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Space–Time Forecasting of Heating & Cooling Energy Needs as an Energy Poverty Measure in Romania

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Abstract: Lack of access to basic energy services, known as energy poverty, remains felt in the country, with seasonal changes and an economic divide. The frameworks to measure energy poverty differ spatially and temporally, with climate change and behavioral culture being the essential influencing factors. This paper is focused on heating and cooling energy demands, which can be defined as an energy poverty metric for the propensity to be at risk of energy poverty caused by climate regime. Employing sophisticated statistical space–time forecasting tools, we build a model incorporating spatial and temporal energy consumption volatility across Romanian regions at the NUTS3 level. The model considers climatic conditions and raw data from 45 years (1979–2023) of cooling and heating degree days to determine local trajectories for the next nine years. Identifying high-energy-poverty-risk areas in our research can provide valuable insights for policymakers, enabling them to develop targeted plans for eliminating energy poverty and ensuring equitable access to heating and cooling. The results underline the necessity of differentiated approaches in energy policies and add value to the general understanding of energy poverty issues and conditions, considering the Romanian climatic and socio-economic context.

Keywords: energy poverty; space–time analysis; curve fit forecast; exclusion risk; behavioral culture

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1. Introduction

The present paper deals with an important problem encompassing issues of energy access, climate change, and social–economic inequalities. Energy poverty, defined initially as accessibility to the energy for heating a house and preparing food, is now more broad as the inadequate access of households to necessary heating, cooling, and energy services is a deepening worry throughout Europe, and especially in Romania. The problem grows worse due to rising energy costs [1,2], aging infrastructure [3,4], and increased climate variability, which increase the need for heating in the winter and cooling in the summer [5–7]. Measuring and forecasting energy needs correctly is important for creating policies and interventions that help vulnerable populations deal with energy poverty, which adversely affects both quality of life and health.

Energy poverty is defined as a lack of ability of households to afford sufficient thermal comfort for their homes because of high costs and low incomes. This is especially the case in the context of the current climatic changes, since high temperatures lead to a need to use more energy for cooling and, hence, energy consumption. In this regard, the adopted indicator of Cooling Degree Days (CDD) is crucial in evaluating the cooling demand and defining the areas most affected by energy poverty. The CDD is defined as the difference between the recorded temperature and the standard temperature of 18 °C (65 °F), giving information about how hot it has been cumulatively [8]. Via Curve Fit Forecasting in Geographic Information Systems (GIS) analysis, we get a clear picture of the spatial and temporal pattern of CDD, and the impacts on households and public policies.

In the cold season, some cannot regularly use electricity, an amplified problem affecting many low-income households, a condition known as energy poverty. Heating degree days (HDD) is a parameter that can help us to estimate the necessity of heating households, and determine which regions are in the high-risk zone regarding the energy poverty problem [9]. HDD sums up the number of days where the temperature drops below a specified level, which means that heating systems must be employed. HDD is one of the most common indicators used to analyze households' heating necessities and determine areas that might be subjected to energy poverty. HDD is the sum of the average daily temperature below a base temperature, commonly around 18 °C (65 °F) as the lower limit for heating for home thermostatic comfort [10,11]. If analysis had been performed using Curve Fit Forecast in GIS, we would have better realized the regional and temporal demands for heating in Romania and their effects on homes.

Essential for understanding and resolving energy poverty is determining the heating and cooling needs of households in Romania during the harsh winters and hot summers. Current energy poverty metrics generally target models concerned with income and expenditures [12], while missing the spatial and temporal changes in energy requirements. This work presents a new way to measure energy poverty using space–time forecasting methods to project heating and cooling energy needs across multiple regions and timeframes in Romania. This strategy permits a richer and more precise comprehension of energy needs, making available a helpful resource for policymakers trying to address energy poverty [13].

The space–time forecasting model combines several elements, such as geographic location, climate conditions, building attributes, and social and economic data, to project energy requirements for heating and cooling in urban and rural regions. Knowing that the climate differs among the regions, this technique permits an understanding of the spectrum of energy needs throughout different territories, conditioned by Romania's diverse nature, weather conditions, and infrastructure [14,15]. In addition, the model considers the seasonal changes in energy demand through the HDD and CDD indicators, reflecting how extreme weather events and enduring climate trends affect household energy use. Multiple factors drive energy demand, in addition to the weather influences of CDD and HDD. Thermal insulation, the type of material, and the efficiency of heating or cooling systems are important characteristics of a habitat that can be used to evaluate energy demand. Socioeconomic factors, such as household income, their capacity to invest in energy-efficient equipment, and consumer behavior, such as how we want or do not want certain indoor temperatures, influence energy demand. The integration of these factors into forecasting models enables a better understanding of the variability in energy demand. Our study is the first on this issue, and represents an essential brick in the larger construction of an integrated framework of energy poverty evaluation.

The study deepens our insights into how energy needs change over time and locations by giving a more nuanced understanding of energy poverty. The findings could help to identify the parts of the population and areas most vulnerable to energy poverty, allowing for targeted interventions and resource allocation. In addition, this forecasting model can act as a context for forthcoming research on energy poverty in other countries facing similar challenges.

2. Literature Background

2.1. Energy Poverty

Energy poverty is defined as the inadequate ability of households to pay for necessary energy services, including heating, cooling, lighting, and cooking [16,17]. It has recently become a major global challenge. This perception is crucial, since it points out economic challenges, the escalating nature of health perils, and social inequity. In the past few years, energy poverty has attracted attention within research and policy communities, notably within the European Union (EU), which designates it as a critical socioeconomic challenge. The International Energy Agency shows the correlation between heating degree days and energy consumption (natural gases) in buildings for 1991–2020 [18].

Scholars and researchers have taken part in clarifying and conceptualizing energy poverty. With the concept's introduction, Boardman [19] pointed out the difficulty in preserving a comfortably warm home resulting from high energy costs, marginal incomes, and insufficient housing. In this original definition, energy poverty was chiefly defined as a lack of appropriate heating. While the earlier literature confined its definition, recent writings have broadened it to include cooling needs, particularly in places affected by severe heat, and reliable access to electricity [20]. The complex nature of energy poverty complicates measurements, requiring the evaluation of income levels, energy prices, and housing conditions.

Energy poverty results from multiple factors, including escalating energy prices, low family incomes, and inefficient building systems. In Europe, liberalized energy markets and rising fuel costs have intensified the problem, especially in Eastern and Southern European nations [21]. Due to aging housing and energy systems combined with significant income gaps, Romania is among the EU nations most affected by energy poverty [22–24].

Energy poverty has extensive outcomes. Homes dealing with energy poverty typically practice the "under-consumption" of energy, resulting in insufficient heating efforts in winter or cooling choices in summer. Inefficient consumption is associated directly with health risks, including respiratory diseases, cardiac problems, and more excellent mortality rates in severe weather situations [25–30]. In addition, energy poverty frequently drives social isolation, as people either scale back their social pursuits or minimize home visits to diminish energy expenses.

Measuring energy poverty is not straightforward because of its multidimensional properties. Years ago, expenditure-based measurements, including the "10% threshold" (spending more than 10% of income on energy bills), saw widespread use. Nonetheless, academics have evaluated this technique as overly simplistic, failing to fully express the nature of energy poverty [31]. As an alternative to simpler measures, the UK's implementation of the "Low Income High Cost" (LIHC) indicator and the "Energy Poverty Vulnerability Index" (EPVI) proposal from Bouzarovski and Petrova [20] seek to merge broader socioeconomic and housing elements into their assessments.

Recent research has also examined energy poverty's geographical and temporal aspects [32]. Bouzarovski and Simcock [33] demonstrate that energy poverty varies across different areas, especially between rural and urban locations. Climate change is worsening the condition by boosting the incidence of extreme weather events, which further overwhelms energy requirements for heating and cooling [34].

Many EU governments, mainly those concerned with energy poverty, have made policy changes to boost energy efficiency and help financially vulnerable households. In 2019, the EU adopted its Clean Energy for All Europeans package, which requires member states to create national strategies that address energy poverty, prioritizing actions such as housing retrofitting and encouraging renewable energy [35]. Karpinska et al. [36] and Mulder et al. [37] maintain that these interventions need to better reflect local conditions and show an understanding of the spatial and socioeconomic challenges of energy poverty.

The available body of literature concerning energy poverty reveals its complex and layered characteristics, which respond to economic, infrastructural, and geographical situations [38–40]. Although substantial attempts have been made to define and quantify energy poverty, a more sophisticated methodology is required, largely due to the impacts of climate change and rising energy costs. Successful policy responses must improve energy efficiency and resolve the structural inequalities that keep energy poverty alive.

2.2. Cooling Degree Days (CDD)

Several studies have shown that climate conditions correlate with energy poverty, stressing how temperature influences energy requirements [41–43]. Locations that experience high temperatures, especially in summer, experience steadily rising cooling demands, leading to more costly energy bills for residential customers, overloading electrical networks not designed for intensive use, and the implied increase in the number of blackouts. Besides the deterioration in well-being, there are more health problems for people with cardio-respiratory diseases. This situation creates a significantly high demand for those households with limited income, who may already struggle to pay for essential energy services [44]. In locations with numerous cooling degree days (CDD), Dubois and Meier [9] pointed out that the financial weight of cooling elevates, deepening energy poverty. CDD, a measurement that predicts energy consumption for cooling, is fundamental to realizing how climate affects expenditures on household energy.

Besides the direct temperature effects, there is rising concern that climate change is heightening energy poverty by raising the variability of energy requirements, especially for cooling. According to Bouzarovski and Simcock [33], as temperatures rise worldwide and extreme heatwaves occur more often, households become ever more susceptible to energy poverty due to the unpredictable and heightened need for cooling. This increased variability disproportionately affects those with limited financial resources, making it hard to respond to shifting climate conditions without further slipping into energy poverty [45].

Even with the identification of CDD's role in energy poverty, there is, as yet, minimal exploration into how CDD growth trends (as a dynamic process) affect diverse regions and demographic segments [46]. Previous studies have presented a broader view of temperature effects or income-dependent drivers of energy poverty. However, they have not entirely examined the geographic and temporal trends associated with CDD growth and their relationship with energy poverty [47,48]. This gap must be addressed to comprehend regional vulnerabilities and develop focused interventions to lessen energy poverty.

2.3. Heating Degree Days (HDD)

Previous research has routinely pointed out the relationship between energy poverty and climatic factors, primarily related to heating demand in regions with high heating degree days (HDD) [46]. Bouzarovski and Simcock [33] pointed out that as HDDs increase, there is an increased need for heating, mainly in winter, which considerably affects energy consumption in disadvantaged households. Households often identified by low-income levels and poor housing efficiency find it hard to pay for the high energy costs they incur [49]. The finding is that many people are under-heating their homes, leading to a fall in quality of life and rising health threats such as respiratory and cardiovascular diseases [50,51].

The relation between HDD and energy poverty in colder regions is significant, given that heating requirements are a key element of household energy needs. In their study, Healy and Clinch [50] pointed out that continued exposure to cold weather without sufficient home heating creates various health problems, stressing energy poverty's economic and social dimensions. Due to their fragile position, they often run into more drastic drawbacks given their inability to afford proper heating for their homes; this brings on quick pain and lasting health consequences [52,53].

2.4. Measuring CDD, HDD and Energy Poverty

Measuring CDD, HDD, and energy poverty highlights the association between climate and socioeconomic elements in energy consumption. Using CDD and HDD, the demand for cooling and heating is estimated. Accurately tracking these metrics allows us to interpret how much energy is used and the ties to energy poverty that families experience in their quest for reliable heating or cooling solutions. Romania has a large area of temperature, from minus 30 degrees in winter to plus 40 degrees in summer, with consistent geographical differences.

Castaño-Rosa et al. [54] stress the role of CDD models in estimating upcoming energy consumption amidst climate change. The research in seven nations shows that a rise in CDDs caused by elevated temperatures will significantly increase cooling requirements and elevate energy poverty threats for lower-income families unable to purchase air conditioners. Pérez-Fargallo et al. [55] implemented a risk assessment model to analyze energy poverty in Chile by linking heat and cold demands to user thermal preferences. This technique delivers a localized analysis of energy poverty risks, including heating and cooling needs.

In Bologna's case study [56], they applied energy performance certificates to pinpoint areas of energy poverty and their heating demands. Their evidence shows that high HDDs are linked with energy poverty, and that households with substandard insulation face struggles with heating costs. Bienvenido-Huertas et al. [57] study the role of natural ventilation in lowering cooling energy use.

Furthermore, numerous methods for assessing energy poverty utilize economic and climatic indicators such as CDD and HDD [58,59]. These measures provide a complete method that considers regional variation and climate-related energy demands. Kelly et al. [60] asserted that an integrated indicator essential for measuring heating energy poverty is important, and called for initiatives that advance a just transition.

Examining CDD and HDD in conjunction with energy poverty using diverse models reveals essential connections between climatic elements and socioeconomic dynamics for policymakers seeking to implement strategies and combat energy poverty effectively. Singh et al. [61] had a space–time approach to trends and waves of heating.

Curve fitting in GIS offers a significant advantage in energy demand forecasting due to its ability to integrate complex spatial and temporal data. Compared to other predictive methods, such as simple linear regression or autoregressive integrated moving average (ARIMA) models, GIS allows a more detailed visual representation of regional variations and the behavior of energy demand according to geographic variables [54]. In addition, recent studies have demonstrated that curve fitting in GIS provides more accurate results when considering multiple layers of climatic and socioeconomic data [55]. Unlike other methods that may omit spatial relationships, GIS allows for in-depth analyses of geographic relationships and the uneven distribution of energy demand at the regional level [11]. This approach makes GIS a superior solution for identifying regional vulnerabilities and developing tailored energy strategies.

There is a lack of space–time studies about energy poverty, except in China [62–64] and for sub-Saharan African countries [65].

The present paper aims to add to current scholarship by applying the Curve Fit Forecast technique through a GIS framework to study the growth trends of CDD across different territories. By performing this analysis, the study contributes a detailed understanding of how increasing CDDs—caused by climate change—affect energy poverty risks in varying locations. This technique enables the more precise and local forecasting of energy needs, providing insights that may guide policy efforts to mitigate the impact of energy poverty in regions particularly vulnerable to climate change.

Despite mounting research that links HDD to energy poverty, there has been little analysis of how upcoming HDD trends, especially those forecasted by advanced methods such as GIS and Curve Fit Forecast, might affect future incidences of energy poverty. These tools allow for more accurate analyses of the changes in heating demand through space and time, furnishing insights into how energy needs could change under different climate scenarios. Future HDD trends might enhance or change regionally because of climate change, modifying the scope and strength of energy poverty in suburban and urban spaces.

This study also aims to fill an essential void in the literature by analyzing how spatial differences in future heat degree day trends may intensify or lessen energy poverty risks. This approach permits a more directed comprehension of where and when the most susceptible households will deal with increased energy burdens, delivering critical information for policymakers who want to lessen the negative consequences of energy poverty.

Moreover, the paper's novelty is that the model is applied to Romania at the Nomenclature of Territorial Units for Statistics Level 3 (NUTS 3), revealing the regional differences in CDD and HDD and the energy needs. This forecast can determine the financial needs for energy and the exposure to energy poverty, offering policy and decision-makers a regional map for governmental interventions.

The hypotheses of the study are:

Hypothesis 1. *The curve fit forecast model gives a reliable approximation of CDD and HDD;*

Hypothesis 2. *The CDD forecast in Romania at the NUTS3 level for 2023–2032 shows different needs;*

Hypothesis 3. *The CDD forecast has an increasing trend;*

Hypothesis 4. *The HDD forecast in Romania at the NUTS3 level for 2023–2032 shows different needs;*

Hypothesis 5. *The HDD forecast has a decreasing trend;*

Hypothesis 6. *Combining CDD and HDD forecasts that the exposure to energy poverty is more homogenous.*

3. Research Methodology and Data Sets

To forecast future trends in CDD and HDD, we applied the ArcGIS Curve Fit Forecast method and identified regions with notable elevations that need warming. The interface permits data to be tested according to different curve types (linear, parabolic, exponential, and Gompertz). By employing the Curve Fit Forecast tool in Arc GIS Pro 3.2.2 [66], we analyzed the CDD and HDD curves at NUTS3 for Romania. We developed a realistic representation of two or three dimensions from data concerning space and time.

Various GIS methods were applied to generate these maps and explore the spatio-temporal relationship. An advanced GIS method called the space–time cube (STC) converts spatial and temporal data into a three-dimensional form, with each cell in the cube representing a unit of space and time. This method assessed and spotted patterns in the CDD and HDD values throughout time. It played a role in uncovering anomalies within the time series represented in the maps. Tools from ArcGIS were utilized to illustrate the data layout in 2D maps with varying symbols.

The research framework is presented in Figure 1.

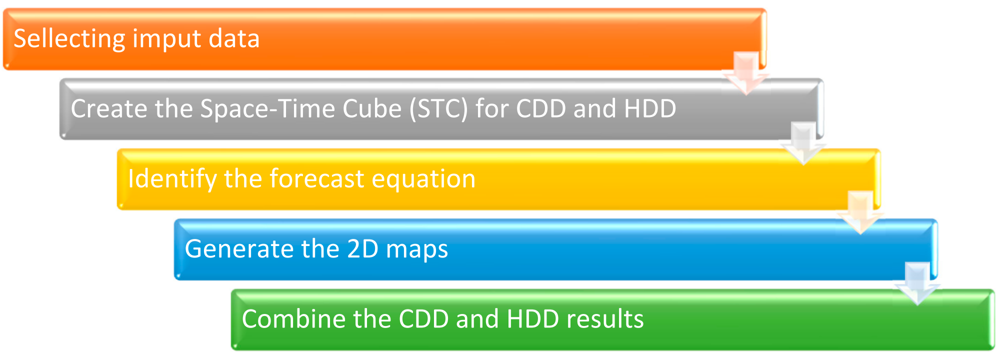

Figure 1. Research framework. *Source: Authors' construct.*

Step 1: Selecting the Input Data

To build the space–time cube, row data must be selected. In our study, we used the Eurostat cooling and heating degree days by NUTS 3 regions annual data [nrg_chddr2_a__custom_12592029], from 1978 to 2023 [67].

Step 2: Create the Space–time Cube (STC) for CDD and HDD

A space–time cube is a data model where spatial (where) and temporal (when) data are combined and stored in one place. It makes it possible to analyze spatial and temporal data series that reflect the phenomena's temporal dynamics. Data from the area of interest (Romania NUTS 3 level) and period of interest (1978–2023) were extracted to develop the space–time cube for forecasting in Arc GIS. There must be location data in the form of addresses or coordinates and time data in the form of dates and times. The space–time cube accommodates these integrated spatio-temporal data. It enables them to be visualized, modeled, and analyzed to understand trends and patterns that help develop tools and methods to forecast future events and outcomes. Therefore, a high-quality space–time cube must be assembled to use the ArcGIS forecast tools well.

The characteristics of the STCs for CDD and HDD are the same and presented in (Table 1).

Table 1. Synthesis of STC characteristics for CDD and HDD.

STC Characteristics	CDD	HDD
Input feature time extent	1979-01-01 00:00:00 to 2023-01-01 00:00:00	1979-01-01 00:00:00 to 2023-01-01 00:00:00
Number of time steps	45	45
Time step interval	1 year	1 year
Time step alignment	End	End
First time step temporal bias	100.00%	100.00%
First time step interval	after 1978-01-01 00:00:00 to on or before 1979-01-01 00:00:00	after 1978-01-01 00:00:00 to on or before 1979-01-01 00:00:00
Last time step temporal bias	0.00%	0.00%
Last time step interval	after 2022-01-01 00:00:00 to on or before 2023-01-01 00:00:00	after 2022-01-01 00:00:00 to on or before 2023-01-01 00:00:00
Coordinate system	Stereo 70	Stereo 70
Cube extent across space	(coordinates in meters)	(coordinates in meters)
Min X	134,105.0196	134,105.0196
Min Y	235,538.6121	235,538.6121
Max X	874,928.8607	874,928.8607
Max Y	753,220.1398	753,220.1398
Locations	42	
% of locations with estimated observations	0.00	
- Total number	0	
Total observations	1890	
% of all observations that were estimated	0.00	
Total number	0	

Source: Research construct and results.

Step 3: Identify the Forecast Equation

The curve fit forecast model tests four types of curves to identify the best shape that fits the row data for each location. The model considers linear, parabolic, exponential, and Gompertz (S-shape) curves, which support the forecast values. These four types of models are selected since they can address a wide variety of growth and decline, and a balance between simplicity (linear and parabolic models) and complexity (exponential and Gompertz models) is found to describe the studied phenomena's behaviors. In addition, these models are both statistically valid and computationally efficient, and are amenable to extension over extensive data drawn from an extended space–time. Our model generates 42 equations for the CDD forecast and 42 for the HDD forecast. Their analysis is not relevant to the economy of the present study.

Step 4: Generate the 2D Maps

The ArcGIS forecast tool allows us to generate 2D and 3D maps with the results for the forecasted values for nine years, with the distribution of the curve type, trends, and forecast confidence. For the present study, the 2D maps for the values forecast for 2032 and curve types for CDD and HDD are relevant. The curve types are selected using the root mean square error (RMSE) for each location; more precisely, the curve with the lowest validation RMSE is considered for forecast, and the forecast RMSE evaluates the accuracy of the forecasting model [66].

Step 5: Combine the CDD and HDD Results

The CDD and HDD forecast results reveal five levels of energy needs in the regions. We set the index from 1 to 5 for both, from the lowest to the highest need, and then summarize them to give a general perspective based on the resulting index.

4. Results

4.1. Cooling Degree Days (CDD) Forecast

The map of Figure 2 represents the forecast results for "Cooling Degree Days" (CDD) in Romania, over a 9-year interval, visualized in 2D for the space–time cube (with data file "CDD_CFF_AUTOd.nc"). The map is divided into Romania's counties, highlighting the variation in CDD values forecast for 1 January 2032.

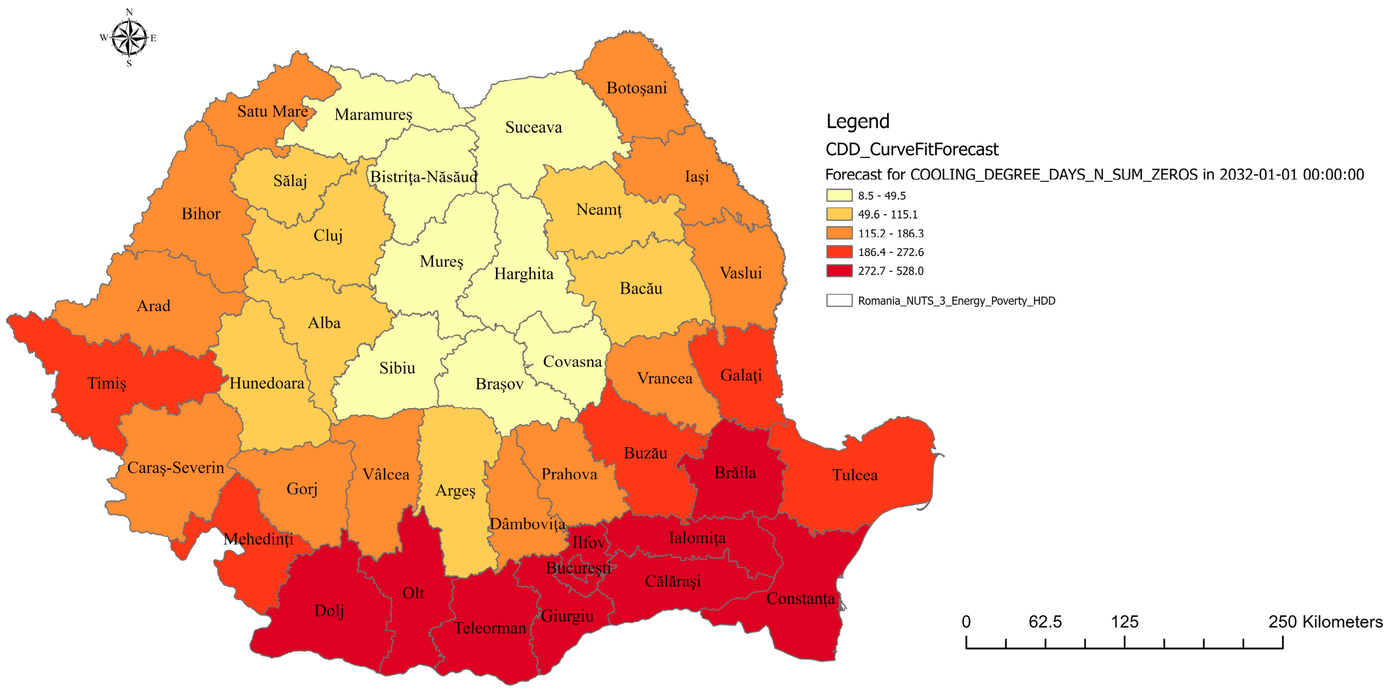

Figure 2. Cooling degree days forecast results for 2023–2032, at NUTS3 level. *Source: Research results, ArcGIS.*

The legend shows "Forecast for COOLING_DEGREE_DAYS_N_SUM_ZEROS", indicating days with high heat that call for cooling measures. The forecast values span five categories, represented by a continuum of colors, from light yellow for the lowest amounts to dark red for the highest. The range includes 8.5 to 528.0, showing where CDD values occur in various country regions.

The spatial distribution of CDD values highlights that in the counties of Braila, Constanta, Ialomita, Calarasi, Bucuresti, Ilfov, Giurgiu, Teleorman, Olt, and Dolj, the highest daily cooling rates occur (272.7–528.0), indicated in dark red. Higher-than-average temperatures forecast cooling requirements in these places. These areas present high potential to use photovoltaic renewable energy technologies, which are less accessible for low-income people (i.e., CASA VERDE Program).

The CDD levels detected in the northern and central zones (Maramureș, Suceava, Bistrita-Nasaud, Harghita, Mureș, Sibiu, Brasov, Covasna) are at their lowest. These zones display a gentler climate with fewer hot days.

The western and eastern sides of Romania reveal moderate levels of cooling days.

The map's differences show that cooling requirements will vary within regions. The south and southeast locations are expected to experience a marked boost in elevated temperatures, while the central and northern areas will continue to be comfortable. This representation considerably aids in formulating energy policies and systems for adapting to changing climates.

The CDD values demonstrate a clear impact from climate change, with warmer temperatures leading in the south and southeast regions. Adopting energy-conserving policies and cooling facilities is necessary. The map is a crucial graphic used by planners in energy and climate areas to grasp the spatial arrangement of upcoming cooling demands. Moreover, the South and Southeast should benefit from state intervention by investing in cooling equipment and other building transformations to reduce the energy needs for cooling or providing financial support to afford housing cooling.

Figure 3 presents the Curve Fit Forecast models for CDD by county in Romania. Different counties are shaded based on how they estimate CDD values in the legend. This map shows the various cooling degree day trends across the regions in Romania. Each county has a climate model, as shown here, along with how CDD values evolve through time using different mathematical approaches to estimate these trends.

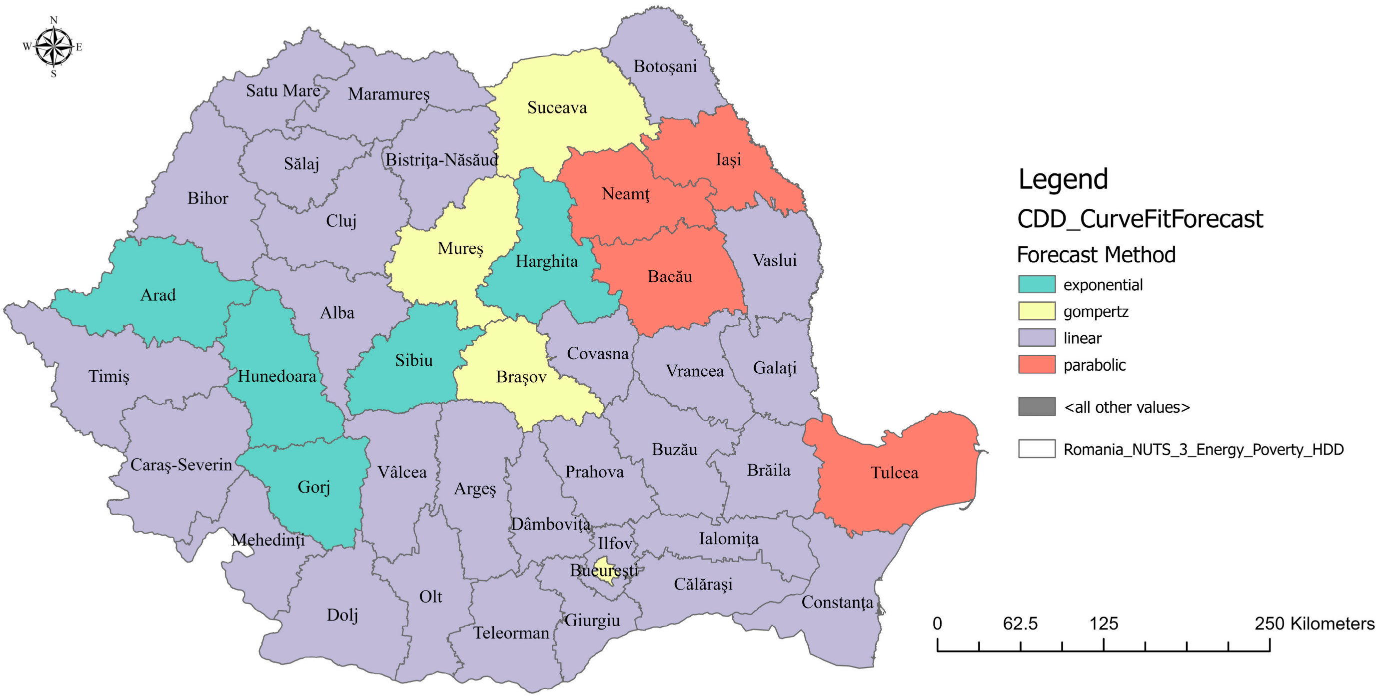

Figure 3. Spatial distribution of the CFF models for CDD, at the NUTS3 level. *Source: Research results, ArcGIS.*

The legend shows that all four forecasting methods covered all the studied locations. The exponential (light green) method applies to counties such as Arad, Hunedoara, Gorj, Sibiu, and Harghita. This model predicts a speeding up of CDD values throughout the years. An accelerated growth demonstrates that occurrences of unseasonably warm days are up in a limited timeframe. The forecast shows that high temperatures may soon spike sharply in areas like Arad, Hunedoara, and others because of climate change.

The Gompertz method (yellow) is applied in the Mureș, Suceava, Brasov, and Bucharest regions. This pattern represents a fast ascent followed by a stabilization, culminating at a limit. Forests tend to rise quickly in Mures, Brasov, and Harghita counties before leveling off. This model shows regions shaped by moderate climate change and surrounding landscape features such as altitude and vegetation.

Neamt, Bacau, Iasi, and Tulcea are forecasted using the parabolic method (Red). Temperatures exhibit a non-consistent trend as CDD values may alter through a curving pattern. Such trends could imply that temperature changes occur in a sophisticated pattern of rises and declines. The model might demonstrate a high level of climate fluctuation in the Iasi, Tulcea, Neamt, and Bacău regions.

The linear model (purple) is the lead approach in numerous regions. This model presents a straightforward trend of either growth or reduction with time. If CDD values increase (or fall) consistently each year, it reflects a linear tendency. This model matches the majority of counties in Romania, showing a predictable climate evolution with minimal fluctuations over time.

The spatial distribution of forecasting methods highlights that in many counties nationwide, the linear method prevails and reflects a consistent and anticipated change in the CDD numbers. Regional analysis reveals exponential and Gompertz methods to depict a more complicated or swift temperature rise. The West and Central counties apply the exponential approach. This may show significant increases in temperature during days needing cooling. In several counties, east and southeast, the parabolic method shows a more intricate model for how the temperature fluctuates through time.

The selection of varied forecasting methods reveals the range of climate types and the complex nature of temperature evolution in both time and place. In regions that adopt more intricate models, such as the exponential or parabolic forecast, climate forecasting may be more variable, leading to a demand for improved prediction methods to recognize these shifts. This map provides insight into the forecasting approaches in different regions of the country, which is essential for analyzing local climate conditions. Forecasting methods arranged spatially indicate the climate dynamics and complexities of various areas.

Recognizing these changes increases the importance of planning, which supports the creation of measures to address climate change. Locations displaying a consistent upward trajectory may call for special measures in energy frameworks and cooling solutions based especially on renewable energy technologies.

Studying how these trends exist nationally offers indications of the unique effects that climate change will have on different locations. Each county requires unique approaches in energy planning and infrastructure adaptation. The map shows CDD projections and embodies climate patterns distinctive to the regions. These patterns give authorities and experts a better understanding of the future of climate change in Romania.

Table 2 reconfirms the CDD trends for each location and temporal aggregation. The most important finding is the INCREASING trend of the CDD for all 42 locations; the speed differs, and it can be analyzed using the detailed results of the model for each location.

4.2. Heating Degree Days Forecast

This legend for "Forecast for HEATING_DEGREE_DAYS_N_SUM_ZEROS" illustrates the estimates for significant heating days (Figure 4). The percentages are organized into five levels marked by shades of blue, from lighter to darker. HDD levels range from 1693.2 to 3275.0, indicating regional differences.

Table 2. Trends direction for CDD.

Overall Data Trend—COOLING_DEGREE_DAYS_N_SUM_ZEROS	
Trend direction	Increasing
Trend statistic	5.2922
Trend *p*-value	0
Overall Data Trend—TEMPORAL_AGGREGATION_COUNT	
Trend direction	Not Significant
Trend statistic	0
Trend *p*-value	1

Source: Research results.

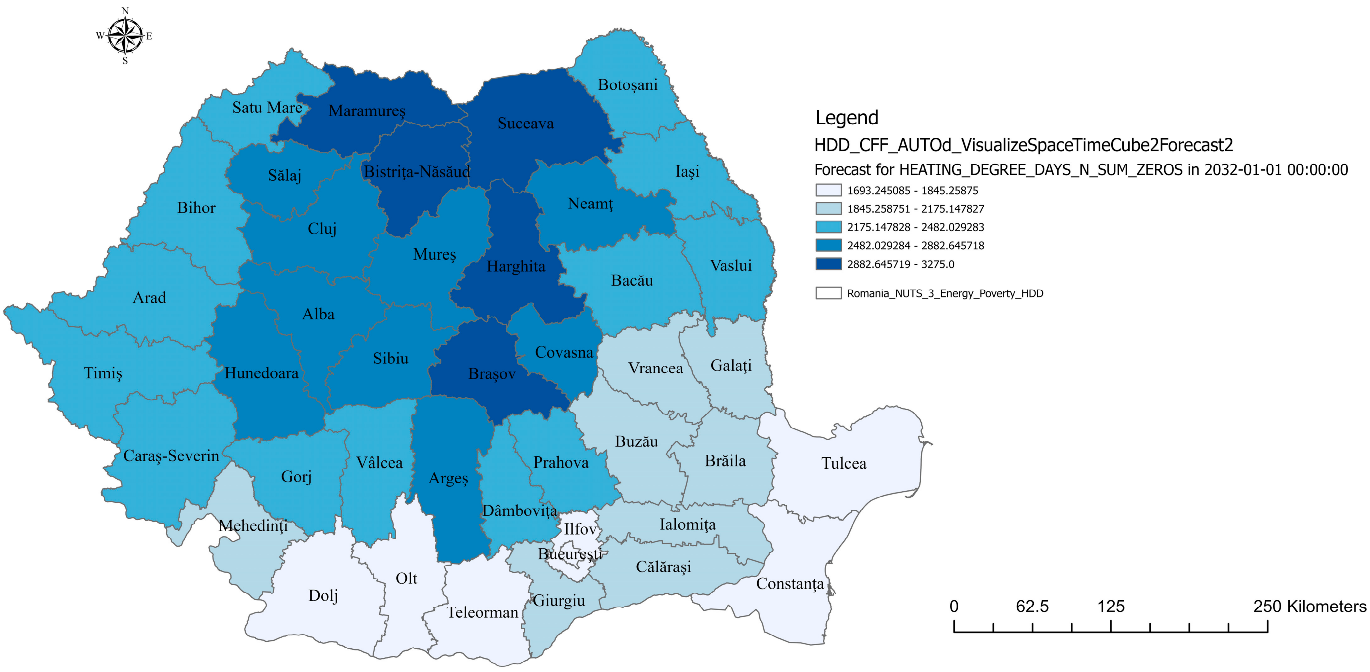

Figure 4. Heating degree days forecast results for 2023–2032, at NUTS3 level. *Source: Research results, ArcGIS.*

HDD shows that counties including Maramures, Bistrita-Nasaud, and Suceava often face the greatest need for heating, indicated by dark blue. Above-average heating requirements are anticipated for these locations. In the central regions of Romania, like Brașov and Harghita, space heating demands are also high.

In Romania's western and eastern regions, heating demands remain relatively modest. The map shows how cooling and heating requirements will differ significantly among areas. Predictions show that both the southern and southeastern regions will endure lower temperatures, while the central and northern areas will face the lowest temperatures. This graphic is beneficial for guiding energy policy and creating resilient systems for responding to climate change.

Figure 5 shows the curve types used to forecast the HDD, where all four types are used. Each county's climate model is shown here, along with how HDD values evolve, using different mathematical approaches to estimate these trends. The western and most of the central regions use linear patterns, while the southern and eastern regions use parabolic patterns.

Table 3 presents the results for the trends identified for HDD. This decreasing trend of HDD reconfirms the effects of climate change, specifically global warming. Considering forecasts for both CDD and HDD, the increasing trends for cooling and the decreasing trends for heating are beneficial for policymakers in drawing next year's requirements for energy consumption.

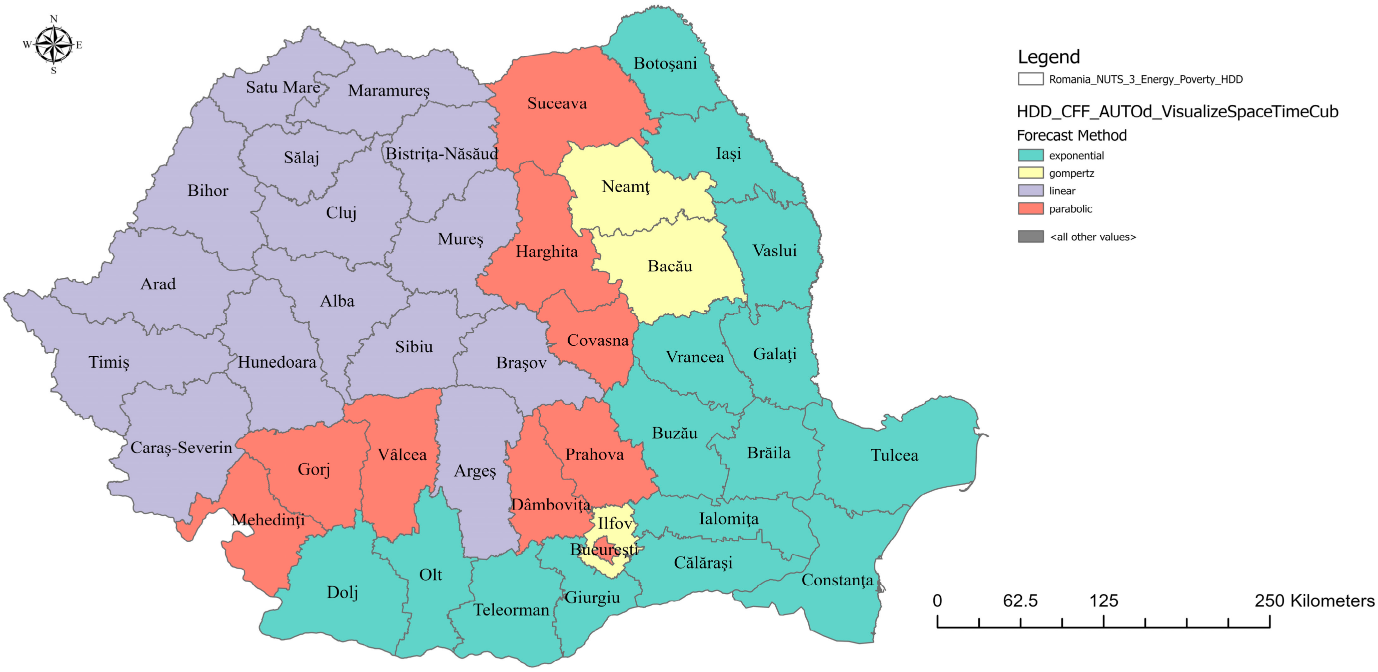

Figure 5. Spatial distribution of the CFF models for HDD at the NUTS3 level. *Source: Research results, ArcGIS*.

Table 3. Trend direction for HDD.

Overall Data Trend—HEATING_DEGREE_DAYS_N_SUM_ZEROS	
Trend direction	Decreasing
Trend statistic	−4.9401
Trend *p*-value	0
Overall Data Trend—TEMPORAL_AGGREGATION_COUNT	
Trend direction	Not Significant
Trend statistic	0
Trend *p*-value	1

Source: Research results.

4.3. CDD and HDD Annual Need

Five classes were identified for both based on the previous results obtained for CDD and HDD forecasts. To create a hierarchy for the annual need for energy for cooling and heating, we propose assigning scores from 1 to 5 (lower to higher need) and cumulating. The cumulative score can have values from 2 to 10, generating nine levels of manual need. Table 4 presents the cumulative scores for the 42 studied locations.

Only three classes were obtained, 5, 6, and 7, placed in the middle of the scale, so a street-liter hierarchy is proposed. The first aspect to be highlighted is that no location has low or high energy needs; most locations can be described as average. Even so, five regions, Calarasi, Giurgiu, Ialomita, Braila, and Timiș, require close attention, even more so knowing that, except Timis, they are less developed and lower-income regions [68]. There are six regions in the green area: Tulcea, Vrancea, Covasna, Mures, Sibiu and Bacau. These have the best CDD and HDD scores and mainly above-average income.

Table 4. Cumulative classes for CDD and HDD.

Id_Loc _Short	NUTS Code	Nume	CDD	HDD	CDD and HDD	Id_Loc _Short	NUTS Code	Nume	CDD	HDD	CDD and HDD
1	RO111	Bihor	3	3	6	22	RO224	Galaţi	4	2	6
2	RO112	Bistriţa-Năsăud	1	5	6	23	RO225	Tulcea	4	1	5
3	RO113	Cluj	2	4	6	24	RO226	Vrancea	3	2	5
4	RO114	Maramureş	1	5	6	25	RO311	Argeş	2	4	6
5	RO115	Satu Mare	3	3	6	26	RO312	Călăraşi	5	2	7
6	RO116	Sălaj	2	4	6	27	RO313	Dâmboviţa	3	3	6
7	RO121	Alba	2	4	6	28	RO314	Giurgiu	5	2	7
8	RO122	Braşov	1	5	6	29	RO315	Ialomiţa	5	2	7
9	RO123	Covasna	1	4	5	30	RO316	Prahova	3	3	6
10	RO124	Harghita	1	5	6	31	RO317	Teleorman	5	1	6
11	RO125	Mureş	1	4	5	32	RO321	Bucureşti	5	1	6
12	RO126	Sibiu	1	4	5	33	RO322	Ilfov	5	1	6
13	RO211	Bacău	2	3	5	34	RO411	Dolj	5	1	6
14	RO212	Botoşani	3	3	6	35	RO412	Gorj	3	3	6
15	RO213	Iaşi	3	3	6	36	RO413	Mehedinţi	4	2	6
16	RO214	Neamţ	2	4	6	37	RO414	Olt	5	1	6
17	RO215	Suceava	1	5	6	38	RO415	Vâlcea	3	3	6
18	RO216	Vaslui	3	3	6	39	RO421	Arad	3	3	6
19	RO221	Brăila	5	2	7	40	RO422	Caraş-Severin	3	3	6
20	RO222	Buzău	4	2	6	41	RO423	Hunedoara	2	4	6
21	RO223	Constanţa	5	1	6	42	RO424	Timiş	4	3	7

Source: Research results.

5. Discussion

As a synthesis of the study's findings, we can start with the confirmation of all hypotheses. The curve fit forecast model gives a reliable approximation of CDD and HDD (H1); both CDD and HDD trends were confirmed with a 99% confidence rate. The curve with the lowest Validation RMSE has been selected for each location and used for the forecast. A forecast RMSE is calculated to evaluate the accuracy of the forecasting model. The RMSE is the indicator used for model validation and forecast accuracy. However, there is no universal threshold for acceptable RMSE values because it depends on the specific context, the scale of the data, and the application. The values of VRMSE and FRMSE are between 12.50 and 34.57 for CDD and 187.39 and 230.95 for HDD, and they are in the range of a confident model.

The CDD forecast in Romania at the NUTS3 level for 2024–2032 shows different needs (H2), as presented in Figure 2. The southern area is the most vulnerable region and has the greatest need for cooling energy. Then, levels 4, 3, and 2 show a "U" shape in western and eastern areas. Finally, regions from the central and northern areas have lower cooling needs. No matter the type of curve used for CDD forecasting, all regions registered an increasing trend (H3).

Similarly, H4 is also confirmed by the HDD forecast in Romania at the NUTS3 level for 2024–2032, which shows different needs. This time, the regions with the highest needs are placed in the northern and central areas in a "T" shape, flanked on the east and west by regions with grades-3 and -4 needs. The southern and southeastern regions need less heating. The HDD forecast shows a decreasing trend, which confirms H5.

The summary of the CDD and HDD forecast grades confirms that the exposure to energy poverty is more homogenous in Romania's NUTS3 regions, but many areas showed average grades. However, the regions' technical solutions significantly differ due to the natural resources and local infrastructure.

Moreover, the increasing trends for CDD and the decreasing trends for HDD reconfirm that climate change drives global warming. Like climate differences, the energy poverty perspective also appears on the map, including probable risky regions. This is shown by the increase in the number of cooling demand days in many regions, which shows that pressure on households to maintain their thermal comfort is rising. On the other hand, the need for heating decreases, but it still represents an issue for households as regards providing a proper temperature. The eradication of energy poverty requires actions to enhance energy usage efficiency, protect low-income households, and retrofit the energy system for climate change [69].

6. Conclusions

The proposed forecast model used to identify trends and estimate the need for energy offers a nine-year time window to implement the best technical solutions to diminish the risk of energy poverty. The outcomes of the space–time cube visualization in 2D maps enable policy- and decision-makers to recognize and depict variations and patterns in CDD and HDD values. From 1978 to 2023, investigations examined the shift in cooling and heating necessities influenced by climate change. The study identifies the regions with a high need for cooling or heating technology investment and offers five levels of intervention priority.

There is not a complete absence of cooling or heating demand, but rather a reduced demand in areas with low values of CDD or HDD. Low CDD or HDD values mean that temperatures outside the thermal comfort limits are not likely, but it does not mean that there is no reason to use cooling or heating equipment. Additionally, just because there is low demand does not mean there should not be some investment in energy-efficient equipment in these areas, just that these areas are not the first priority. With low CDD and HDD values everywhere, energy-efficient technologies such as heat pump systems or passive cooling solutions can contribute to energy poverty reduction and assure energy-efficient mitigation in the face of climate change [55]. Moreover, such investments help decrease consumption intensity during the most extreme climate events, which may become more frequent [11]. This shows that, although the CDD and HDD values may be low in certain regions, there is no lack of heating and cooling needs.

Finally, the analysis of the CDD forecast shows a considerable enhancement in the number of days when cooling demand is required, especially in southern and eastern Romanian counties. The results show that regions with an exponential or parabolic CDD growth trend are more at risk of energy poverty. However, these areas will also see disproportionate increases in energy expenditures, hardening the downside risk for low-income households [53]. The HDD analysis highlighted the decreasing trends for all regions, which is favorable as regards energy needs.

A question to be discussed is whether the model using the standard temperature for a comfortable environment in the household of 18 °C (65 °F) reflects the reality for Romania. There are no scientific studies, but press investigations noted that more than 94% of Romanians prefer to have a temperature of 20 °C and above in their bedrooms. We can estimate that an average comfortable household temperature degree is between 20 °C and 24 °C, depending on the presence of small children or elderly persons among the tenants. A recalibration of the model following the behavioral data has to be considered.

The vulnerability of households to energy poverty comes from the pronounced increases in CDD, which will require additional cooling resources, without forgetting the heating need, even if the HDD shows a decreasing trend. The energy cost significantly influences the affordability of energy for cooling and heating. The energy cost calculation per CDD and HDD (if it differs) combined with the forecast maps will provide estimations of the financial efforts to be made. Overlapping the energy cost effort for cooling and heating with the income map will provide a comprehensive view of regional energy poverty. These studies are necessary because they highlight that such vulnerability is even more acute in densely populated urban regions, where the need for thermal comfort is higher (Dubois and Meier [9]), while rural areas face no-income and low-income issues.

The rise in the CDD forecast stresses the need for energy efficiency measures, such as bolstering insulation and modernizing cooling technologies while building a supply of renewable energy sources [70]. A more profound transformation to prevent energy poverty is the development of renewable energy sources such as solar, hydro, wind, biomass, etc. [71]. Again, overlapping the CDD and HDD forecast maps with the natural resources, considering the geographic variety of Romanian regions, will provide the decision-makers and investors valuable insights into where (location) and on what (type of renewable energy) to concentrate their efforts.

The key measures to address energy shortages are pursuing energy efficiency, promoting renewable energy, and offering financial subsidies and fiscal incentives. One central strategy concerns the energy efficiency of buildings, developed through thermal insulation, the improvement of heating and cooling equipment, or the implementation of a digital energy management system that can significantly reduce energy consumption [56]. Investments in renewable sources like solar, hydro, thermal, and wind energy reduce dependence and the supply fluctuation of conventional energy sources [6]. The investment decision should consider at least the energy demand forecast and the local resources. At the same time, governments should subsidize vulnerable households to ensure access to energy-efficient technologies and diminish shortages' impacts on the most vulnerable groups [55]. Fiscal incentives can be offered to the ones (householders, companies, and real estate developers) that rehabilitate or build new habitats using advanced energy-saving technologies. These combined measures can reduce the incidence of energy poverty and stabilize energy demand.

Space–time analyses were performed on the CDD and HDD series to construct the map, and the results show no large or significant anomalies except for CDD in the eastern and central areas. Climate stability implies more continued temperature behavior. Nevertheless, climate stability does not totally eliminate the risk of energy poverty, as other factors, such as income and infrastructure, are essential [33]. The results demonstrate that adaptation interventions are needed to curb the financial risk to vulnerable households in areas that identify more anomalies in the time series.

Synthetically, the findings of the study are:

- Regional differences in cooling and heating energy needs at the NUTS 3 level;
- Five levels of intervention priority as a base for strategy design;
- The expected values for the next nine years of CDD and HDD, identifying the hottest and the coldest regions;
- Evolution curves and trends identification, offering information about the simplicity or complexity of the phenomenon, the direction, and the speed of evolution at the regional level;
- By combining cooling and heating energy needs, the discrepancies are diminished, and the regions are grouped into three categories;
- A base to be combined with other influence factors (income, energy price, natural resources, technologies, etc.) for multifactorial analysis.

The identified trends and potential anomalies are caused by climate change, especially global warming. The IPCC [72] states that integrated policies will be needed to simultaneously address climate change adaptation and energy poverty.

The study's limits relate to the reference temperature of 18 °C (65 °F) generally used by data set providers. The approximation of the curves used to generate the forecasts is limited to the four types (linear, parabolic, exponential, and Gompertz), which are considered the most appropriate. The model is based on historical CDD and HDD data. Consequently, unexpected extreme climate conditions can significantly influence forecast accuracy. Our model is designed to predict energy demand over nine years, and we may not be able to capture the long-term impact of climate change. The limitation of the forecast period to nine years (2024–2032) was practically reduced to eight due to the gap between the row data series (up to 2023) and processing data and model design.

The present model relies mostly on climatic and geographical variables. However, socioeconomic variables, such as demographic growth, technological changes, or changes in energy consumption behavior, that can significantly affect long-term energy demand are not fully integrated. The model's validation was based on limited data, and an increased validation on a bigger sample of climate and temporal data would produce even better results (RMSE).

The study's main contribution and novelty regard the forecast of the CDD and HDD in the NUTS3 region and the visualization of the map results. These findings are critical for building a real-world-based framework to evaluate the risk of energy poverty. The obtained maps are left to be overlayed with costs, resources, energy infrastructure, regional development, income, household expenditure, etc., representing further research developments. The multicriterial space–time studies based on combining the CDD and HDD forecasting maps with other influencing factors will provide better support for governmental strategies, policies, and interventions. The study can be extended to the European regional NUTS 3 level to identify the needs and to offer insights into the energy strategy of the EU. Moreover, the model can be applied to other regions or to factors influencing energy poverty.

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