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Predicting Energy and Emissions in Residential Building Stocks: National UBEM with Energy Performance Certificates and Artificial Intelligence

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Featured Application: The nUBEM model offers a powerful AI-driven framework for evaluating the energy performance and greenhouse gas emissions of residential buildings on a national scale. By enabling urban and nationwide insights, it supports comprehensive analysis of building characteristics and energy performance across residential building stock. This model is useful for the design of targeted energy efficiency policies and assessing their effectiveness in reducing greenhouse gas emissions.

Abstract: To effectively decarbonize Europe's building stock, it is crucial to monitor the progress of energy consumption and the associated emissions. This study addresses the challenge by developing a national-scale urban building energy model (nUBEM) using artificial intelligence to predict non-renewable primary energy consumption and associated GHG emissions for residential buildings. Applied to the case study of Spain, the nUBEM leverages open data from energy performance certificates (EPCs), cadastral records, INSPIRE cadastre data, digital terrain models (DTM), and national statistics, all aligned with European directives, ensuring adaptability across EU member states with similar open data frameworks. Using the XGBoost machine learning algorithm, the model analyzes the physical and geometrical characteristics of residential buildings in Spain. Our findings indicate that the XGBoost algorithm outperforms other techniques estimating building-level energy consumption and emissions. The nUBEM offers granular information on energy performance building-by-building related to their physical and geometrical characteristics. The results achieved surpass those of previous studies, demonstrating the model's accuracy and potential impact. The nUBEM is a powerful tool for analyzing residential building stock and supporting data-driven decarbonization strategies. By providing reliable progress indicators for renovation policies, the methodology enhances compliance with EU directives and offers a scalable framework for monitoring decarbonization progress across Europe.

Keywords: urban building energy model (UBEM); energy performance certificates (EPCs); machine learning; national building stock; data driven approaches; progress indicators; building energy efficiency; building carbon footprint; energy renovation policies

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1. Introduction

In the European Union (EU), member states (MSs) have committed to achieving climate neutrality by 2050 [1]. Achieving this ambitious target requires addressing the energy and emissions impact of the building sector, which accounts for 40% of energy consumption and 36% of GHG emissions [2]. To this end, the EU has launched initiatives such as the Renovation Wave [3] and the 2024 Energy Performance of Buildings Directive (EPBD) recast [2], aiming to accelerate the renovation of existing buildings across Europe.

However, achieving these goals is not without challenges. Monitoring the progress of national strategies and ensuring their effectiveness requires robust, reliable, and comparable data across MSs. To address this need, the 2018 EPBD recast Directive [4] introduced a set of progress indicators to measure decarbonization advancements of the national building stocks. The list of indicators is extensive, covering a wide range of aspects. These include the general characteristics and energy performance of the national building stock, deep renovation status, the worst-performing segments, rented properties, energy poverty, the capacities in the building industry, actual energy savings, the broader benefits of building renovations, estimated energy savings, and reduced healthcare costs due to renovations, as well as policies and measures for mobilizing investments in building renovations, among other things [5]. Measuring these indicators is crucial for optimizing national renovation strategies based on data and demonstrating to the EU the effective use of European funds for decarbonizing the built environment.

Despite the importance of these indicators, many remain difficult to measure [6]. This challenge stems from the following:

1. Data fragmentation and lack of interoperability: Data are often collected at regional or municipal levels without a common format, hindering their combination to create larger-scale information [7].
2. Disparate data structures: Data collected from various sources are in incompatible formats, lacking application programming interfaces (APIs) for direct access, complicating large-scale analysis. Some data are provided in non-machine-readable formats, impeding automation [8].
3. Difficulty accessing data: Much of the information is not open and requires a request, blocking constant automation and updating [9].
4. Labeling errors and missing data: Information is sometimes incomplete or contains errors that need filtering or correction [10].

As a result, these barriers significantly limit the ability of MSs to collect and utilize essential data for effective decision-making [11]. Emerging technologies such as georeferencing, big data analysis, and machine learning (ML) present an excellent opportunity to overcome these barriers and improve data collection [7].

For these technologies to deliver maximum utility, the data they rely on must:

- Be standardized across all MSs to facilitate cooperation and comparability between European countries.
- Be open to enable automation for constant updates.

To address these needs, the EU has launched several directives and proposals such as the Infrastructure for Spatial Information in Europe (INSPIRE) Directive [12], Directive (EU) 2019/1024 [13] and the Data Act [14]. These directives aim to enhance access to and use of data within the EU, creating a common and secure interoperable space in the European Union. As discussed in [15], the use of open big data from public information sources within interoperable frameworks established by these directives allows for large-scale analysis and benefits from georeferencing and data cross-referencing to monitor decarbonization progress and building conditions, among other advantages.

One promising approach to leverage these technologies is the use of urban building energy models (UBEMs). Historically, building energy models (BEMs) have been key tools for understanding a building's energy performance and proposing improvements for energy efficiency. These models use detailed information about building materials, their thermal properties, occupancy patterns, and systems. However, when generating these models at the neighborhood scale and beyond, developing highly detailed models may not be cost-effective in terms of time and expense [16]. Thus, the urban building energy models (UBEMs) were developed. These models use simplified building physics to simulate large groups of buildings and are generated to cover large building sets within reasonable time and cost constraints [17].

Typically, an UBEM covers a spatial scale ranging from a group of buildings to a district, neighborhood, or city [18]. However, this scale can be expanded as data availability allows. In this paper, we propose a national-scale model to analyze the entire residential building stock of a country. We call this model a national-scale urban building energy model enhanced with AI (nUBEM). It is a country-scale model which allows us to obtain certain progress indicators required by the 2024 EPBD recast and is helpful in generating valuable information for developing large-scale decarbonization strategies, enabling data-driven policy decisions. This model is a substantial improvement over a previous one [9], which generated a powerful country-scale model mapping and characterizing the energy performance of buildings that have energy performance certificates (EPCs), which is based on open data and automatically updates. However, it could only provide data for buildings with EPCs, which, in Spain, represent 10% of existing buildings. In this paper, we propose an enhanced model that provides the energy performance of all buildings in a country and evaluate it in comparison with other existing models in the scientific literature. The improved model achieves greater precision with shorter computation times by employing a hybrid approach that combines data from heterogeneous sources and AI to predict the energy performance of buildings. It incorporates geospatial techniques to enrich existing data and artificial intelligence algorithms to predict the energy performance of all residential buildings across a country. In this paper, Spain is taken as a case study. As this model is created using open data from public information sources established through European directives, it can be applied to all EU MSs that have incorporated the data frameworks set by these directives.

Literature Review

In large-scale analysis, UBEMs are useful tools to evaluate the energy performance of the buildings and potential improvements. UBEMs are classified depending on their purpose and objectives into four categories [19]:

- UBEMs for urban planning and new neighbourhood design
- UBEMs for stock-level carbon reduction strategies
- UBEMs for building-level recommendations
- UBEMs for building-to-grid (B2G) integration

Since the objective of our nUBEM is obtaining progress indicators for the evaluation of the evolution of building decarbonization and of the impact of energy renovation policies at a national scale, our model falls into the category of UBEM for stock-level carbon reduction strategies.

Regarding the methodology employed in the creation of UBEMs, these can be classified into two main types [20]: top-down models and bottom-up models. Top-down models are primarily based on the interrelations between the energy sector and the broader economy, and they do not require detailed building information, whereas bottom-up models represent energy consumption, leveraging detailed information about energy end uses through aggregation.

Specifically, bottom-up models can be developed using either statistical data about the energy use of individual buildings (statistical approach) or physical models that estimate energy consumption by modeling buildings' energy characteristics [21]. To determine a building's energy performance, the model can use either simplified methods, such as engineering approximations, or detailed approaches that characterize the building's energy behavior with greater precision [21].

Simplified engineering models offer lower accuracy compared to detailed models. Detailed models began utilizing individual buildings for smaller-scale analyses (individual approach) and archetypes for larger-scale studies (representative building approach). However, despite the use of archetypes, a significant challenge for detailed physics-based bottom-up UBEMs lied in optimizing their development process to reduce computational demands and time requirements [22]. In a previous study [9], we addressed the issue of the high computational demands of physics-based UBEMs by leveraging the energy performance certificates (EPCs) of buildings, proposing a new way of building detailed physics-based UBEMs. However, this UBEM was limited to energy data from the relatively small proportion of buildings that possessed EPCs. In this paper, we significantly enhance our previous model by integrating machine learning techniques into its framework. Figure 1 summarizes the possible methodological strategies for generating an UBEM as suggested in our previous study [9], with the addition of a hybrid approach.

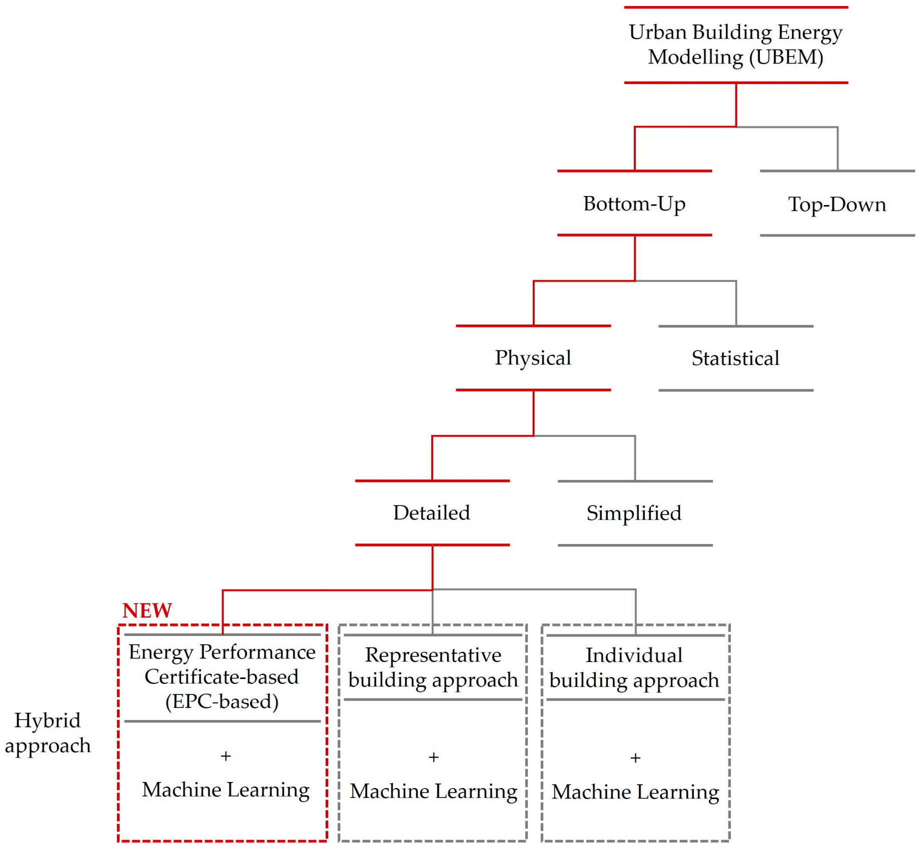

Figure 1. Scheme of different UBEM methods. The approach selected in this document (in red) and the new methodology proposed for national-scale UBEMs enhanced with AI (nUBEM) are marked.

A hybrid model, according to Bass [10], Oraiopoulos [23], and Li [24], combines energy models with machine learning techniques to generate models that not only include information about buildings with existing data but also predict the behavior of buildings without data. This hybrid methodology offers significant potential for developing UBEMs for stock-level carbon reduction strategies, as it allows us to expand the knowledge from the existing data collected to the rest of the buildings for which we have no energy performance information.

As can be seen in Figure 1, there are three main ways to generate detailed physical bottom-up UBEMs: individual buildings, archetypes, and EPCs. For large scales, only the archetype and EPC approaches are suitable, as it is not feasible to model each building individually. Building archetypes are representations of a group of individual buildings through the use of a typical building, which are used to simplify the modeling of large areas [9]. Archetype-based UBEMs are widely used for stock-level carbon reduction strategies at different scales. For example, García-López et al. [25] generate a residential model of a district in Jaén (Spain), creating archetypes based on the Spanish typologies. Groppi et al. [26] generate a neighborhood-scale UBEM based on archetypes combined with rooftop photovoltaic potential. Heindertaler et al. [27] create a bottom-up UBEM with archetypes based on TABULA to determine hourly heat load profiles in residential buildings at the neighborhood scale and compare simulation results with real measurements from two district heating systems. Blázquez et al. [28] establish a protocol to study the energy performance of specific building typologies in Mediterranean countries, using Córdoba (Spain) as a case study. García-Perez et al. [29] combine geographic information system (GIS) and life cycle assessment (LCA) analysis to calculate different renovation strategies in Barcelona using cadastral and statistical data. Januário et al. [30] developed a UBEM at regional level in Portugal. Sokol et al. [31] generate UBEMs based on Bayesian statistics in the Sicily region.

Archetype-based UBEMs face challenges in generating accurate and representative archetypes, mainly due to the lack of data needed to generate accurate and representative models for all buildings. This limitation affects the precision and reliability of the resulting models. As highlighted by Eggimann et al. [32], there are different spatiotemporal upscaling errors that occur when clustering buildings. De Jaeger et al. [33] study the effectiveness of building clustering and its importance for generating reliable models at district scale, as well as the main variables used in the literature, highlighting that analyzing building characteristics, such as building geometry, construction year, or number of floors, to generate archetypes is a viable alternative for urban energy simulations.

Currently, many archetypes are experience-based archetypes [33,34], archetypes developed based on researchers' experience or prior results, rather than on detailed, territory-specific information, as generally there are not enough detailed data at the district, city or bigger scales to generate buildings. These models allow for modeling with less information and computational requirements but risk containing errors or making incorrect generalizations that do not represent the buildings in the case study. As Alguacil et al. [35] point out, the use of archetypes based on statistics is complex in Spain, as projects like the Typology Approach for Building Stock Energy Assessment (TABULA) Project do not provide sufficient information to generate an adequate energy panorama for Spain. A significant point, as emphasized by Fabbri et al. [36], is that energy performance depends not only on the construction period but also on the architectural, morphological, and technological solutions that characterize each building. This is a critical point of archetypes, and creating them poses challenges that require a detailed understanding of each building, which archetype grouping often cannot achieve.

The other approach for large scale simulations is generating a detailed physical bottom-up UBEM based on EPCs. The EPC is a rating system created in Europe to summarize the energy efficiency of buildings, aiming to provide consumers with insights into properties they plan to buy or rent in European countries. This scheme is governed by Directive 2010/31/EU, and it implies the generation of an energy model for every building, office, or housing unit that is sold or rented in Europe [37]. EPCs have been utilized as a data source in various scientific studies at different scales [38–40]. EPC-based UBEMs offer a viable alternative to the problem of the precision of archetype-based UBEMs, as the use of EPCs created specifically for each building allows us to obtain more precise data on a building-by-building basis. However, the problem of the use of EPCs for large-scale simulations is that only a reduced percentage of buildings have such certificates. For example, as previously mentioned, in Spain, only 10% of existing buildings have EPCs.

With the advancement of new technologies like artificial intelligence (AI), the hybrid methodology has recently emerged, combining bottom-up models with machine learning (ML) or statistical models [10]. Through ML, a subset of AI that allows machines to learn from data and improve over time without being explicitly programmed for each task, it is possible to analyze patterns of energy behavior that are characterized by the variables of the building [41]. This approach enhances the potential and representativeness of the models, addressing a significant challenge: the treatment, analysis, and communication of massive amounts of data on building energy efficiency [17]. This potential can be highly valuable for creating large-scale models, as the most limiting factor is the lack of data and the complexities in the interoperability of various datasets [18].

The hybrid approach has been combined with the archetype-based one. Bass et al. [10] identify two primary sources of bias in data: the absence or limitation of data at the building scale and the presence of mislabeled data. To enhance model accuracy, they suggest employing hybrid models that integrate machine learning or statistical inference with physics-based models. Various techniques have been studied for both building clustering and energy consumption prediction. Ali et al. [42] conducted a comparative study of ML techniques for building clustering to define archetypes. Ali et al. [43] and Li et al. [24] use ML to predict energy consumption, testing different ML algorithms to determine the most accurate approach. Garbasevschi [44] employs machine learning to predict building age using random forest techniques and incorporating geospatial variables to enrich the model, which is applied to eight cities in Germany. Piras et al. [45] developed a model that compares various machine learning algorithms to forecast energy consumption in renewable energy communities.

In this study, a novel approach is proposed by combining a model based on EPCs and other open sources, such as land registries, with machine learning. This enriched model allows for the prediction of the energy performance of buildings, specifically obtaining their GHG emissions and NRPEC, based on their physical and geospatial characteristics.

Building upon previous studies, this model will encompass the entire residential building stock of a country as large as Spain, offering an optimal solution to provide insights into residential energy performance while ensuring efficient resource consumption.

2. Materials and Methods

2.1. Calculation

This paper proposes a novel model which combines a national-scale EPC-based UBEM [9] with ML/AI. The methodology employed consists of seven steps: (1) case study selection; (2) preliminary data collection; (3) geospatial data enhancement; (4) algorithm selection; (5) training and testing the models; (6) model validation; and (7) model applicability.

2.2. Case Study Selection

The case study selected is the residential building stock in Spain. It is considered a suitable case study as it has open data available on a building-by-building basis from multiple information sources, as already discussed in previous studies [9]. Moreover, these sources of information, which are detailed in Section 2.3, are common across European countries, which allows the findings to be extrapolated to other EU countries.

2.3. Preliminary Data Collection

A national-scale EPC-based model was developed following the methodology defined by Beltrán-Velamazán et al. [9]. This model includes a GIS database that combines data from EPCs, Spain's cadastral data, the INSPIRE cadastral data of Spain, climate zones, and the size of the municipality where the building is located. The input data used are those existing and valid as of 1 January 2024.

This preliminary model contains the geographic and physical data of all buildings in Spain available in Spain's cadastre, excluding the regions of Navarra and the Basque Country, which have their own cadastral systems. It also contains the energy information of all buildings with at least one EPC available in the open databases published by the regions of Spain. EPCs provide information on the energy performance of buildings, specifically the NRPEC (non-renewable primary energy consumption) in kWh/(m^{2}y) and the GHG emissions in kgCO$_2$eq/(m^{2}y).

As of 1 January 2024, Spain, excluding the regions of Navarra and the Basque Country, has 11 million existing buildings, of which 8.7 million are residential, and 1.2 million of them have open EPC data. Therefore, energy performance data are available for 13.8% of existing residential buildings. Since the objective is to train a model capable of predicting the NRPEC and the GHG emissions of all residential buildings of the country, the energy performance data and physical characteristic of the buildings will be used to train the algorithm. From the open EPCs, only the target variables to be predicted, NRPEC and GHG emissions, are used. To ensure the model's applicability, it uses information from other accessible sources for all buildings in Spain as input data to learn NRPEC and GHG emissions patterns.

This database is generated with open data provided by public sources, and the tool for generating the database is available on the GitHub of the article [9]. The steps related to pre-processing the data, feature extraction, and outlier detection have already been developed in the input database as detailed in [9]. By means of the cadastral reference, it is possible to link the information available on a building from different information sources. This data will be used to train the model and relate its physical characteristics to its energy performance (Figure 2).

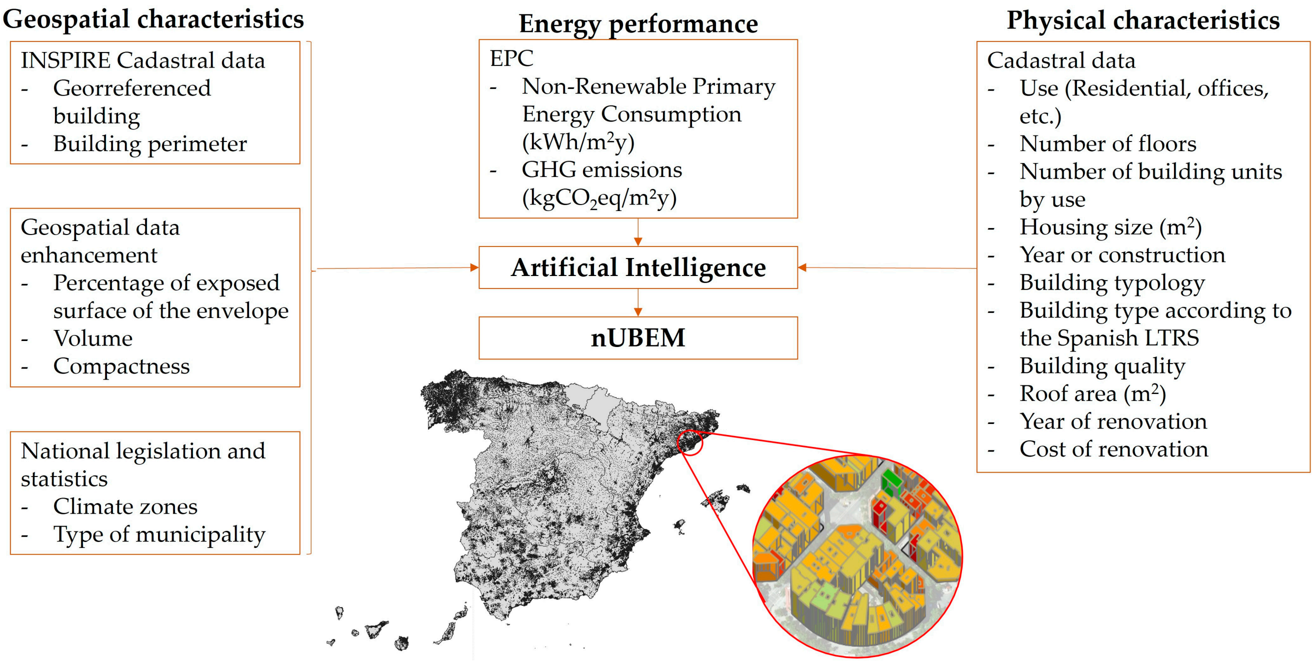

Figure 2. Data obtained from different data sources.

2.4. Geospatial Data Enhancement

To produce more accurate predictions, several geospatial features have been added to the dataset. As outlined by Xie et al. [46], it is possible to enhance our understanding of buildings using technology that enriches simpler geospatial data.

This geospatial information is obtained from the 2D GIS and alphanumerical data of the cadastre through programming, combining the available information to obtain the following characteristics of the buildings:

- Facades and Party Walls

An important feature is to differentiate between the building surfaces in contact with the external air (facades) and the surfaces in contact with adiabatic elements (party walls). The surface area in contact between buildings is calculated in GIS, knowing the building's floor plan geometry and its number of floors, both data obtained from the Spanish cadastre. A standard story height of 3 m is assigned for the calculation, following the methodology developed in [47]. For better machine learning training, these data are expressed as a percentage of facade surface area relative to the total envelope area.

- Envelope and Compactness

Knowing the building's floor plan geometry and its number of stories, the square meters of the envelope and the cubic meters of volume are calculated. Compactness is calculated according to Spanish legislation [48], considering the entire envelope in contact with the external air and the ground and excluding the party wall surface area. The formula used is Equation (1).

$$Compactness = \frac{V}{\sum A_i} \mathrm{m^3/m^2} \quad (1)$$

where:

$V = Volume\ enclosed\ by\ the\ energy\ envelope$

$A_i = Area\ of\ the\ envelope\ in\ contact\ with\ external\ air\ or\ the\ ground$

2.5. Algorithm Selection

Six supervised machine learning techniques have been employed to predict the energy performance of buildings: generalized linear model, deep learning, decision tree, random forest, gradient boosted trees, and support vector machine (SVM). The algorithms were selected to represent a diverse range of machine learning approaches, ensuring a comprehensive evaluation of several of the most used predictive performance algorithms to find the optimal solution for this problem.

For all six techniques, a grid search system was implemented, testing different hyperparameter combinations to determine the configuration that best fits the regression problem. The results obtained for each technique are detailed in Section 3.1.

2.6. Training and Testing the Models

To train the model, Python 3.12.0 and XGBoost 2.0.3 [49] were used. XGBoost is an optimized gradient boosting library that builds decision tree ensembles to solve classification and regression tasks efficiently. An important aspect of model training is mitigating overfitting and underfitting. To achieve this, XGBoost implements various techniques. To address underfitting, it allows for controlling model complexity through parameters such as the maximum tree depth and the number of boosting rounds. To prevent overfitting, XGBoost incorporates mechanisms such as regularization, the minimum child weight for leaf nodes, and random sampling of data and features, effectively reducing model complexity and improving generalization.

The algorithm was calibrated, and 10-fold cross-validation was employed, generating a model with 90% of the data and testing it with the remaining 10%. This means that alternately in 10 subgroups, all the data were used to test the model, obtaining more robust validation data and preventing overfitting and underfitting of the model. This procedure was carried out analogously to [43].

The input variables for training the models include physical and geographic characteristics. The target variables to be predicted are the energy information, the NRPEC in kWh/(m^2y) and the GHG emissions in kgCO_2eq/m^2y, using as predictor variables the geographic and physical information.

The data used were:

- Energy information
- NRPEC (kWh/m^2y)
- GHG emissions (kgCO_2eq/m^2y)
- Physical characteristics
- Use (residential, offices, etc.)
- Number of floors
- Number of building units by use
- Housing size (m^2)
- Year or construction
- Building typology
- Building type according to the Spanish Long-Term Renovation Strategy (LTRS)
- Building quality
- Roof area (m^2)
- Year of renovation
- Renovation cost
- Type of municipality
- Geographical characteristics
- Georeferenced building
- Building perimeter
- Climate zone
- Percentage of exposed surface of the envelope
- Volume
- Compactness

2.7. Model Validation

Model validation is a critical point in the development of UBEMs to ensure they meet their intended objectives. Currently, there is no consensus in the literature on which indicators or acceptable values to use when evaluating an UBEM, resulting in widely varying acceptable accuracy values. Ramos Ruiz et al. [50] study the validation of energy models, highlighting NMBE, CV(RMSE), and R^2 as the most used indicators in literature, referencing the ASHRAE guideline as the primary standard in the field. Oraiopoulos et al. [23] evaluate the accuracy of different UBEMs, both for single buildings and aggregated buildings, based on NMBE, CV(RSME) and R^2, finding UBEM accuracies ranging from NMBE -15 to +4% and CV(RMSE) between 3–50%, with aggregated CV(RMSE) values of 10–20%.

The ASHRAE Guideline 14-2014 Measurement Of Energy, Demand, And Water Savings [51] uses NMBE and CV(RMSE) to validate models, considering acceptable results at a monthly scale with NMBE $\pm$ 5% and CV(RMSE) < 15%. However, the ASHRAE Guideline applies this validation to district-scale models, categorized as 'UBEM for building-level recommendations' according to the Ang et al. [19] categorization, where each model type requires different precision levels. As noted in [23] aggregated building precision often exceeds ASHRAE's recommended values, while single-building precision, especially CV(RMSE), tends to be higher.

At a national scale, Bass et al. [10] study simulation accuracy using AutoBEM software to create a national-scale UBEM in the US with OpenStudio and EnergyPlus, validating the model using median error (MdE) and R^2. They achieved an R^2 of 0.069 due to high model dispersion and median errors of -3% in residential use, indicating a balance between overestimation and underestimation.

Based on the review of existing scientific literature, we identified the most pertinent indicators for model evaluation as those outlined in Equations (2)–(4). These indicators are the most frequently employed in UBEM studies and have established reference values. They are as follows:

Normalized mean bias error (NMBE (%)):

$$NMBE(\%) = \frac{\sum_{i=1}^{n}(m_i - s_i)}{\sum_{i=1}^{n}(m_i)} * 100 \tag{2}$$

Coefficient of variation of root mean square error (CV(RMSE) (%)):

$$CV(RSME)(\%) = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(m_i - s_i)^2}}{\overline{m}} * 100 \tag{3}$$

Coefficient of determination (R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(m_i - s_i)^2}{\sum_{i=1}^{n}(m_i - \overline{m})^2} \tag{4}$$

where

$m_i = measured\ values$
$s_i = simulated\ values$
$n = number\ of\ measured\ data\ points$
$\overline{m} = mean\ of\ measured\ values$

The selected metrics, NMBE, CV(RMSE), and R^2, are widely used to evaluate predictive models in this field, but each has inherent limitations that must be considered, particularly when applied to energy models with large datasets, such as those at the national scale.

NMBE quantifies the average bias of predictions normalized by the observed mean. This metric is particularly useful at large scales to assess whether the model adequately represents the 'mass' of buildings, capturing the values of the most frequent building types. However, when positive and negative errors offset each other, it may falsely indicate a good model fit. For this reason, it is important to include scatter plots of measured versus predicted values in the results to better understand the model's behavior.

CV(RMSE) measures the variability of normalized errors but does not distinguish between systematic (bias) and random errors. Due to the quadratic nature of RMSE calculations, this metric is highly sensitive to outliers, disproportionately penalizing cases with large errors. Models dealing with large datasets at national scales often contain outliers, including mislabeled or erroneous data, as well as correct data from statistically infrequent buildings that the model struggles to predict. These outliers significantly impact the CV(RMSE) value.

R^2 is a metric with a limited capacity to evaluate the model comprehensively. It assesses the overall model fit relative to variability, but a high R^2 value does not guarantee accuracy, as it may be misleading in the presence of systematic errors or overfitting.

Moreover, R^2 does not provide information about the actual magnitude of errors, which is crucial for practical applications.

While these metrics are effective for smaller datasets, their interpretation becomes more complex at the national scale. Although the primary objective is to calculate energy performance for large numbers of buildings rather than to represent each individual building precisely, the data are presented both at the individual building level and aggregated into groups of 100 buildings. This dual approach ensures that the model functions well for building groups without masking potential errors in specific building types or regions.

Since no single metric is perfect, several are evaluated, and the graphs are analyzed so that the metrics complement each other and allow for an appropriate interpretation of the performance of the generated model.

Big data models often use data partitioning for validation. This technique enables developers to train the model on one subset, validate its performance on another, and assess its generalization ability on unseen data. By partitioning, models can effectively address the challenges posed by the size and complexity of Big Data, ensuring the model does not overfit to the training data. To avoid validation biases caused by partitions that fail to adequately reflect geographic and climatic diversity, a 10-fold cross-validation approach was adopted, reducing the risk of fitting too closely to the training set. This method ensures that all building types, climates, and other determining factors are evaluated. Since cadastral data are organized by region, the entire dataset was randomly shuffled before performing the cross-validation to minimize potential biases.

These cross-validation strategies, combined with the use of multiple metrics and visualizations, provide a more comprehensive approach to addressing the inherent limitations of each metric, thereby increasing confidence in the model's performance. Despite the challenges of working with large datasets and multiple building types, this methodological approach offers a reliable representation of energy predictions at both aggregate and individual building levels.

To evaluate the model, all available data were used, covering the 1,246,864 residential buildings. The NMBE, CV(RMSE), and R^2 values were obtained for both individual buildings and aggregated buildings, along with figures showing the relationship between EPC values and the predictions. The results of the model validation are presented in Section 3.2, while a specific case study predicting data for Madrid, a region excluded from the training dataset, is detailed in Section 3.3.2.

2.8. Model Applicability

The potential of the nUBEM model is demonstrated according to the following points:

- Its ability to cover the current lack of data;
- Its capacity for mapping zones with better and worse energy performance at the building level;
- The potential to calculate progress indicators.

Several of the progress indicators required by the 2024 EPBD recast for the MS [2] were obtained using the nUBEM model. The selected indicators are those considered to best define the characteristics of the residential building stock and its energy performance:

- Number of buildings and total floor area per energy performance class;
- Number of buildings, number of dwellings and total floor area per the 43% worst-performing buildings (including a definition);
- Annual operational greenhouse gas emissions per building type.

In relation to the applicability of the model, several issues must be defined:

Spain is divided into different climate zones, which are defined in Spanish regulations [48] using letters from A to E for winter climates and the letter alpha for the

Canary Islands, and numbers from 1 to 4 for summer climates, both ranging from mild to harsh. This results in a total of 15 climate zones from the combination of values for winter and summer.

The energy classes in Spain are divided into NRPEC energy classes and GHG emissions energy classes, with labels ranging from A to G, and the threshold values are organized according to [52]. This document sets threshold values for each energy class depending on three factors: the climate zone, the type of building (single-family house and multi-family house), and whether the building is in a peninsular or extrapeninsular climate.

Figure 3 shows, as an example, the threshold value ranges to determine the energy class of multi-family buildings in peninsular climates according to their climate zone. The figure illustrates how the threshold values for the classes vary significantly by climate zone, as the heating and cooling requirements vary greatly. The model automatically assigns the corresponding class to each building according to the regulation. The results of the model validation are presented in Section 3.3.

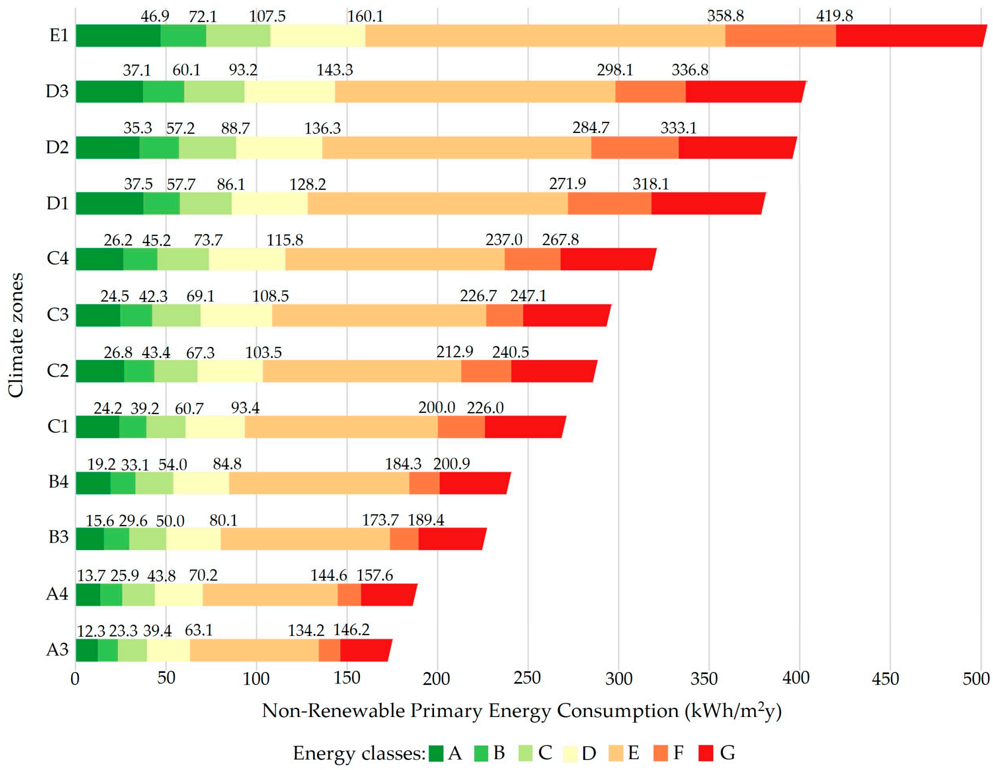

Figure 3. NRPEC ranges for the energy classification of multi-family buildings in peninsular climates according to Spanish legislation [52].

3. Results

3.1. Algorithm Evaluation

Comparing the results of the algorithms, the findings are summarized in Table 1. The technique that yielded the best results is gradient boosted trees, with XGBoost as the algorithm that performed the best for this problem, while deep learning also produced similar results. The algorithm with the best results was XGBoost, featuring hyperparameters of 500 trees, a learning rate (eta) of 0.05, and a maximum depth which allowed for each tree of 10. XGBoost outperformed other algorithms in the nUBEM framework due to its ability to manage complex, high-dimensional datasets and capture non-linear relationships critical for energy performance modeling. Additionally, XGBoost's efficiency with large datasets and its interpretability through feature importance analysis make it ideal for understanding key drivers of energy performance.

Table 1. Performance of the different algorithms. In green: best performance. In light green: alternatives with close performance. In white: alternatives with lower performance.

Model	NMBE %	CV(RMSE) %	R^2
Generalized linear model	0.031	42.2	0.24
Deep learning	0.028	38.7	0.36
Decision tree	0.030	40.8	0.29
Random forest	0.029	39.4	0.36
Gradient boosted trees	0.028	38.4	0.38
Support vector machine	0.029	39.5	0.32

3.2. Model Evaluation

Based on the results obtained in the previous section, the XGBoost algorithm was chosen to be used, calibrating its parameters to develop the complete model. In Figures 4 and 5, we can see the graph comparing the simulated values using ML and the actual values from the EPCs, in both NRPEC and GHG emissions. The results show a capability to predict the aggregate energy performance of buildings with high precision.

The results of the NRPEC model at the single-building scale show a normalized mean bias error (NMBE) of −0.027% and a coefficient of variation of the root mean square error (CV(RMSE)) of 37.7%. These metrics indicate that the model performs accurately in aggregate, as its NMBE of −0.027%—closer to 0 than the ASHRAE standard of ±5%—demonstrates minimal bias in predictions. However, its CV(RMSE) of 37.7% (ideally closer to 0) surpasses the ASHRAE benchmark of 15%, suggesting less reliable precision in individual building estimates. When buildings are analyzed in aggregate, the model's performance improves markedly, meeting or exceeding ASHRAE standards. In fact, aggregating buildings by typology and city achieves compliance with ASHRAE criteria in 99% of cases for groups with over 100 buildings.

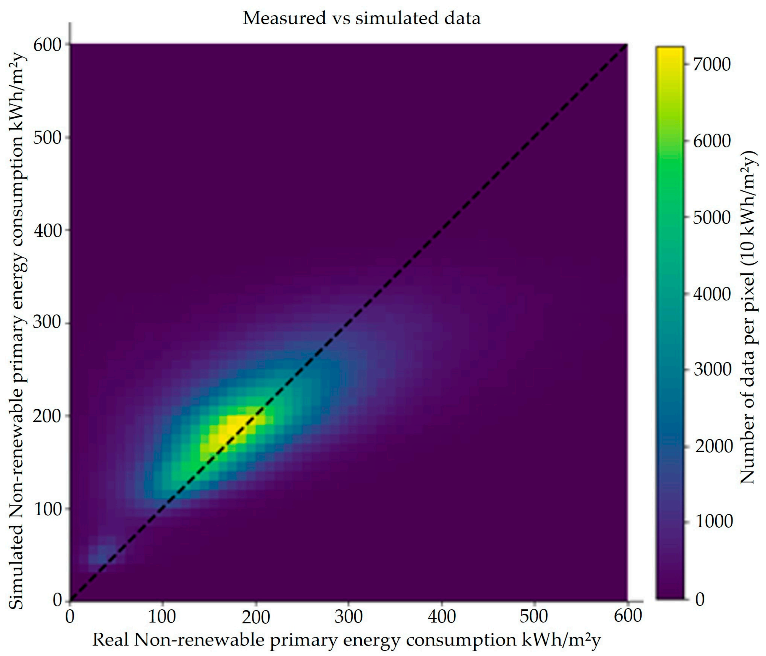

Figure 4. Heatmap comparing NRPEC measured versus predicted data. Each pixel represents a range of 10 kWh/(m^2y), and the color indicates the number of data points in each pixel.

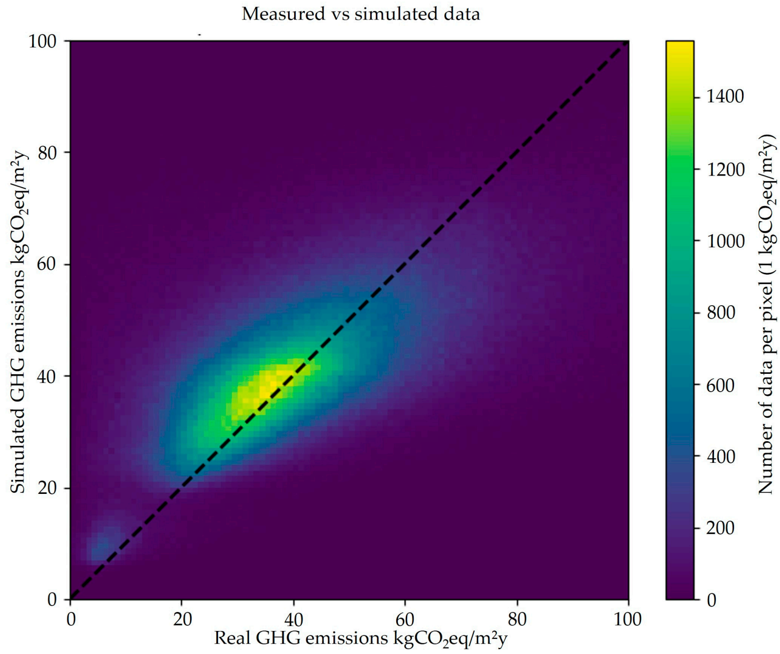

Figure 5. Heatmap comparing GHG measured versus predicted data. Each pixel represents a range of 1 $kgCO_2eq/(m^2y)$, and the color indicates the number of data points in each pixel.

It is important to note that the ASHRAE guidelines apply specifically to models in the 'UBEM for building-level recommendations' category, which require detailed knowledge and high precision for each individual building—expectations that exceed the objectives and capabilities of this model. The presented nUBEM falls under the 'UBEM for stock-level carbon reduction strategies' category, where precision requirements are less stringent. Despite this, the model performs commendably close to ASHRAE standards. The low NMBE value shows it is highly capable of predicting overall building stock performance, while the higher CV(RMSE) reflects expected limitations, particularly due to limited information on outliers. Notably, these results align well with findings from Oraiopoulos et al. [23], who documented similar trends in accuracy for aggregated building data in UBEM studies. Consistent with existing literature, the elevated CV(RMSE) at the individual-building level is a typical outcome for large-scale urban building energy models (UBEMs). Figures 4 and 5 further illustrate these results, showing that the model performs well in predicting aggregate building performance but encounters challenges with anomalous individual values.

In a similar manner, the GHG emissions prediction shows similar trends, with an NMBE of 0.049% and a CV(RMSE) of 43.3%, leading to conclusions similar to those presented in NRPEC. It should be noted that the increase in data dispersion is due to the lack of information regarding the energy vector in the open data, which adds a layer of uncertainty when making predictions.

The model's primary aim is to estimate NRPEC and GHG emissions for large groups of buildings, facilitating the calculation of progress indicators and the identification of poorly performing areas. While it does not provide precise predictions for every individual building in the Spanish residential stock—due to limitations in available data—it effectively assesses the performance of different city areas and analyzes the characteristics of buildings with low energy efficiency.

In Table 2, a comparison is presented between the model proposed in this study, referred to as nUBEM, and other models in scientific literature. The table indicates the type of model according to its purpose, the number of buildings used to evaluate the model, the scale of the model, and its accuracy in terms of individual building values and aggregated building results. As can be seen in the table, the nUBEM results are very satisfactory, with the model accurately predicting the building stock and achieving very positive values compared to those found in the scientific literature, especially in comparison with studies analyzing large scales, such as the presented study.

Table 2. Comparison of UBEM models by purpose according to [19], number of buildings, scale and accuracy obtained for single building and aggregate total values. (2: UBEM for stock-level carbon reduction strategies, 3: UBEM for building-level recommendations, UBEM for buildings-to-grid (B2G) integration, NMBE: normalized mean bias error, CV(RMSE): coefficient of variation of root mean square error, R^2: coefficient of determination, NRPEC: non-renewable primary energy consumption, GHG: greenhouse gas emissions, EC: energy consumption, AEU: annual energy use, HD: heating demand, AED: annual energy demand).

Characteristics				Accuracy in Single Building			Accuracy in Aggregated Buildings	
Model	**Type of Model**	**Number of Buildings**	**Scale**	**NMBE %**	**CV (RMSE) %**	**R^2**	**Deviation in Total Values %**	**R^2 Total Values**
nUBEM (this paper's model)	2	1,246,864	Country	−0.027	37.7	0.39	−0.177 (NRPEC)	0.998
nUBEM (this paper's model)	2	1,246,864	Country	−0.049	43.3	0.36	0.198 (GHG emissions)	0.998
AutoBEM [10]	2	50,843	Country	-	-	0.069	-	-
Filogamo et al. [53]	2	1,717,000 (dwellings)	Region	-	-	-	−7.77 (EC)	-
Olivo et al. [54]	2	859,740	City	-	-	-	5 (AEU)	0.74
Gassar et al. [55]	2	-	City	-	-	-	-	0.998
CESAR [56]	3	78	City	-	-	-	−1.05 (HD)	-
Johari et al. [57]	3	2044	City	10	54	-	10 (AED)	-
Johari et al. [58]	4	2326	City	-	-	-	14 (AED)	-
Aguacil et al. [35]	3	400 (dwellings)	City	25	-	-	-	-
Li and Yao [24]	3	573	District	-	17.3	-	-	-
Heinderthaler et al. [27]	3	53	District heating 1	10	32	0.83	-	-
Heinderthaler et al. [27]	3	13	District heating 2	−9	44	0.76	-	-
Garbasevschi et al. [44]	2	245,490	City	-	-	-	4.5	-

At larger scales, the model achieves an R^2 value that is more precise than the one obtained with the AutoBEM model (where values closer to 1 indicate better performance). Moreover, by examining the graphs included in their paper [10], it becomes clear that the nUBEM model handles both deviation and data dispersion more effectively, resulting in a model that better represents energy performance. As highlighted in the same paper [10], the challenge of predicting the type of energy carrier used for heating adds complexity, which increases the margin of error. This is also reflected in the nUBEM model, where the results for predicting GHG emissions are slightly lower than those of the NRPEC model, partly due to the lack of information about the energy vector. A significant difference lies in the source of the data used. For similar data, such as physical and geographical characteristics of buildings, the information was obtained from very different sources.

AutoBEM employs data derived from open-access sources that are not collected by official organizations (e.g., cadastral records or EPCs) but instead extracted from digital terrain models (DTMs), surveys, and annual maps of global artificial impervious areas. This approach has a great potential for direct application in other countries. However, it also increases the risk of mislabeled data and raises the computational requirements for processing the information. In contrast, leveraging public information sources such as cadastral records, responsible for collecting, processing, and publishing data, facilitates easier access to information. These public sources enable the collection of reliable building data, such as use, construction date, or number of dwellings, while demanding fewer computational resources to manage.

Regarding the regional-scale model presented by Filogamo et al., the model classifies the housing in the region of Sicily into archetypes, obtaining aggregate results that underestimate the total energy consumption by 7.77%, which is considered within acceptable limits. However, as the results can only be compared at a regional scale, it is not possible to determine whether the generated archetypes accurately represent the housing or if overestimations and underestimations are compensated for at the regional level. At this point, the use of EPCs to generate the model allows for a more detailed analysis of the results, enabling the assessment of whether the simulations accurately reflect the energy behavior of buildings. The nUBEM model achieves a total deviation much lower than that of Filogamo et al. (where closer to 0 is better). However, it is important to note that as more data are incorporated, the results are likely to improve. Additionally, the model should be compared at an individual scale to facilitate more accurate assessments of its performance.

Compared to city-scale models, this model still achieves very good results, both at the individual and aggregate levels, as it has been able to learn from a large number of patterns due to the availability of a significant amount of data. District-scale models, however, show better performance than our model, mainly because they are able to identify and handle infrequent cases more effectively, as they typically have a much more detailed and higher-level information, resulting in higher CV(RMSE) and R^2 values.

For instance, Heinderthaler et al. present two district heating systems with satisfactory results in terms of precision, particularly in the R^2 metric, especially when incorporating additional results. By examining their figures, the model reflects reasonable accuracy across various building types. However, as the authors highlight, the model fails to provide valid results at the individual archetype scale due to high CV(RMSE) values and a limited number of samples. Nonetheless, the aggregated results are already acceptable for small numbers of buildings.

Li and Yao employ a hybrid approach for modelling heating and cooling energy consumption of building stock at the district scale, utilizing diverse data sources on buildings and supplementing them with national statistical data. This results in highly detailed archetypes, incorporating factors such as air infiltration, window-to-wall ratio, and occupant, equipment, and lighting density, among others. These detailed models are used to train various machine learning models, achieving a high level of result precision.

3.3. Model Usefulness

As mentioned above, Europe is committed to measuring the decarbonization of existing buildings in order to evaluate the effectiveness of building retrofitting policies. The model here proposed allows for the measurement of decarbonization progress at the country level by periodically and automatically checking the NRPEC and GHG emissions. With this information, data-driven policies can be supported, and a national renovation strategy based on data can be defined.

As an example of the model applicability, the potential applicability and the data improvement obtained is shown, obtaining various progress indicators required by the 2024 EPBD recast. These indicators help define the residential building stock and its characteristics, aiding in the formulation of national renovation goals and plans.

3.3.1. Potential of the Model to Cover the Lack of Currently Existing Data

Currently, the existing data on residential buildings with EPCs in open databases cover approximately 13.8% of Spanish residential buildings. In Figure 6, the evolution of the available nationwide data that can be obtained with this model can be observed.

The buildings encompass all climate zones of Spain, and the number of certified buildings allows for the generation of an almost complete overview of the Spanish residential sector.

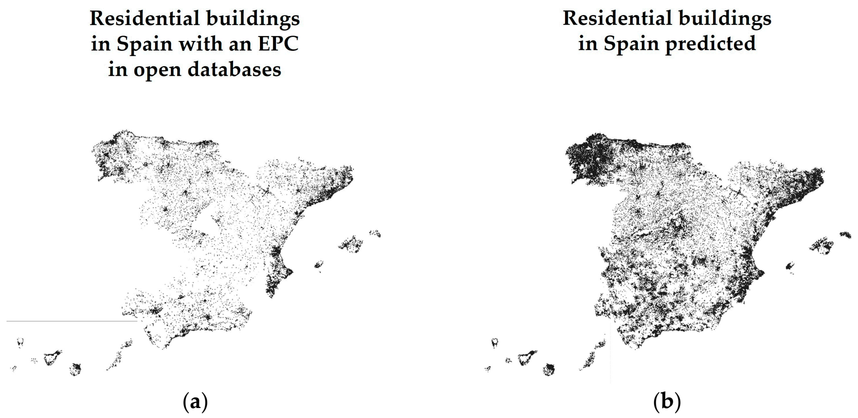

Figure 6. (**a**) Actual residential buildings in Spain with an EPC available in open databases; (**b**) residential buildings in Spain predicted using the nUBEM model.

3.3.2. Mapping Zones with Better and Worse Energy Performance at Building Level

In Figure 7, a zoomed-in view of the nUBEM model in the Barajas area of Madrid is shown, contrasting newly constructed residential buildings with the historic center of Barajas. The buildings are ranked by their NRPEC, and their corresponding energy performance class is displayed. It is noteworthy how the historic center of Barajas (in red, on the right) shows much lower energy efficiency compared to the new larger blocks (in green, on the left), where the most efficient buildings were constructed in 2017 and the least efficient in 2008. The green buildings on the left side of the image were constructed in 2023, in contrast to the historic center buildings, which date from 1950–1980. This case is particularly interesting as Madrid is not among the regions of Spain that provide open access to their EPCs, making it a valuable study in how the model can fill information gaps. The model has learned the relationships between variables on a national scale and applies them appropriately across all regions.

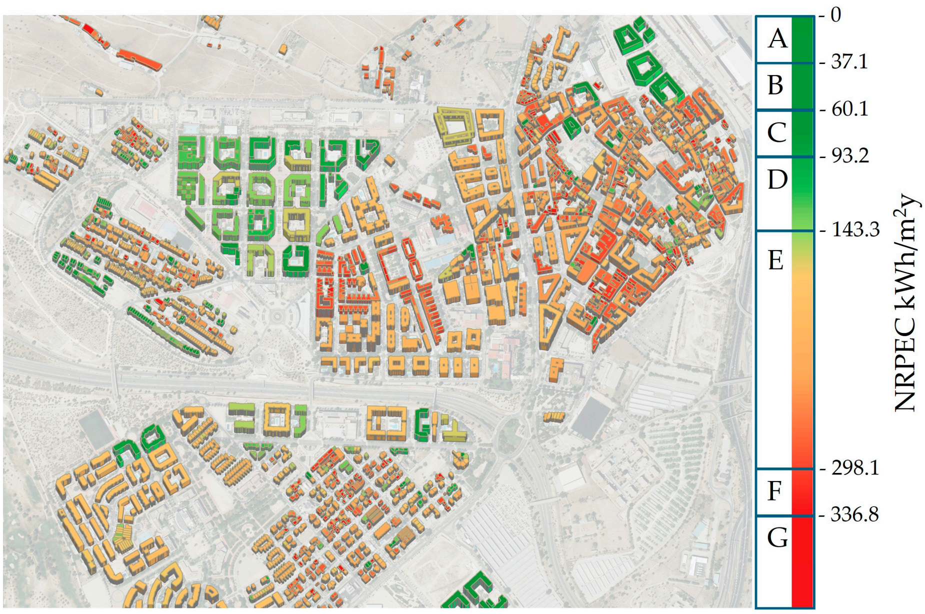

Figure 7. Closer view of the nUBEM at Madrid. In green to red: residential buildings ranged by NRPEC, energy classes values displayed for multi-family buildings in D3 climate zone. In grey: non-residential buildings. NRPEC: non-renewable primary energy consumption.

This model provides acceptably accurate NRPEC and GHG emissions values for evaluating districts, neighborhoods, and larger scales, helping to identify energy-inefficient areas. The value obtained for each building is a statistical estimate based on its characteristics, derived through the ML algorithm. While statistically accurate when grouping buildings, it is important to note that the individual NRPEC value predicted for each building cannot be considered accurate for every precise building, as a building may have unique characteristics that fall outside the usual parameters and having unpredictable NRPEC for the algorithm. Therefore, individual validation of a building is necessary to accurately determine its energy performance. This single building exact energy performance prediction of individual buildings exceeds the model's capabilities, as this is not the model's objective and surpasses the capacities of the currently available data.

3.3.3. Number of Buildings and Total Floor Area per Energy Performance Class

Energy classes in Spain show a strong tendency towards class E, which dominates with 81% of buildings and covers the majority of the Spanish residential sector, followed by class F with 7.7%, class D with 5.2%, class G with 4.4%, and the most efficient classes (A, B, and C), which account for 1.4%. These results seem to align with the trends shown in the official report [59], which, although showing more positive results, indicates that 80% of EPCs fall within the three worst letters. The reality of the current building stock, where new buildings must be certified but existing ones only if they are rented or sold, seems to confirm that the percentage of inefficient ratings is much higher.

Tables 3 and 4 shows the average and total values of NRPEC and GHG emissions per energy class. As shown in Figure 3, since the ranges vary by climate zone and building type, many of the G ratings in the Canary Islands (with lower ranges) cause the average value of the G ratings to be lower than those of classes E and F, which at first glance seems odd.

Table 3. Number of buildings, built surface area, average NRPEC kWh/(m^2y) and total NRPEC kWh/y per energy performance class in Spain. NRPEC: non-renewable primary energy consumption, GHG: greenhouse gas emissions.

Energy Class	Number of Buildings	Built Surface Area	Average NRPEC kWh/m^2y	Total NRPEC kWh/y	Average GHG Emissions kgCO_2/m^2y	Total GHG Emissions kgCO_2/y
A	10,983	3,417,313	46.24	145,579,347	11.11	32,216,048
B	45,363	16,755,555	64.78	946,536,410	14.15	197,355,494
C	73,090	32,431,374	94.31	2,514,654,132	20.14	519,241,248
D	451,393	118,902,156	165.95	17,956,642,013	37.16	3,962,400,366
E	7,054,623	2,238,048,969	246.58	473,078,264,181	53.57	101,165,823,218
F	664,791	144,744,180	275.06	34,500,491,341	58.56	7,302,608,855
G	378,870	125,572,100	184.23	20,621,312,769	41.84	4,781,965,848

Table 4. Number of buildings, built surface area, average GHG emissions kgCO_2/(m^2y) and total GHG emissions kgCO_2/y per GHG emissions class in Spain. NRPEC: non-renewable primary energy consumption, GHG: greenhouse gas emissions.

GHG Class	Number of Buildings	Built Surface Area	Average GHG Emissions kgCO_2/m^2y	Total GHG Emissions kgCO_2/y	Average NRPEC kWh/m^2y	Total NRPEC kWh/y
A	15,474	6,214,555	9.57	51,271,987	52.37	292,471,440
B	54,397	23,280,581	13.97	267,932,772	68.65	1,395,593,965
C	79,213	32,594,351	21.39	578,346,685	103.86	2,866,056,800
D	711,303	190,294,671	35.00	6,116,364,525	168.69	29,479,214,410
E	7,124,092	2,267,940,997	53.94	1.034×10^{11}	248.96	4.838E11
F	458,036	79,337,176	66.52	4,603,973,106	290.79	20,157,771,543
G	236,598	80,209,316	39.99	2,936,866,706	159.86	11,674,277,526

3.3.4. Number of Buildings and Total Floor Area per the Worst-Performing 43% of Buildings

The 2024 EPBD recast establishes the identification of the worst-performing 43% of buildings, establishing the number of buildings and total floor area of the worst-performing 43% of residential buildings as mandatory indicators [2]. The European directive requires establishing the definition of worst-performing buildings. For this study, we hold that the NRPEC value is the most appropriate indicator to determine which buildings are the least efficient.

With this model proposed, the 43% with a higher NRPEC per m^2 is identified, obtaining a total of 3,732,037 buildings with 5,748,002 dwellings which correspond to a built surface area of 612,877,691 m^2. The average NRPEC of this group of buildings is 303.46 kWh/($m^2 \cdot$y), and the total NRPEC of 179,919,636,781 kWh/y.

Analyzing the worst-performing 43% of buildings, we observed the following outlines:

- Single-family houses are 92% of the worst-performing buildings.
- The buildings located in climate zones D and E, the coldest, represent 80.10% of the buildings.
- The buildings built before 1940 are 35.34%; between 1941–1960, 16.15%; between 1961 and 1980, 25.41%; and between 1981 and 2007, 22.62%.
- The limit to be considered a building in the worst-performing 43% of buildings is an NRPEC of 253.22 kWh/(m^2*y).

This model enables targeted identification of building zones with specific energy performance across municipalities, districts, regions, and climate zones. Given that NRPEC values vary significantly by climate zone, the model is able to isolate the lowest-performing 43% of buildings within each climate zone in Spain. This approach identifies not just the highest-consuming buildings, which are generally concentrated in colder zones, but those with the poorest energy performance relative to the energy demands of their respective climate zones. Table 5 outlines the NRPEC and GHG emissions thresholds that categorize a building within the lowest 43% of performers in each climate zone. These findings highlight the significance of the climatic zone, with the top 43% of energy consumption being 2.6 times higher in cold zones compared to warm zones, alongside emissions that are 2.3 times greater. This underscores the pressing need for targeted interventions in these areas, as they present the highest potential for energy savings.

Table 5. Limit value of the NRPEC to be considered a building in the worst-performing 43% of buildings in every climate zone in Spain.

Climate Zone	Limit Value kWh/m^2y	GHG Limit kgCO_2eq/m^2y
Alpha 3	125.4	32.2
A2	148.6	34.8
A3	146.9	28.7
A4	153.4	29.5
B3	194.1	42.8
B4	192.1	38.0
C1	250.0	56.0
C2	229.3	49.4
C3	220.1	45.5
C4	230.8	47.2
D1	293.7	67.4
D2	284.7	63.4
D3	278.8	60.5
E1	328.3	74.3

3.3.5. Annual Operational Greenhouse Gas Emissions ($kgCO_2eq/m^2y$) per Building Type

Residential buildings in Spain have an average NRPEC of 239.35 kWh/m^2y and average GHG emissions of 52.04 $kgCO_2eq/m^2y$. The data is shown in Table 6, classifying the types of buildings according to the classification used by Spain's Long-Term Renovation Strategy (LTRS-ERESEE) [60,61]. This classification has also been used in previous studies [62–67] and is structured based on the building type: single-family housing, multi-family blocks with three or fewer floors, and multi-family blocks with four or more floors, followed by the building's construction period.

Table 6. Number of buildings, built surface area, average GHG emissions $kgCO_2/(m^2y)$ and total GHG emissions $kgCO_2/y$ per residential building type in the Spanish LTRS (ERESEE). SFH: single-family house, MFH-A: multi-family house with 3 or fewer floors, MFH-B: multi-family house with more than 3 floors.

Building Type	Number of Buildings	Built Surface Area	Average NRPEC kWh/m^2y	Total NRPEC kWh/y	Average GHG Emissions $kgCO_2/m^2y$	Total GHG Emissions $kgCO_2/y$
SFH < 1940	2,134,183	301,957,824	266.36	76,066,608,307	57.95	16,697,047,758
SFH 1941-60	933,516	127,930,130	268.90	32,719,342,689	58.56	7,146,662,044
SFH 1961-80	1,461,467	212,817,509	262.20	53,086,111,371	57.20	11,642,788,779
SFH 1981-07	2,464,120	387,925,847	224.34	82,938,611,561	49.22	18,338,783,131
SFH 2008-11	222,509	39,467,137	171.80	6,341,922,091	37.49	1,394,566,222
SFH 2012-23	195,711	38,363,725	111.66	3,817,920,395	23.64	808,278,271
MFH-A < 1940	91,408	26,152,128	237.64	5,979,520,959	51.42	1,291,723,803
MFH-A 1941-60	71,817	20,638,135	238.01	4,836,948,841	51.16	1,037,677,545
MFH-A 1961-80	149,544	54,103,556	224.35	11,890,514,820	48.19	2,543,450,158
MFH-A 1981-07	251,349	208,529,917	196.73	39,098,724,933	42.04	8,288,545,922
MFH-A 2008-11	28,532	32,523,999	162.83	5,110,705,256	34.34	1,067,181,849
MFH-A 2012-23	11,379	14,596,361	99.93	1,276,785,871	20.91	260,238,373
MFH-B < 1940	48,503	40,228,068	221.33	8,636,836,437	46.74	1,823,774,145
MFH-B 1941-60	57,417	60,688,978	234.77	13,757,176,878	49.32	2,896,350,094
MFH-B 1961-80	277,315	455,999,315	214.47	93,474,623,910	45.03	19,700,388,275
MFH-B 1981-07	239,096	537,966,687	188.02	96,028,587,556	39.34	20,027,333,473
MFH-B 2008-11	28,888	74,935,487	153.71	10,862,847,649	31.65	2,232,384,138
MFH-B 2012-23	12,358	45,046,627	94.11	3,839,665,175	18.94	764,431,671

It is noteworthy that NRPEC and GHG emissions have significantly decreased over recent decades, primarily due to energy regulations introduced in 2008 and 2019 within the construction sector. This trend underscores the critical challenge of decarbonizing the building stock, as a substantial portion of energy consumption and emissions originates from buildings constructed between 1960 and 2007.

4. Discussion

The results validate the model's effectiveness for its intended purpose: creating a national-scale representation of building energy performance to inform data-driven decarbonization policies. The model estimates NRPEC and GHG emissions for over 1,246,000 buildings across Spain, enabling a comprehensive analysis of the residential building stock. Its high reliability in aggregating building data supports decarbonization strategy development and impact assessment at multiple levels—district, neighborhood, city, region, and national—and across building typologies within urban or regional areas. Additionally, the model identifies characteristics and locations of the lowest-performing building typologies.

While the model lacks precision at the individual building scale due to limited energy system data and the influence of unidentifiable outliers, this limitation does not detract from its purpose. Its design centers on large-scale analysis rather than single-building specificity, making it well suited for informing broad decarbonization strategies.

4.1. Key Variables in the Model

To understand which variables in the model are most important for predicting NRPEC, we can use the XGBoost algorithm to obtain the total gain of each input variable in the model. This allows us to determine the improvement in accuracy that each variable contributes to the overall model.

Figure 8 highlights that climate zone is the most influential variable in the model by a significant margin, followed by construction date, compactness, and housing size. These four variables are crucial for accurately characterizing NRPEC, underscoring their high relevance. Additionally, the percentage of exposed envelope surface is identified as a significant factor within the ML algorithm, contributing valuable insights derived from the model. Another noteworthy variable is building quality, an internal metric from the Spanish cadastre primarily used for tax purposes. Interestingly, it enhances the model by providing supplementary information that improves its predictive accuracy. It is important to note the limited impact of the year of renovation and renovation cost variables, which, while theoretically vital for assessing building energy performance, are of limited relevance in the current model. Although recorded in Spain's cadastre, these variables lack specificity, as the cadastre does not indicate whether the renovations were energy-related or focused on other aspects of the building, such as an interior home renovation for aesthetic reasons. This lack of detail is compounded by the absence, until the 2024 EPBD, of a legal definition at the EU level for what qualifies as a deep renovation. The new EPBD defines deep renovation as one in line with the 'energy efficiency first' principle, focusing on essential building elements and transforming a building into a nearly zero-energy building. However, member states, including Spain, have not yet fully incorporated this definition into their national regulations.

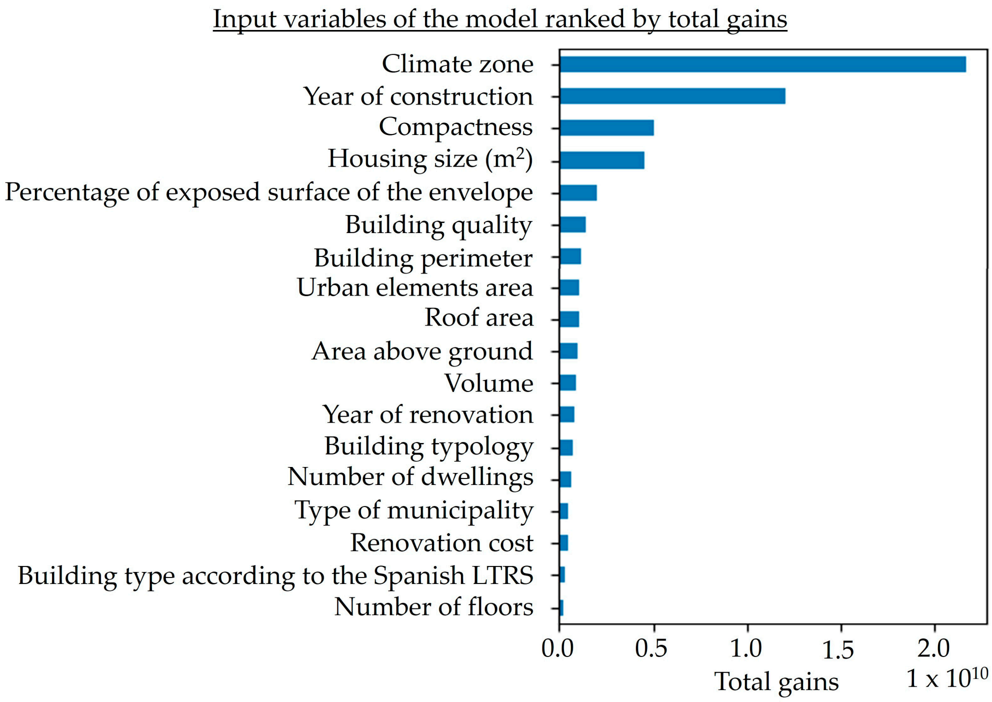

Figure 8. Total gains of the main input variables of the model. LTRS: long-term renovation strategy.

This limitation could significantly skew predictions for older versus newer buildings because the lack of detailed renovation data makes it difficult to accurately assess the energy performance improvements made over time. For older buildings, the absence of information on whether these renovations qualify as deep renovations (or any energy-related upgrades) could lead to over- or underestimations of their energy performance.

As renovation efforts expand across building stock, these variables will become essential for understanding energy consumption more precisely. To ensure the future success of tools such as this nUBEM, Spain should integrate detailed renovation data—aligned with the 2024 EPBD—into its cadastre to better capture the decarbonization of its building stock. This data should clearly indicate which renovations qualify as deep renovations under the EPBD definition. Additionally, it should include information on other levels of energy improvement, allowing for a more granular assessment of the building stock's progress toward decarbonization. Ensuring detailed data collection on renovation types will be vital for the continued development of accurate and actionable energy performance models.

4.2. Limitations

The model's limitations are influenced by the data access restrictions and data completeness and detail. For instance, as noted in [9], the Basque Country and Navarre maintain their own cadastres and cadastre INSPIRE datasets, which are excluded from this model, limiting geographic comprehensiveness. Additionally, the lack of detailed data on building systems and energy carriers is a significant source of bias; including such data would substantially enhance model accuracy. Another challenge is the presence of mislabeled or erroneous entries in available databases, especially in the energy performance certificates (EPCs). These issues necessitate extensive data cleaning, introducing potential errors into the algorithm and affecting precision.

Although the model's validation is adequate, individual building predictions may not be fully reliable due to missing data on building systems, a low percentage of buildings with EPCs, and inconsistencies in EPC data. Therefore, while the model is a robust tool for analyzing patterns and trends among groups of buildings within specific areas or typologies, it is less suited for precise, single-building analysis.

4.3. Future Research

Future work could involve creating an EU-BEM, European Union building energy model, encompassing all EU countries that adhere to common frameworks for obtaining the necessary information to develop these models. This would enable the analysis of decarbonization progress at a supranational scale, facilitate data pooling among different countries, and evaluate the effectiveness of various energy renovation strategies and policies within the community framework. This would allow for the following:

- Evaluating different policies and technologies for reducing energy consumption and emissions from buildings.
- Obtaining progress indicators in different MSs in a consistent method and using the same procedures.
- Gathering large-scale information to support data-driven decision-making.
- Developing strategies to achieve climate goals.
- Evaluating and comparing the performance of different renovation policies and strategies.
- Assessing in what way some renovation policies have performed better than others, depending on the chosen case scenario.
- Increasing the amount of data to enhance the algorithm's understanding of the patterns defining energy behavior.

To make the EU-BEM a reality, several challenges must be addressed, mainly concerning data availability, processing, privacy, and standardization. While it is possible to process INSPIRE cadastral buildings data across Europe, a thorough examination and standardization of each country's data is still required.

Moreover, the integration of data-rich sources such as building information modeling (BIM), digital twins, and digital building logbook (DBL) data represents a significant advancement in both precision and scope [68]. These technologies provide access to detailed information about key energy-related characteristics, thereby substantially enhancing the model's predictive capabilities. Additionally, this integration addresses current gaps associated with the lack of data on construction systems, offering a more robust foundation for evaluating the energy performance of the building stock.

5. Conclusions

This study proposes the development of a model named nUBEM, national-scale urban building energy model, which, based on the physical and geospatial characteristics of buildings, is capable of predicting NRPEC and the GHG emissions through artificial intelligence. For this, the XGBoost algorithm was trained with a dataset containing all residential buildings in Spain that have an open EPC and open data on their physical and geospatial characteristics.

The generated model uses open data from the cadastre, cadastre INSPIRE, digital terrain models (DTMs), and national statistics. To train the model, it employs the NRPEC and the GHG emissions from the EPCs as target variables. All this information is provided by open government sources and under the common frameworks of various European directives, making it potentially applicable to all EU member states that have implemented these common frameworks.

It is observed that gradient boosted trees, and in particular, the XGBoost algorithm, is the best-performing algorithm for this type of data and purpose, achieving better results in NMBE and RMSE and R^2 compared to the other techniques analyzed. This aligns with other similar analyses that also find Gradient Boosted Trees to be the most effective predicting building energy performance [43].

The nUBEM was shown to accurately predict the primary non-renewable energy consumption of buildings on a national scale. As of 1 January 2024, only 13.8% of residential buildings in Spain have an EPC. This model allows for the assessment of energy performance across all existing buildings nationwide, encompassing a total of 1,246,864 structures.

By identifying the least efficient buildings, the model aids in developing targeted renovation strategies focused on the 43% of residential buildings that perform the worst, in accordance with the requirements of the 2024 recast of the EPBD. The nUBEM demonstrated its effectiveness as a tool for generating progress indicators that facilitate the analysis of the residential building stock and its energy behavior, ultimately promoting data-driven policies and effective building renovation plans.

Furthermore, the results obtained have proven to be accurate compared to existing scientific literature, achieving national-scale outcomes that surpass those of previous studies.

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References

1. European Commission. *European Green Deal: Commission Proposes Transformation of EU Economy and Society to Meet Climate Ambitions*; European Commission: Brussels, Belgium, 2021.
2. European Parliament; Council of the European Union. *Directive (EU) 2024/1275 of the European Parliament and of the Council of 24 April 2024 on the Energy Performance of Buildings (Recast)*; Official Journal of the European Union: Brussels, Belgium, 2024; pp. 1–68.
3. European Commission. *Communication from the Commission to the European Parliament, the Council, the European and Social Committee and the Committee of the Regions. A Renovation Wave for Europe—Greening Our Buildings, Creating Jobs, Improving Lives*; European Commission: Brussels, Belgium, 2020.
4. European Parliament; Council of the European Union. *Directive (EU) 2018/844 of the European Parliament and of the Council of 30 May 2018 Amending Directive 2010/31/EU on the Energy Performance of Buildings and Directive 2012/27/EU on Energy Efficiency*; Official Journal of the European Union: Brussels, Belgium, 2018; pp. 75–91.
5. Beltrán-Velamazán, C.; Gómez-Gil, M.; López-Mesa, B. Analysis of Institutional Frameworks of Indicators to Measure the Effectiveness of Building Renovation Policy and Decarbonization Progress in Europe. In *Assessing Progress in Decarbonizing Spain's Building Stock: Indicators and Data Availability*; López-Mesa, B., Oregi, X., Eds.; Springer Nature Switzerland: Cham, Switzerland, 2024; pp. 17–55. ISBN 978-3-031-51829-4.
6. Gómez-Gil, M.; Arbulu, M.; Hernández-Minguillón, R.J.; López-Mesa, B. On the Availability and Quality of Data in Spain for the Development of Indicators to Measure Building Renovation Policies Effectiveness and the Decarbonization of the Building Stock. In *Assessing Progress in Decarbonizing Spain's Building Stock: Indicators and Data Availability*; López-Mesa, B., Oregi, X., Eds.; Springer Nature Switzerland: Cham, Switzerland, 2024; pp. 291–316. ISBN 978-3-031-51829-4.
7. Gómez-Gil, M.; Espinosa-Fernández, A.; López-Mesa, B. Contribution of New Digital Technologies to the Digital Building Logbook. *Buildings* **2022**, *12*, 2129. [CrossRef]
8. Gómez-Gil, M.; Sesana, M.M.; Salvalai, G.; Espinosa-Fernández, A.; López-Mesa, B. The Digital Building Logbook as a Gateway Linked to Existing National Data Sources: The Cases of Spain and Italy. *J. Build. Eng.* **2023**, *63*, 105461. [CrossRef]
9. Beltrán-Velamazán, C.; Monzón-Chavarrías, M.; López-Mesa, B. A New Approach for National-Scale Building Energy Models Based on Energy Performance Certificates in European Countries: The Case of Spain. *Heliyon* **2024**, *10*, e25473. [CrossRef] [PubMed]
10. Bass, B.; New, J.; Clinton, N.; Adams, M.; Copeland, B.; Amoo, C. How Close Are Urban Scale Building Simulations to Measured Data? Examining Bias Derived from Building Metadata in Urban Building Energy Modeling. *Appl. Energy* **2022**, *327*, 120049. [CrossRef]
11. López-Mesa, B.; Beltrán-Velamazán, C.; Gómez-Gil, M.; Monzón-Chavarrías, M.; Espinosa-Fernández, A. New Approaches to Generate Data to Measure the Progress of Decarbonization of the Building Stock in Europe and Spain. In *Assessing Progress in Decarbonizing Spain's Building Stock: Indicators and Data Availability*; López-Mesa, B., Oregi, X., Eds.; Springer Nature Switzerland: Cham, Switzerland, 2024; pp. 317–346. ISBN 978-3-031-51829-4.
12. European Parliament; Council of the European Union. *Directive 2007/2/EC of the European Parliament and of the Council of 14 March 2007 Establishing an Infrastructure for Spatial Information in the European Community (INSPIRE)*; Official Journal of the European Union: Brussels, Belgium, 2007; pp. 1–18.
13. European Parliament; Council of the European Union. *Directive (EU) 2019/1024 of the European Parliament and of the Council of 20 June 2019 on Open Data and the Re-Use of Public Sector Information (Recast)*; Official Journal of the European Union: Brussels, Belgium, 2019; pp. 56–83.
14. European Parliament; Council of the European Union. *Regulation (EU) 2023/2854 of the European Parliament and of the Council of 13 December 2023 on Harmonised Rules on Fair Access to and Use of Data and Amending Regulation (EU) 2017/2394 and Directive (EU) 2020/1828 (Data Act)*; Official Journal of the European Union: Brussels, Belgium, 2023; pp. 1–71.
15. Beltrán-Velamazán, C.; Gómez-Gil, M.; Monzón-Chavarrías, M.; Espinosa-Fernández, A.; López-Mesa, B. Measuring the Decarbonisation Progress of Buildings Based on European Open Big Data. *CONECT Int. Sci. Conf. Environ. Clim. Technol.* **2024**, 30. [CrossRef]
16. Buckley, N.; Mills, G.; Reinhart, C.; Berzolla, Z.M. Using Urban Building Energy Modelling (UBEM) to Support the New European Union's Green Deal: Case Study of Dublin Ireland. *Energy Build* **2021**, *247*, 111115. [CrossRef]
17. Reinhart, C.F.; Cerezo Davila, C. Urban Building Energy Modeling—A Review of a Nascent Field. *Build Environ.* **2016**, *97*, 196–202. [CrossRef]

18. Hong, T.; Chen, Y.; Luo, X.; Luo, N.; Lee, S.H. Ten Questions on Urban Building Energy Modeling. *Build Environ.* **2020**, *168*, 106508. [CrossRef]
19. Ang, Y.Q.; Berzolla, Z.M.; Reinhart, C.F. From Concept to Application: A Review of Use Cases in Urban Building Energy Modeling. *Appl. Energy* **2020**, *279*, 115738. [CrossRef]
20. Li, Y.; Liu, C. Estimating Solar Energy Potentials on Pitched Roofs. *Energy Build* **2017**, *139*, 101–107. [CrossRef]
21. Li, Z.; Lin, B.; Zheng, S.; Liu, Y.; Wang, Z.; Dai, J. A Review of Operational Energy Consumption Calculation Method for Urban Buildings. *Build Simul.* **2020**, *13*, 739–751. [CrossRef]
22. Apostolopoulou, A.; Boyd, D.; Carlos, C.; Cavazzi, S.; Wilson, R.; Jimenez-Bescos, C. Optimization of Computational Time for Urban Building Energy Modelling, through Generalizing the Building Footprint. A Case Study in London, UK. In Proceedings of the 31st GISRUK Conference 2023, Glasgow, UK, 19 April 2023.
23. Oraiopoulos, A.; Howard, B. On the Accuracy of Urban Building Energy Modelling. *Renew. Sustain. Energy Rev.* **2022**, *158*, 111976. [CrossRef]
24. Li, X.; Yao, R. Modelling Heating and Cooling Energy Demand for Building Stock Using a Hybrid Approach. *Energy Build* **2021**, *235*, 110740. [CrossRef]
25. García-López, J.; Sendra, J.J.; Domínguez-Amarillo, S. Validating 'GIS-UBEM'—A Residential Open Data-Driven Urban Building Energy Model. *Sustainability* **2024**, *16*, 2599. [CrossRef]
26. Groppi, D.; de Santoli, L.; Cumo, F.; Astiaso Garcia, D. A GIS-Based Model to Assess Buildings Energy Consumption and Usable Solar Energy Potential in Urban Areas. *Sustain. Cities Soc.* **2018**, *40*, 546–558. [CrossRef]
27. Heidenthaler, D.; Deng, Y.; Leeb, M.; Grobbauer, M.; Kranzl, L.; Seiwald, L.; Mascherbauer, P.; Reindl, P.; Bednar, T. Automated Energy Performance Certificate Based Urban Building Energy Modelling Approach for Predicting Heat Load Profiles of Districts. *Energy* **2023**, *278*, 128024. [CrossRef]
28. Blázquez, T.; Suárez, R.; Ferrari, S.; Sendra, J.J. Addressing the Potential for Improvement of Urban Building Stock: A Protocol Applied to a Mediterranean Spanish Case. *Sustain. Cities Soc.* **2021**, *71*, 102967. [CrossRef]
29. García-Pérez, S.; Sierra-Pérez, J.; Boschmonart-Rives, J. Environmental Assessment at the Urban Level Combining LCA-GIS Methodologies: A Case Study of Energy Retrofits in the Barcelona Metropolitan Area. *Build Environ.* **2018**, *134*, 191–204. [CrossRef]
30. Januário, M.; Gomes, R.; Baptista, P.; Ferrão, P. Integrated Energy and Environmental Modeling to Design Cost-Effective Building Solutions at a Regional Level. *Energies* **2024**, *17*, 5730. [CrossRef]
31. Sokol, J.; Cerezo Davila, C.; Reinhart, C.F. Validation of a Bayesian-Based Method for Defining Residential Archetypes in Urban Building Energy Models. *Energy Build* **2017**, *134*, 11–24. [CrossRef]
32. Eggimann, S.; Vulic, N.; Rüdisüli, M.; Mutschler, R.; Orehounig, K.; Sulzer, M. Spatiotemporal Upscaling Errors of Building Stock Clustering for Energy Demand Simulation. *Energy Build* **2022**, *258*, 111844. [CrossRef]
33. De Jaeger, I.; Reynders, G.; Callebaut, C.; Saelens, D. A Building Clustering Approach for Urban Energy Simulations. *Energy Build* **2020**, *208*, 109671. [CrossRef]
34. Martín-Consuegra, F.; de Frutos, F.; Oteiza, I.; Agustín, H.A. Use of Cadastral Data to Assess Urban Scale Building Energy Loss. Application to a Deprived Quarter in Madrid. *Energy Build* **2018**, *171*, 50–63. [CrossRef]
35. Aguacil, S.; Lufkin, S.; Rey, E.; Cuchi, A. Application of the Cost-Optimal Methodology to Urban Renewal Projects at the Territorial Scale Based on Statistical Data—A Case Study in Spain. *Energy Build* **2017**, *144*, 42–60. [CrossRef]
36. Fabbri, K.; Zuppiroli, M.; Ambrogio, K. Heritage Buildings and Energy Performance: Mapping with GIS Tools. *Energy Build* **2012**, *48*, 137–145. [CrossRef]
37. European Parliament; Council of the European Union. *Directive 2010/31/EU of the European Parliament and of the Council of 19 May 2010 on the Energy Performance of Buildings (Recast)*; Official Journal of the European Union: Brussels, Belgium, 2010; pp. 13–35.
38. Cespedes-Lopez, M.-F.; Mora-Garcia, R.-T.; Perez-Sanchez, V.R.; Marti-Ciriquian, P. The Influence of Energy Certification on Housing Sales Prices in the Province of Alicante (Spain). *Appl. Sci.* **2020**, *10*, 7129. [CrossRef]
39. Tajani, F.; Morano, P.; Di Liddo, F.; Doko, E. A Model for the Assessment of the Economic Benefits Associated with Energy Retrofit Interventions: An Application to Existing Buildings in the Italian Territory. *Appl. Sci.* **2022**, *12*, 3385. [CrossRef]
40. Droutsa, K.G.; Kontoyiannidis, S.; Dascalaki, E.G.; Balaras, C.A. Mapping the Energy Performance of Hellenic Residential Buildings from EPC (Energy Performance Certificate) Data. *Energy* **2016**, *98*, 284–295. [CrossRef]
41. Farzaneh, H.; Malehmirchegini, L.; Bejan, A.; Afolabi, T.; Mulumba, A.; Daka, P.P. Artificial Intelligence Evolution in Smart Buildings for Energy Efficiency. *Appl. Sci.* **2021**, *11*, 763. [CrossRef]
42. Ali, U.; Shamsi, M.H.; Alshehri, F.; Mangina, E.; O'Donnell, J. Comparative Analysis of Machine Learning Algorithms for Building Archetypes Development in Urban Energy Modeling. In Proceedings of the Building Performance Analysis Conference and SimBuild, ASHRAE/IBPSA-USA, Chicago, IL, USA, 26 September 2018; Volume 8, pp. 60–67.
43. Ali, U.; Bano, S.; Shamsi, M.H.; Sood, D.; Hoare, C.; Zuo, W.; Hewitt, N.; O'Donnell, J. Urban Building Energy Performance Prediction and Retrofit Analysis Using Data-Driven Machine Learning Approach. *Energy Build* **2024**, *303*, 113768. [CrossRef]

44. Garbasevschi, O.M.; Estevam Schmiedt, J.; Verma, T.; Lefter, I.; Korthals Altes, W.K.; Droin, A.; Schiricke, B.; Wurm, M. Spatial Factors Influencing Building Age Prediction and Implications for Urban Residential Energy Modelling. *Comput. Environ. Urban Syst.* **2021**, *88*, 101637. [CrossRef]
45. Piras, G.; Muzi, F.; Ziran, Z. Open Tool for Automated Development of Renewable Energy Communities: Artificial Intelligence and Machine Learning Techniques for Methodological Approach. *Energies* **2024**, *17*, 5726. [CrossRef]
46. Xie, X.; Liu, Y.; Xu, Y.; He, Z.; Chen, X.; Zheng, X.; Xie, Z. Building Function Recognition Using the Semi-Supervised Classification. *Appl. Sci.* **2022**, *12*, 9900. [CrossRef]
47. Beltran-Velamazan, C.; Monzón-Chavarrías, M.; López-Mesa, B. A Method for the Automated Construction of 3d Models of Cities and Neighborhoods from Official Cadaster Data for Solar Analysis. *Sustainability* **2021**, *13*, 6028. [CrossRef]
48. Ministry of Transport Mobility and Urban Agenda. *Código Técnico de La Edificación, Documento Básico de Ahorro de Energía 2019*; Ministry of Transport Mobility and Urban Agenda: Madrid, Spain, 2019.
49. Chen, T.; Guestrin, C. XGBoost: A Scalable Tree Boosting System. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining; Association for Computing Machinery: New York, NY, USA, 2016; pp. 785–794.
50. Ruiz, G.R.; Bandera, C.F. Validation of Calibrated Energy Models: Common Errors. *Energies* **2017**, *10*, 1587. [CrossRef]
51. Ashrae, A.G. *Guideline 14-2014: Measurement of Energy, Demand, and Water Savings*; American Society of Heating, Refrigerating, and Air Conditioning Engineers: Atlanta, Georgia, 2014.
52. Instituto de Ciencias de la Construcción Eduardo Torroja; Asociación de Investigación y Cooperación Industrial de Andalucía. *Calificación de La Eficiencia Energética de Los Edificios*; Ministerio de Industria, Energía y Turismo: Madrid, Spain, 2015.
53. Filogamo, L.; Peri, G.; Rizzo, G.; Giaccone, A. On the Classification of Large Residential Buildings Stocks by Sample Typologies for Energy Planning Purposes. *Appl. Energy* **2014**, *135*, 825–835. [CrossRef]
54. Olivo, Y.; Hamidi, A.; Ramamurthy, P. Spatiotemporal Variability in Building Energy Use in New York City. *Energy* **2017**, *141*, 1393–1401. [CrossRef]
55. Ahmed Gassar, A.A.; Yun, G.Y.; Kim, S. Data-Driven Approach to Prediction of Residential Energy Consumption at Urban Scales in London. *Energy* **2019**, *187*, 115973. [CrossRef]
56. Wang, D.; Landolt, J.; Mavromatidis, G.; Orehounig, K.; Carmeliet, J. CESAR: A Bottom-up Building Stock Modelling Tool for Switzerland to Address Sustainable Energy Transformation Strategies. *Energy Build* **2018**, *169*, 9–26. [CrossRef]
57. Johari, F.; Shadram, F.; Widén, J. Urban Building Energy Modeling from Geo-Referenced Energy Performance Certificate Data: Development, Calibration, and Validation. *Sustain. Cities Soc.* **2023**, *96*, 104664. [CrossRef]
58. Johari, F.; Lindberg, O.; Ramadhani, U.H.; Shadram, F.; Munkhammar, J.; Widén, J. Analysis of Large-Scale Energy Retrofit of Residential Buildings and Their Impact on the Electricity Grid Using a Validated UBEM. *Appl. Energy* **2024**, *361*, 122937. [CrossRef]
59. Ministry for Ecological Transition and the Demographic Challenge; Ministry of Transport Mobility and Urban Agenda. *Estado de La Certificación Energética de Los Edificios (11o Informe)*; Ministry for Ecological Transition and the Demographic Challenge: Madrid, Spain, 2022.
60. Spain's Ministry of Transport Mobility and Urban Agenda (MITMA). *2020 Update of the Long-Term Strategy for Energy Renovation in the Building Sector in Spain (ERESEE)*; Ministry of Transport Mobility and Urban Agenda: Madrid, Spain, 2020.
61. Spain's Ministry of Transport Mobility and Urban Agenda (MITMA). *"Segmentación Del Parque Residencial de Viviendas En España En Clústeres Tipológicos". Estudio (01) Para La ERESEE 2020*; Ministry of Transport Mobility and Urban Agenda: Madrid, Spain, 2020.
62. Beltran-Velamazan, C.; Monzón-Chavarrías, M.; López-Mesa, B. Clasificación y Caracterización Del Parque Habitacional En Zonas Rurales. In *RuralREGEN Estudio Sobre el Estado de la Rehabilitación Energética de Viviendas en el Ámbito Rural en España: Diagnóstico, Barreras y Soluciones*; ECODES—Fundación Ecología y Desarrollo: Madrid, Spain, 2022; pp. 16–37. ISBN 978-84-18321-64-1.
63. Beltrán Velamazán, C.; Monzón Chavarrías, M.; López Mesa, B. Caracterización Energética Del Parque Edificado Español a Escala Nacional a Partir de Datos En Abierto: El Caso de Zaragoza. In Proceedings of the Jornada de Jóvenes Investigadores del I3A, Zaragoza, Spain, 26 June 2024.
64. López-Ochoa, L.M.; Las-Heras-Casas, J.; Olasolo-Alonso, P.; López-González, L.M. Towards Nearly Zero-Energy Buildings in Mediterranean Countries: Fifteen Years of Implementing the Energy Performance of Buildings Directive in Spain (2006–2020). *J. Build. Eng.* **2021**, *44*, 102962. [CrossRef]
65. Jareño Escudero, C.I.; Navarro Escudero, M.; Mifsut García, C.D.; Flores Fillol, M.; Salmerón Lissen, J.M. Potential of Energy Savings in the Public Housing Stock of Comunitat Valenciana Region by Applying the MedZEB Cost-Optimal Methodology. *Appl. Sci.* **2021**, *12*, 138. [CrossRef]
66. Civiero, P.; Pascual, J.; Arcas Abella, J.; Salom, J. Innovative PEDRERA Model Tool Boosting Sustainable and Feasible Renovation Programs at District Scale in Spain. *Sustainability* **2022**, *14*, 9672. [CrossRef]

67. Arcas Abella, J.; Pagès Ramon, A.; Bilbao, A. Herramienta UrbanZEB. Hacia El Desarrollo de Estrategias Urbanas de Transición Energética de Edificios. *ACE Archit. City Environ.* **2021**, *16*, 9888. [CrossRef]
68. Beltrán-Velamazán, C.; Gómez-Gil, M.; Monzón-Chavarrías, M.; Espinosa-Fernández, A.; López-Mesa, B. Harnessing Open European Data for a Data-Driven Approach to Enhancing Decarbonization Measurement in the Built Environment. *Environ. Clim. Technol.* **2024**, *28*, 776–793. [CrossRef]