing, and controlling urban energy consumption, promoting sustainable and efficient futures by providing comprehensive energy consumption models [11]

1) Top-down modeling approach

Top-down models provide a comprehensive view of energy consumption at a local or regional level, estimating consumption at district-neighborhood level rather than individual buildings [12]. The method uses data from surveys, utility companies, and census records to analyze energy consumption trends, focusing on socio-demographic and economic characteristics. It also incorporates physical parameters for high-energy consumption location identification and action [13].

2) Statistical method

Statistical methods guide research from planning to data collection, transforming raw data into meaningful insights for accuracy and reliability [14]. This study employs multiple linear regression analysis to categorize variables into independent and dependent energy-related aspects, identifying key factors influencing energy consumption patterns and providing valuable insights.

III. CASE STUDY: MENDOZA, ARGENTINA

In Argentina, most of the primary energy used comes from non-renewable energy sources, where 89% corresponds to natural gas and oil. Mendoza, situated in western Argentina, is the most populous city in the Cuyo region and the fourth largest in the country. According to Argentina's National Institute of Statistics and Censuses (INDEC) [15], Mendoza's population is growing at a rate of 1.2% annually, exceeding the national average. The city is localized on the East of the Andes Mountains, bordering Chile, and its terrain is characterized by foothills, semi-arid plains, and sub-mountain drylands. Mendoza is divided into six departments: Capital, Guaymallén, Las Heras, Godoy Cruz, Maipú, and Luján. Each department has unique characteristics, such as architectural style, population density, and altitude. Each department has separate districts, where energy consumption data is collected. Census tracts are also established within each district to collect information about housing stock, building materials, population and other relevant factors.

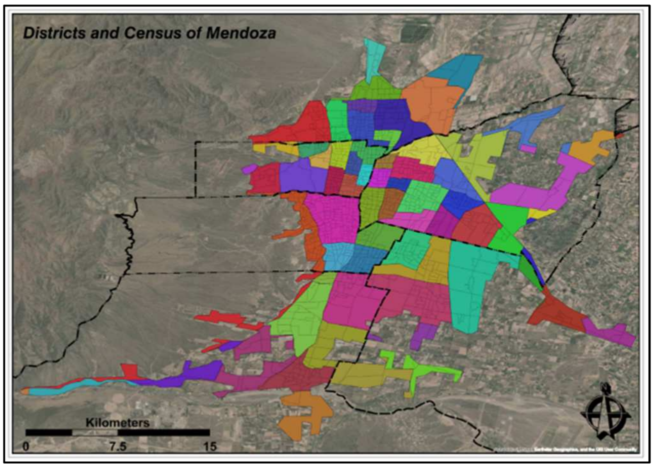


Fig. 1. Six departments, 62 districts and 1132 census sections of the Metropolitan City of Gran Mendoza

Climate condition: Mendoza has an altitude-dependent, dry subtropical climate characterized by hot, humid summers and dry, temperate winters that can become cool at night. These climatic conditions have significant impacts on both energy production capabilities and energy needs. To ensure the accuracy of the predicted gas consumption, the energy model takes into account local weather conditions. Three weather stations located near Mendoza were examined: El Plumerillo, Russel, and Perdriel (in Figure 2). Understanding how altitude affects the air temperature and other meteorological factors is important for energy models. At each district the closest weather station with similar altitude was assign to increase the accuracy of the energy model.

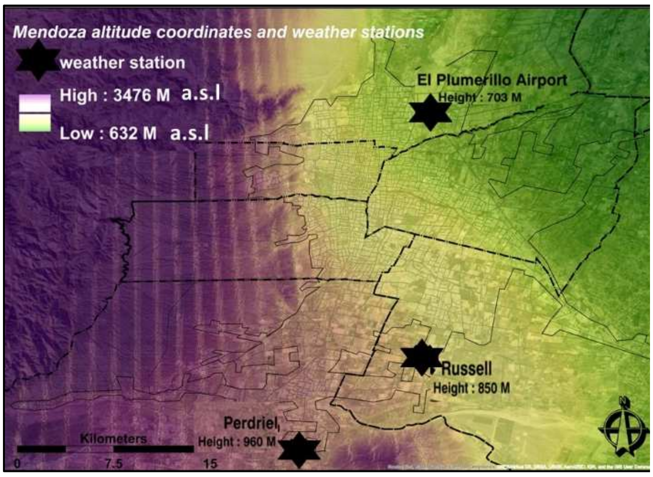


Fig. 2. Altitude coordinates and weather stations in the Metropolitan City of Gran Mendoza [16]

The altitude difference between the three weather stations is up to 257 meters. These differences in altitude have a significant impact on air temperature patterns and space heating need. Higher elevations often experience cooler temperatures, resulting in increased energy consumptions for space heating. By considering air temperature and consequently the heating degree days (HDD) variations for altitude differences, the forecast of energy consumption for space heating in each district of the Metropolitan City of Gran Mendoza is more accurate (in Table I).

TABLE I. AIR TEMPERATURES REGISTERED BY THE WEATHER STATIONS IN MENDOZA IN THE REFERENCE YEAR 2017 [16]

	Altitude (m a.s.l.)	**T mean (°C)**	**T max (°C)**	**T min (°C)**	**HDD at 18°C in 2017**
Plumerillo	703	17.48	27.41	8.98	1093
Russel	850	16.3	26.7	8	1382
Perdriel	960	13.41	23.9	2.5	2000

IV. MATERIAL AND METHODS

This section describes the databases and methods used in this study. The main goal was to develop top-down urban energy models that can accurately predict and evaluate gas consumption. This method is particularly useful when analyzing energy consumption at a regional level or when detailed building-level data is missing. The procedures of the methodology are described with the flowchart in Figure 3 for a better understanding of the different steps and details. In this work only heating consumptions were analysed because of the availability of the data and because the cooling season is very short in Mendoza with low cooling loads.

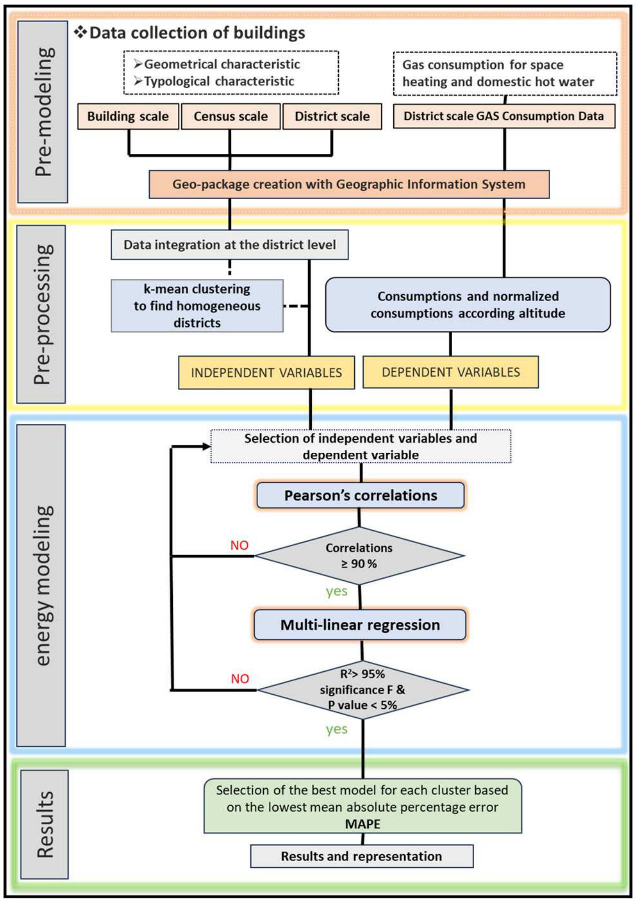


Fig. 3. Flowchart of the methodology

A. Data Collection

Accurate and reliable energy models rely on data collection to understand building characteristics, energy consumption patterns, and environmental factors. These data can be classified in:

*1) Building-scale Database **(Independent Variables)***

This research uses Geographic Information System (GIS) data to analyze buildings in Mendoza. GIS databases provide accurate information about buildings, allowing for top-down models to assess energy consumption. The data is divided into two categories: geometric parameters, which detail building shape, size, orientation, and arrangement, and typological parameters, which offer insights into land use and building types.

*2) Census-scale Database **(Independent Variables)***

The 2010 census data (more recent data are not available at census section scale) is utilized to understand energy consumption trends in Mendoza by examining socioeconomic and housing characteristics of the population, which significantly influence energy consumption behavior. This comparison considers about 58 independent variables to capture a comprehensive range of energy consumption patterns and behaviors (summarized in Table II).

TABLE II. CENSUS DATA FOR INDEPENDENT VARIABLES

Population database	Household database	Dwellings database
•Gender •Age groups •Nationality •Educational •Employment	•Number of families •Building's material •Number of rooms •Home crowding •Number of people	•Types of housing •Occupancy situation •Materials quality •Construction quality •Connection to service

*3) District-scale database **(dependent variables)***

Gas consumption statistics from local gas distribution companies provide data on natural gas use for domestic hot water and space heating. These statistics, while lacking information on individual buildings, serve as a benchmark for comparing model-generated data with actual consumption figures, assessing model accuracy and precision between 2010 and 2021.

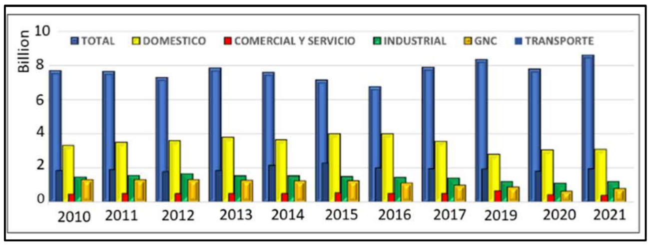


Fig. 4. Gas Consumption in Mendoza by year and sector (2010-2021)

B. Normalization of Energy Consumption

The altitude variations in Mendoza districts, ranging from 650 to 930 meters, are crucial for understanding energy-use. Two scenarios have been developed to analyze these variations. The first uses actual consumption data in kWh, while the second uses a normalization method to adjust kWh data for altitude variations. Heating degree days (HDD) were calculated based on average altitude, allowing more accurate comparison of energy statistics. The normalized temperature T and HDD were determined using data from a reference weather station at altitude Z with a correction factor d (°C/m):

$$d\ (°C/m) = (HDD - HDD_{ref}) / (Z - Z_{ref}) \quad (1)$$

$$T = T_{ref} - (Z - Z_{ref}) * d\ . \quad (2)$$

The process of calculating heating degree days (HDD) in Mendoza involves three weather stations and the normalization it based on the local elevation, allowing for more detailed results. Normalized HDD values were used to correct energy consumption data, considering Russell as a reference weather station and the days of the heating season:

$$HDD_{(district)} = HDD_{ref} - (Z - Z_{ref}) * d * 214_{(winter\ days)} \quad (3)$$

The study generates four additional outputs for original and normalized kWh data, including kWh/m^2 and kWh/m^3, which show energy consumption normalized per net floor area and per gross volume, respectively (in Table III).

TABLE III. DEPENDENT VARIABLE FOR THE ENERGY-USE MODEL FOR NOT-NORMALIZED AND NORMALIZED (NOR) SCENARIOS

kWh	kWh(nor-alt)
kWh/m^2	kWh(nor-alt) /m^2
kWh/m^3	kWh(nor-alt) /m^3
kWh/ inhabitants	kWh(nor-alt) / inhabitants
kWh/family	kWh(nor-alt) /family

C. Clustering

Identifying homogeneous areas with common characteristics and analyzing similar spatial patterns is instrumental in unraveling the complexity of Mendoza's urban landscape. In this study, clustering is performed using the K-means method and serves as a first step to identify patterns in Mendoza's building inventory. K-means clustering offers several advantages. First, it mitigates the effects of heterogeneity within the data set by grouping regions with similar characteristics, thereby promoting a more nuanced understanding of the relationships between variables, which is essential for building accurate predictive models. Because the presence of noise and outliers in the data can reduce the effectiveness of these studies.

D. Correlations

In the Mendoza case study, correlation analysis is utilized to explore the relationships between independent variables and dependent variables related to energy consumption. This statistical approach examines the degree and direction of association between different factors, providing valuable insights into potential correlations between changes in one variable and changes in another Regression analysis.

Regression analysis is a statistical technique that predicts future energy consumption values based on previous data. It illustrates the linear relationship between a dependent variable and independent variables, identifying the Pearson's correlation coefficient (r) that indicates the strength and direction of the relationship. This helps in resource allocation, policy formulation, and energy planning in the Mendoza region, supporting informed decision-making.

E. Regression Analysis and Significance Test

After conducting multiple linear regression analyses, a regression analysis significance test is used to determine whether there is a statistically significant relationship between the dependent and independent variables. The coefficient of determination R-squared value (R^2) measures the fit of the regression line to data points, while F-tests determine the equation's significance. A large p-value indicates no significant impact of independent variable on the dependent variable.

F. Calibration of the Models

The best model is chosen based on the smallest discrepancy between predicted and actual energy consumption, evaluated using the mean absolute percentage error (MAPE), which measures the average absolute difference between predicted and observed values:

$$\text{MAPE} = \frac{|\text{ measured data } - \text{predicted data}|}{\text{measured data}} * 100. \quad (4)$$

V. RESULTS AND DISCUSSION

One of the most important phases of UBEMs analysis is the pre-modeling with the organization of the resources required to create energy models; this will consent the correlation analysis and the evaluation of multi-linear regressions. After all components were assembled in a geo-package, the modeling phase can start. The methodological framework outlined in Figure 3 was implemented to analyze and describe the results of this study.

A. Homogeneous districts cluster based on common variables

Using Euclidean distance alongside the K-means method, the research identified five homogenous clusters within the city (in Figure 5 and Table IV). Each cluster consists of districts with similar residential building characteristics. Key variables in this study included: building coverage ratio, building density, population density, surface-to-volume ratio of the buildings and the characteristics of inhabitants and the materials used for the buildings. Some variables were more influential than others, leading to the identification of five clusters described in Table IV. The findings indicate a predominance of detached houses, characterized by their individual entrances and isolated structures, highlighting a preference for single-family homes among Mendoza area. Detached houses dominate the residential landscape and are categorized into three subgroups based on their geographical distribution: central, peripheral, and rural. The departments with the highest concentration of detached houses are Las Heras, Luján, and Maipú, which together constitute the majority of Mendoza's housing stock. Vice versa, the other three departments have a higher percentage of apartments, although the exact ratio varies, with some areas showing a greater prevalence of apartment buildings.

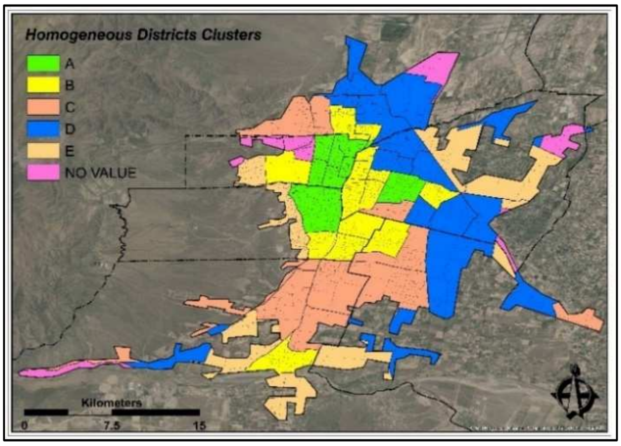


Fig. 5. Homogeneous districts cluster

TABLE IV. SOME OF THE MAIN CHARACTERISTICS OF CLUSTER

	CLUSTERS				
	A	B	C	D	E
Volume percentage of detached house %	67.29	94.49	96.99	98.80	98.01
Buildings with good material	82.54	71.50	60.72	45.95	40.40
Mean of buildings coverage ratio (%)	33.49	33.84	24.41	22.61	20.72
Average of surface-to-volume ratio S/V	1.16	1.34	1.40	1.44	1.46
Number of components per family	2.16	3.22	3.34	3.46	3.59
Average of number of people per volume	3.73	3.93	8.80	11.70	21.28

B. Identifying Key Variables through correlations

The most significant variables influencing the buildings energy-use were the focus of the sensitivity analysis in this section. Then, the main energy-related variables were used to represent the complex relationships of buildings, population and urban context. Iterative analysis was used to identify patterns and significant factors. Correlations exceeding +90% or below -90% were considered significant, indicating strong associations that warrant further investigation.

C. Best prediction energy models from regression analysis

After all components were assembled, the implementation of the models can start. As mentioned previously, a clustering technique was used to categorize urban areas with homogeneous characteristics. To increase the accuracy, the gas consumption data were normalized considering altitude variations. This normalization resulted in ten different types of dependent variables (in Table III). related to gas consumption, according to area, volume, inhabitants, and number of families. Correlation analysis was then used to identify the most highly correlated independent and dependent variables within each cluster. Through regression analysis for each cluster, muti-linear regression models were employed to determine natural gas use; the results were calibrated using actual consumption data provided by energy suppliers.

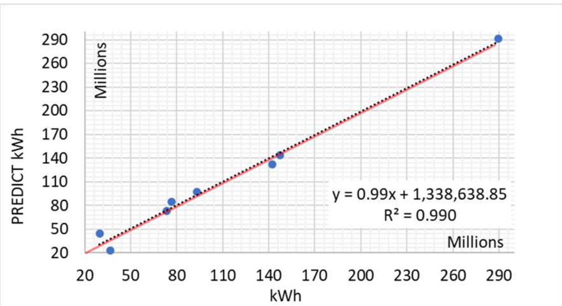
By this analysis several regression models were developed for each cluster, assessing their performance using the coefficient of determination R^2, the probability value P-value, the statistical distribution F-significance, and the mean absolute percentage error (MAPE). The best model was chosen based on prediction accuracy, showing a R^2 and Adjusted R^2 greater than 95%, P-values below 5% and MAPE lower than 10% (in Table V).

TABLE V. MULTIPLE LINEAR REGRESSIONS RESULTS SUMMARY

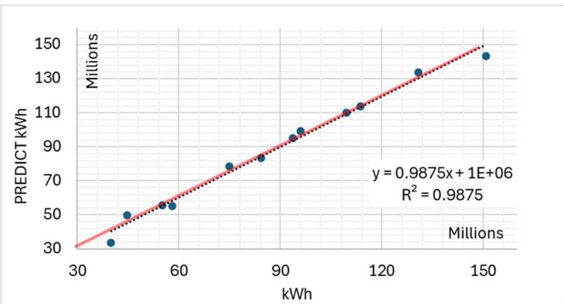
Cluster	Multiple R	Adjusted R^2	Standard error	P-value -	MAPE %
A	0.9939	0.9789	1.2169	0.0023	5.09
B	0.9937	0.9724	5.7812	0.0009	4.28
C	0.9900	0.9644	9.4696	0.0186	7.19
D	0.9930	0.9814	4.6390	0.0003	9.05
E	0.9995	0.9966	2.0037	0.0316	5.62

The main independent variables that were used for the model are (highlighted in red in equations of Figure 6): the dimensions of the buildings (volume, area, height, number of people-families-floors, buildings coverage ratio, …) and other characteristics of the buildings such as:

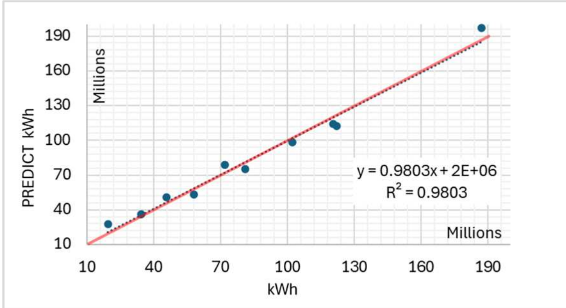
- MC1: % of buildings with "asphalt roof " in external
- MC3: % of buildings with "stone or tile" in external
- MC5: % of buildings with "Fiber cement" in external
- agr1: Number of people with (0 - 14) years old
- agr3: Number of people over 65 years old
- HA2: % of buildings with (0.51 - 0.99) people per room
- HA4: % of buildings with (1.50 - 1.99) people per room
- MP2: % of buildings with "cement" interior material
- MP3: % of buildings with "brick" interior material.



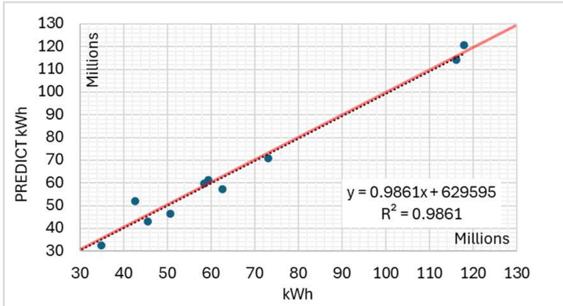
$$C_A(kWh) = 126668710 + 23854505.4 \cdot n.floors + 6260641 \cdot MP_2 + 6534.5 \cdot n.family$$



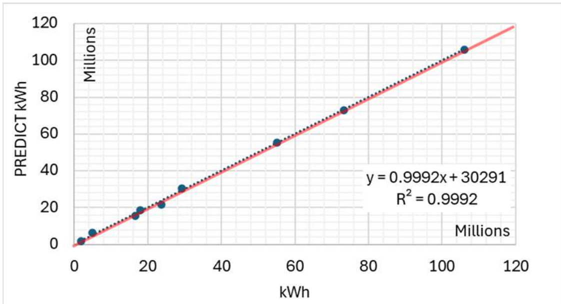
$$C_B(kWh) = 692112459.5 + 113.37 \cdot build.area + 78708212.6 \cdot build.height - 107681 \cdot MC_1 - 22774450 \cdot MC_3 - 3007961.1 \cdot mean.BCR - 581371.4 \cdot agr_3$$



$$C_c(kWh) = 101614474.5 + 16338.4 \cdot n.family - 2318572.6 \cdot MC_1 + 24578922.8 \cdot MC_5 + 5.35 \cdot build.volume$$



$$C_D(kWh) = 85741504.3 + 2542.8 \cdot n.people - 414398.9 \cdot agr_1 - 13871311.7 \cdot people/family - 21628559.5 \cdot HA_4$$



$$C_E(kWh) = 223686618.7 + 21136.2 \cdot build.area + 72241.5 \cdot mean.alt + 96750607 \cdot build.height - 359119.1 \cdot agr3 + 6652.8 \cdot build.volume + 53114235.6 \cdot MP_3 + 3282.8 \cdot n.people$$

Fig. 6. Multiple Linear Regressions for energy consumption by Cluster A, B, C, D, and E.

D. Energy Prediction for districts and identifying Intervention Priorities

From the previous regressions, the size of the buildings (e.g., volume, area, height, and number of inhabitants-families) and the quality of materials have the higher impact on energy consumption. Predicting energy consumption for each district is crucial for informed decisions, resource optimization, and sustainability in energy management. Then, in Figures 7 and 8, the districts were classified into Urgent, High, Medium, and Low priorities, establishing an order of priority for the interventions.

Urgent Priorities: districts with immediate energy criticalities-challenges, showing both high consumption and high energy intensity. These districts have higher energy consumption in both kWh and kWh/m² than the relative median values.

Highest Priorities: districts with significant energy consumptions, though not as critical as Urgent priorities. These districts have higher energy consumption in kWh but lower energy intensity (kWh/m²) than the median values.

Medium Priorities: districts with higher energy intensity in kWh/m² and lower energy consumption in kWh than the median values.

Low Priorities: districts with low energy consumption and energy intensity. These areas have lower energy consumption in both kWh/m² and kWh than the median values, then lower priority.

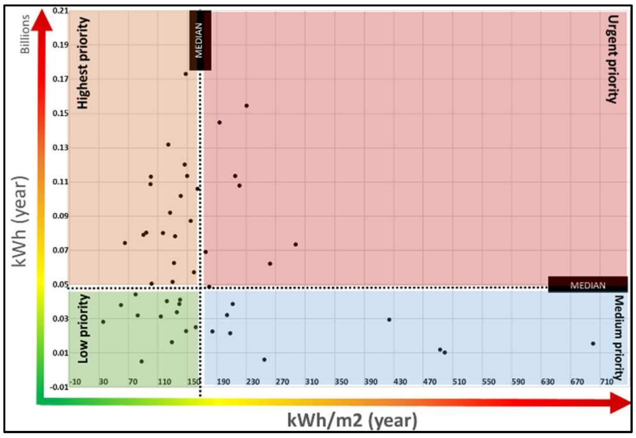


Fig. 7. Quadrants graph to identify the four levels of priority

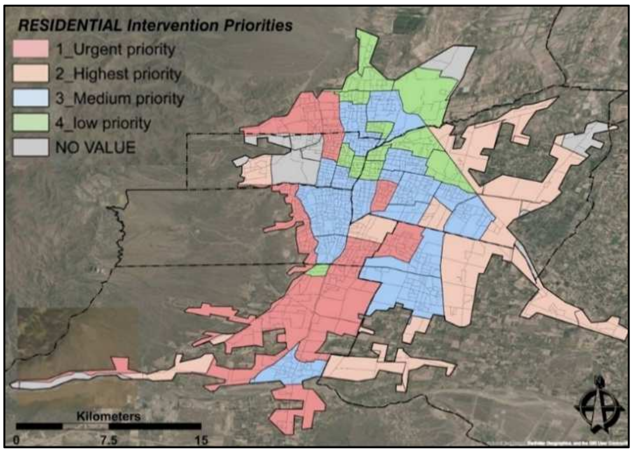


Fig. 8. Districts Intervention Priorities.

VI. CONCLUSIONS

This work explores urban energy consumption in Mendoza, using a statistical UBEM to simulate energy consumption. It focuses on behavioral, climatic, and architectural factors affecting space heating and domestic hot water in residential buildings. The study uses building data, inhabitants' attributes, and energy consumptions to create a top-down prediction models for Mendoza's urban energy landscape, addressing challenges at district level. The historical narrative of Mendoza's census data highlights the transformative potential of energy-efficient measures. This research acknowledges real data and then the actual constraints in determining energy-use at the district level, posing a challenge in assessing resilience and efficiency in urban environments. Validating models with data at different scales presents uncertainties and challenges, necessitating careful extrapolation beyond the validated timeframe. This necessitates cautious interpretation for more targeted interventions like the quality of buildings with better materials. Comprehensive data collection, including building materials, insulation, occupancy patterns, and heating and technological systems, is certainly the more important phase to improve energy models' accuracy and understanding of building characteristics and energy-use trends in urban environments. Monitoring energy consumption with a spatial detail is recommended as a crucial strategy for a sustainable urban development strategy.

This paper describes an exhaustive methodology that can be used to define guidelines for a sustainable development of cities by exploiting: existing databases, consumptions' monitoring, statistical models to identify how to intervene and the quadrants graph to define the areas with the highest priority for intervention. The results of this analysis enable researchers, policymakers, and urban planners to respond quickly to real energy dynamics, ensuring that actions and policies are aligned and tailored with the specific urban environment. This proactive approach aims to create a responsive and adaptable framework, enhancing resilience and sustainability in the urban energy landscape.

The next step will be to integrate energy efficiency measures with renewable energy sources, a forward-looking strategy for sustainable urban development. The integration of renewable technologies, such as solar, into the urban environment is crucial to sustainable practices, further reducing dependence on traditional fossil fuels and improving urban resilience and self-sufficiency.

REFERENCES

[1] International Energy Agency. (2022). World Energy Outlook 2022 https://www.iea.org/reports/world-energy-outlook-2022

[2] United Nations. (2015). Transforming Our World: The 2030 Agenda for Sustainable Development. A/RES/70/1, https://sdgs.un.org/2030agenda

[3] Bulkeley, D. (2013). Cities and climate change. Routledge. http://ndl.ethernet.edu.et/bitstream/123456789/43568/1/45.Harriet%20Bulkeley%20and%20Michele%20Betsill.pdf

[4] Kaza, N. (2020). Urban form and transportation energy consumption. Energy Policy, 136(2), 111049. https://doi.org/10.1016/j.enpol.2019.111049

[5] IRENA (2022). WET Outlook 2022. https://www.irena.org/Digital-Report/World-Energy-Transitions-Outlook-2022

[6] World Commission on Environment and Development. (1987). Our Common Future. https://shift-sustainability.co.uk/wp-content/uploads/2022/03/Shift-Sustainability_Teaching-Sustainbility-Whitepaper_v1.pdf

[7] Sustainable Business. (n.d.). Sustainable Development Goals (SDGs). Retrieved from https://sdgs.un.org/goals: https://sdgs.un.org/goals

[8] Carozza M., Mutani G., Coccolo S, Kaempf J.H., Introducing a Hybrid Energy-Use Model at the Urban Scale: The Case Study of Turin (Italy), https://doi.org/10.18280/ti-ijes.630102

[9] Mutani, G, Fontanive, M, Arboit, M.E. (2018), Energy-use modelling for residential buildings in the metropolitan area of Gran Mendoza (AR), TI-IJES 61+1(2), 74-82, 10.18280/ti-ijes.620204

[10] Keirstead, J., Jennings, M., & Sivakumar, A. (2012). A review of urban energy system models: Approaches, challenges and opportunities. Renewable and Sustainable Energy Reviews, 16(6), 3847-3866. doi: 10.1016/j.rser.2012.02.047

[11] S Hao, T Hong. (2021). Rethinking Sustainability Towards a Regenerative.https://library.oapen.org/bitstream/handle/20.500.12657/50031/978-3-030-71819-0.pdf?sequence=1#page=72

[12] Akbari, H., & Taha, H. (2001). The impact of heat island mitigation strategies on residential cooling energy use in Chicago. Energy and Buildings, 33(1), 103-112. doi: 10.1016/S0378-7788(00)00067-X.

[13] Ali, U., Shamsi, M. H., Hoare, C., Mangina, E., & O'Donnell, J. (2021). Review of urban building energy modeling (UBEM) approaches, methods and tools using qualitative and quantitative analysis. https://doi.org/10.1016/j.enbuild.2021.111073

[14] Montgomery, D. C., & Runger, D. C. (2010). Applied statistics and probability for engineers 5th ed. John Wiley & Sons. https://selvyblog.files.wordpress.com/2015/10/buku-stat-montgomery-5.pdf

[15] Argentina INDEC. (2023). https://www.indec.gob.ar/

[16] Climatestotravel argentina https://www.climatestotravel.com/climate/argentina .