



Solar energy production in EU + countries using space–time forecasting

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Abstract

The need for renewable energy is underscored by the shift from fossil fuels without compromising economic growth. The European Union's strategy for resilient energy recognizes solar energy as a crucial resource. In recent years, there has been a significant focus on evaluating renewable energy production, distribution, consumption, storage, and applications. One key aspect of this evaluation is exploring production capacity trends using forecasting models. Our study proposes a space–time forecasting approach using the Curve Fit Forecast tool integrated in ArcGIS Pro 3.3, applied to solar energy in 37 European locations based on 1990–2022 data. The model tested four curved types and identified exponential growth patterns in 54% of cases, with consistent upward trends confirmed through RMSE validation. Outlier detection and 3D spatial–temporal visualization provide diagnostic insight into regional disparities and transformation regimes. This digitally enabled, geostatistical method aligns with the EU's data-driven energy transition agenda, offering a scalable and interpretable tool for policymakers and planners.

Keywords Renewable energy · Solar energy · Curve Fit Forecast · Space–Time Cube · EU resources · Digital forecasting · Energy transition · Spatial analysis

1 Introduction

European Union (EU) is at a crossroads in energy policy development. While the world is plagued with increasing environmental worries, increasing global geopolitical instability, and the fact that fossil fuels are finite, there is an urgent need for a paradigm shift to the use of renewable energy

sources. Historically, the energy policies of EU member states have been focused on the utilization of non-renewable energy sources such as coal and shale gas, and oil, commodities that are not only crippling to the environment but also economically frisky. Given the crying need for a more sustainable and self-sustaining energy footprint, solar energy has emerged as a strategic priority and key focus of the hefty European ambition for climate neutrality by 2050 [1].

The switch to a renewable-based energy sector is not only essential in environmental affairs but also economically and politically strategic. Solar energy, in particular, has become more prominent due to its scalability, decreasing costs, and ability to produce local energy. Unlike fossil fuels, solar energy is not localized; instead, it is plentiful and easily accessible in Europe. In such a case, it provides a platform where energy security can be improved, greenhouse gas (GHG) emissions can be minimized, and green economic growth can be implemented. In 2022, the EU installed a record 41.4 GW of solar photovoltaic (PV) capacity, representing an increase of almost 50% year-on-year, underscoring the rapid growth of the sector [2].

The EU's ambitious goals, including a 55% reduction in GHG emissions by 2030 and a net-zero state by 2050,

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require both policy reform and the rollout of technological innovations, as well as the provision of proper tools to facilitate investments and infrastructure development. In this framework, forecasting models are critical in influencing the strategies of national governments, energy corporations, and research institutions. With these models providing projections of solar energy generation, consumption, and its integration, they guide the choices that are made about energy infrastructure, storage systems, grid building, and legislative models.

Among various analytical tools, curve fitting is particularly useful for modeling solar trends, and curve-fitting approaches, such as exponential smoothing, logistic growth modeling, and polynomial regressions, have proven to be particularly helpful. These techniques can measure nonlinearities and seasonal variations in solar radiation, and therefore, researchers can use them to predict energy output under different climatic and technological conditions. Since solar energy generation is greatly tied to diurnal and seasonal weather patterns, high-quality temporal modeling is essential to accurate forecasting. This study suggests the use of curve-fitting approaches to enhance the accuracy of predicting energy production from solar energy, which will contribute to improving the planning of integrating solar energy into the EU energy package.

Many studies have been conducted to discover various mathematical and computational models used to predict trends in solar energy. For example, time series analysis methods such as ARIMA (auto-regressive integrated moving average) have been used for modeling solar irradiance and PV output with positive outcomes [3–5]. More sophisticated techniques, including machine learning algorithms such as neural networks, support vector regressors, and random forest models, have further improved the accuracy of forecasts by utilizing multiple input variables, such as humidity, cloud cover, and panel efficiency [6, 7]. Nevertheless, simpler curve-fitting techniques remain essential when interpretability and reduced computational cost are required.

Furthermore, this study acknowledges that forecasting cannot be confined to production estimates alone. Policy changes, market trends, and technological evolution also must be addressed by a comprehensive approach. That is, the European Solar PV Industry Alliance, launched in 2022, targets increasing the deployment of 600 GW of solar PV capacity by 2030, from an estimated 208 GW in 2023 [8]. Policy-supporting arrangements, including feed-in tariffs, renewable energy auctions, and taxes, will significantly impact the speed and extent of solar adoption, requiring the use of dynamic models for regulatory changes.

This article presents a methodological framework that stakeholders can use to assess and plan for the deployment of solar energy by integrating data from EU-level statistics,

national renewable energy plans, and peer-reviewed forecasting studies. The results of this study are particularly important for policymakers and investors seeking to mitigate risk while maximizing returns on sustainable energy infrastructure. They also offer practical recommendations to scientists and technologists involved in enhancements in PV efficiency and related storage.

One of its major findings is the importance it places on geographic variation in solar potential through the EU. Even though Southern European nations, such as Spain, Italy, and Greece, enjoy high solar irradiance, Northern and Central European countries are taking an interest in observing solar technologies that suit low-light conditions. Regional disparity demonstrates the need for localized forecasting and planning for infrastructure. Models that take into account geographic and climatic data will help develop better regional strategies, adjust resource allocation, and ensure a balanced and robust energy grid.

In addition, the incorporation of accurate forecasting in energy planning results in cost reduction in energy generation and supply. By being able to predict demand and productivity shifts, utilities can handle energy storage systems more efficiently while lowering curtailment and avoiding expensive backup power sources. According to the EEA [9], there is a significant need for the accuracy of energy forecasting, which is crucial for the stability and affordability of energy supply, especially in environments where renewables are becoming the primary source of energy.

Solar energy has inherent challenges despite its numerous benefits, particularly in terms of weather and daylight availability. Nevertheless, there are now growing efforts to overcome these limitations due to technological improvements in energy storage, grid integration, and hybrid renewable systems. Solar energy is a clean, inexhaustible, and environmentally friendly form of energy, which, if well forecast and integrated into our energy plans, can play a significant role in reducing carbon footprints and contributing to a sustainable economy.

Lastly, with the EU remaining a pioneer in the world in renewable energy policies, the findings from this study have transferable lessons for other zones. So, this capacity to forecast, plan, and deploy on a large-scale causal energy equals a blueprint for a cleaner and more secure future of our energy global world.

2 Literature background

2.1 Renewable energy and the global shift

The European Commission adopted the “Framework Strategy for a Resilient Energy Union with a Forward-Looking Climate Change Policy” [10], the framework that supported

the formation of a standard energy policy in the EU consisting of five separate pillars: energy security, the decline in carbon-related emissions, enhanced energy efficiency, enhancement of the EU's internal energy market and promotion of research, innovation, and industrial competitiveness. Renewable energy is the backbone of these goals; the European Green Deal targets 32% of renewable energy in the European Union's overall energy consumption by 2030 [1].

Switching to renewable energy is contributing to a global push to address climate change, mitigating greenhouse and carbon emissions, and fostering consistent energy stability. Increasingly serious environmental problems and unpredictable energy prices, as well as geopolitical concerns, have triggered an increase in the implementation of clean energy [11, 12]. As noted by Guchhait and Sarkar [13], overdependence on non-renewable sources of energy presents threats to the environment and economy, hence the firm commitment of the EU to incorporate renewables.

However, the shift to renewables indeed comes with significant obstacles. Barriers such as decayed infrastructure, limited storage alternatives, and technological disparities among member states are hindrances to the rapid adoption of renewable energy [14]. Additionally, the inconsistent nature of solar and wind energy underscores the need for accurate energy estimation and effective storage mechanisms to ensure grid stability. Østergaard et al. [15] argue that eliminating these obstacles depends on effective system coordination, investing in new technologies, and diversifying the structural energy sources.

It has been widely recognized that renewable energy plays a significant role in reducing air pollution and carbon emissions [16]. However, deployment plans also have to contend with environmental justice issues, especially where the renewed initiatives threaten to displace local people or even over three existing land resources [17]. Policymakers should create renewable plans that will include equitable and inclusive policies while achieving a balance between economic growth and environmental and social well-being.

2.2 Solar energy as a strategic option

The drive to prioritize renewable energy stems from the need to reduce pollution and conserve resources despite the lower technological costs and regional dependencies [18]. The interdependence between energy and the environment must be carefully managed to achieve an optimal balance between power generation and environmental protection [19].

Solar power's charm, compared to other forms of renewable energy, stems from its abundant resource, scalability, and significant cost reduction. Solar energy plays a significant role in the local plans for energy independence in the EU. Solar energy has been able to break into one of the fastest-growing industry sectors internationally due to the reduction

in costs of PV technology, the increased storage capacity, and supportive regulatory environments [20, 21].

Detailed research has examined the potential, economic viability, technical effectiveness, deployment approaches, and integration into various energy scenarios for solar power [22, 23]. Research also highlights its relevance in sectors like agriculture, urban planning, and transportation [24, 25]. Its modular nature allows for both small-scale applications, such as rooftop solar panels and large-scale solar farms, making it a flexible solution adaptable to different national contexts.

Due to its modularity, solar technology can be scaled out at various levels, ranging from individual homes to large-scale solar parks that fit well into different national settings.

Solar energy production, despite its benefits, is very weather-sensitive. The efficiency of solar energy depends on deployment location, local cloud patterns, and seasonal changes [26]. Therefore, for constant and dependable output, the operations of the national grid systems have to depend on accurate forecast models and available storage mechanisms, as done by Falope et al. [27].

The benefits of solar energy do not only extend to the environment in terms of sustainability. Economic analysis shows that solar projects not only increase job creation but also attract financial capital, especially to rural and economically disadvantaged populations [28]. Politically, developing solar infrastructure reduces the country's dependence on imports of foreign fossil fuels, thereby augmenting its energy independence [29].

The viability of solar energy programs is, to a great extent, dependent on government support [30]. Succinct, exclusive rules, appealing tax incentives, and policies that project for long-term framers are necessities for attracting private investment and encouraging public adoption. Timilsina et al. [31] assert that to ensure effective implementation and amplify the role of solar in energy objectives, it is necessary to adopt coordinated policy measures, both at the national and local levels.

The shift from fossil fuels to renewable energy is one of the European Union's most important objectives for the following years. Hydro, solar, thermal, and wind energies are the most valuable renewable sources for the region. A consistent number of researchers explored solar energy's potential from various perspectives, such as potential, development, costs, applications, generation, and storage [20, 21, 32]. As with all sources of energy, there are advantages and disadvantages of solar energy usage [33, 34].

2.3 Forecasting models for solar energy

Due to the unpredictability of solar irradiance, accurate predictions of solar energy potential are crucial. It gives utilities the ability to schedule the grid, increase energy trading

activities, and make informed storage decisions. Energy forecasting thus became an important research direction that utilizes a variety of approaches, from statistical models to machine learning to hybrid ones.

In the early research concerning the forecasting of solar, classical methods such as ARIMA and multiple linear regressions were applied [35–37]. These approaches provide clear insights and are easy to implement, but they tend to lack the ability to address nonlinear data and sudden weather disruptions.

To compensate for these weaknesses, researchers have employed machine learning methods. Neural networks, such as artificial neural networks (ANNs), long short-term memory (LSTM), and gated recurrent units (GRUs), have demonstrated their ability to process complex, time-evolving solar data effectively [38, 39]. For example, using artificial neural networks, Galván et al. [40], Abedinia et al. [41], and Bassey [42] reported high accuracy in solar radiation and PV output modeling.

That combination of statistical approaches and artificial intelligence has resulted in the development of hybrid models that have promise. In an investigation spanning Europe, the USA, and Asia, Blaga et al. [43] tested hybrid models and found that they consistently yield better results than non-hybrid models. The system proposed by Basurto et al. [44] is an intelligently constructed system that combines the fuzziness and learning done by a machine to achieve better outcomes despite uncertain data.

Probabilistic models, however, have benefited multi-regional studies. Alkhayat and Mehmood [45] demonstrated that probabilistic hybrid systems offer increased accuracy and flexibility, which are particularly valuable in variable solar conditions, such as the high resource fluctuation experienced in some regions. Similarly, fuzzy logic models are ingeniously employed in situations where uncertain inputs, such as meteorological forecasts, influence the accuracy of predictions [46, 47].

There has been a growing popularity of combining deep learning and ensemble methods in recent years. Jamil et al. [48] proposed a highly advanced three-stage deep learning method for large-scale PV systems, which outperformed earlier approaches. Kumar et al. [49] proposed a machine learning framework, while Kumar et al. [50] combined multi-point time series with a multi-column convolutional neural network to optimize spatial and temporal forecasting accuracy.

Acceptable predictions are highly dependent upon robust techniques of validation and model refinement. According to Jensen et al. [51] and Perez et al. [52], compliance with standardized numerical indicators (RMSE/MAPE) is the cornerstone for comparing the performances of models across disparate studies to ensure fairness and effectiveness. Standardization of such error metrics as RMSE and MAPE

enables energy operators to estimate the practical value of forecast models in terms of managing grids in real time.

Being of great interest, the forecasting models for renewable energy were also explored as tools to support decision-making and policymakers, as well as business models [53]. This constant interest in identifying the best methods of forecasting aligns with the determination to mitigate environmental protection, climate change, and resource conservation without compromising economic growth and quality of life.

Aiming to create a tool to support policymakers and energy strategy designers, we explore a new statistical forecasting tool offered by ArcGIS Pro Statistical Tools [54, 55], which is user-friendly. Our research question is: What curve-fitting model best fits the solar energy production data for European countries and their neighbors?

The novelty of the present study lies in the application of the Curve Fit Forecast model to European locations using raw data.

Hypothesis 1: *The Curve Fit Forecast models offer consistent estimation for solar energy production (1990–2022).*

Hypothesis 2: *Solar energy production is on an uptrend from 1990 to 2025 in all European countries.*

3 Methods and data

Methodological steps were: (1) extract the raw data for solar energy production from 1990 to 2022 for European countries and the UK, Turkey, Island, Norway, Liechtenstein, Switzerland, Albania, Serbia, and Macedonia; (2) the Space–Time Cube data format was created; and (3) graphical representation using ArcGIS was generated 2D.

The dataset was extracted from EUROSTAT [54] in June 2023 NRG_INF_EPCRW_custom_6447077].

The study employs new methods that apply data engineering to analyze data in a space–time format, using the NetCDF format and Space–Time Cube. Due to this conversion, the tools available in various software libraries and the machine independence format of data creation, access, and sharing of the standard panel data of Eurostat were employed. There are several benefits to using NetCDF data formats, including self-descriptiveness, portability, scalability, dependability, shareability, and archivability. Therefore, the primary result of the study is derived from input and output data in NetCDF format.

Space–Time Cube characteristics for solar energy are presented in Table 1.

The study utilized the Curve Fit Forecast tool of ArcGIS Pro Statistical Tools [54, 55] to estimate solar energy production in European countries and their neighbors (a total of 37 countries) over a 33-year period (1990–2022) with row

Table 1 Space–Time Cube characteristics

Characteristic	Description
Input feature time extent	1990-01-01 00:00:00 to 2022-01-01 00:00:00
Number of time steps	33
Time step interval	1 year
Time step alignment	End
First time step temporal bias	100.00%
First time step interval	After 1989-01-01 00:00:00
First time step interval	To on or before 1990-01-01 00:00:00
Last time step temporal bias	0.00%
Last time step interval	After 2021-01-01 00:00:00
Last time step interval	To on or before 2022-01-01 00:00:00
Cube extent across space	(coordinates in meters)
Min <i>X</i>	− 2,823,672.4431
Min <i>Y</i>	− 3,076,354.2174
Max <i>X</i>	10,026,276.2776
Max <i>Y</i>	6,404,813.2250
Locations	37
% of locations with estimated observations	13.51
Total number	5
Total observations	1221
% of all observations that were estimated	6.22
Total number	76

Source: Authors' construct

data and a three-step forecast (2025). Four curve types, linear, parabolic, exponential, and S-shaped (Gompertz), were tested for each of the 37 locations using Space–Time Cube data. These curve types are widely used in the literature to capture different adoption and growth patterns in renewable energy forecasting. Specifically, it reflects different dynamics of renewable energy adoption and has been validated in the literature on solar forecasting.

- *Linear models* represent steady, incremental growth in solar energy, confirmed by studies applying regression and ARIMA-type approaches [3, 9, 35, 36]. For instance, linear-type regressions have provided robust baseline forecasts under conditions of stable solar power growth [35], while GM(1,1) and ARIMA applications demonstrated their suitability for capturing medium-term linear expansion in energy use [36]. Similarly, solar radiation studies confirm that linear approximations remain adequate in

contexts with no abrupt climatic or policy shifts [3]. Reports of the European Environment Agency also emphasize that in several EU countries, PV deployment has followed relatively constant, near-linear growth trajectories, especially in early adoption phases [9].

- *Parabolic functions* capture initial acceleration followed by saturation or decline, consistent with cases where early policy incentives are followed by market stabilization [6, 9, 32, 37]. They are suitable for modeling solar energy trajectories that exhibit rapid early increases followed by deceleration, saturation, or even decline. Such patterns are often observed when deployment accelerates initially due to favorable policies or subsidies, but then slows as markets mature or technological and infrastructural limits are reached. For example, Atique et al. [37] and Yuan et al. [36] demonstrated that quadratic and polynomial regressions can capture nonlinear turning points in energy generation data, reflecting phases of acceleration followed by stabilization. Similarly, Hayat et al. [32] highlight that solar PV deployment curves often present diminishing marginal growth when grid capacity constraints or cost barriers emerge, which can be approximated by parabolic models. The European Environment Agency [9] also documents cases where national solar capacity expansions initially surged but later plateaued, consistent with a parabolic growth trajectory.
- *Exponential models* are suitable for describing accelerating solar PV deployment driven by technological improvements, declining costs, and supportive policies [2, 4–6, 8, 43]. Exponential models are particularly appropriate for capturing the accelerating dynamics of solar PV deployment, where technological improvements, declining costs, and strong policy incentives create compounding growth effects. Numerous empirical studies confirm that exponential functions best approximate the rapid adoption phase of renewable energy technologies. For example, Sharadga et al. [4] showed that solar power generation in large-scale plants followed exponential-type increases under supportive market conditions. Chodakowska et al. [5] found similar evidence when applying ARIMA models to solar radiation forecasting across diverse European contexts, where exponential trends dominated long-term trajectories. At a broader level, the European Commission [8] and Solar Power Europe [2] report that EU solar capacity nearly doubled in just a few years, consistent with exponential growth behavior. Previous forecasting reviews [43] also emphasize the suitability of exponential forms to describe accelerating energy transition patterns, particularly in the case of solar energy.
- *S-shaped (Gompertz/logistic) curves* are well established in the literature for modeling the diffusion of innovations, including renewable energy technologies [9, 21, 43, 44]. These curves capture a three-phase dynamic:

initial slow adoption, rapid acceleration as technologies become competitive, and eventual stabilization as markets mature. In solar energy studies, Kabir et al. [21] emphasized the suitability of logistic-type models to represent the diffusion of PV technologies across different national contexts. Vakulchuk et al. [29] similarly highlighted S-shaped dynamics in the geopolitical deployment of renewables, noting that early adoption is typically slow before exponential expansion sets in. Blaga et al. [43] and Basurto et al. [44] also demonstrate that Gompertz-type models provide robust fits to solar energy production data when adoption follows a saturation trajectory. More generally, diffusion theory confirms that renewable energy deployment often follows an S-shaped curve, making this model particularly appropriate for long-term forecasting of solar capacity.

The model performance was measured using root-mean-square error (RMSE), specifically forecast RMSE and validation RMSE (Eqs. 1 and 2) [57, 58].

$$\text{Forecast RMSE} = \sqrt{\frac{\sum_{t=1}^T (c_t - r_t)^2}{T}} \quad (1)$$

where T is the number of time steps, c_t is the value of the curve resulting from the quadratic model, and r_t is the raw value of the time series at time t . It allows us to see the best trajectory that fits the row data.

$$\text{Validation RMSE} = \sqrt{\frac{\sum_{t=T-m+1}^T (c_t - r_t)^2}{m}} \quad (2)$$

where T is the number of time steps, m is the number of time steps withheld for validation, c_t is the value forecasted from the first $T - m$ time steps, and r_t is the raw value of the $T - m$ to T time steps. For the “ m ” time steps, the curve values were the forecasted values.

Analysis characteristics are presented in Table 2.

4 Results

The results in this section are structured along five analytical dimensions that, together, offer a space–time diagnosis of solar energy development in Europe. Using the Space–Time Cube (STC) model, the analysis moves beyond static mapping to identify distinct regimes of transformation speed, capturing both the magnitude and trajectory of solar adoption over time.

This tool combines geostatistical modeling with curve-fitting algorithms, enabling time-aware forecasting at the intersection of spatial and temporal energy dynamics [54, 55].

Table 2 Analysis details

Input Space–Time Cube	Forecast method
NUTS0_Solar_RA400_2024.nc	Curve fitting
Number of forecast time steps	1
Time steps excluded for validation	3
% locations modeled with seasonality	N/A
First forecast time step interval	After 2022-01-01 00:00:00 to on or before 2023-01-01 00:00:00
Last forecast time step interval	After 2022-01-01 00:00:00 to on or before 2023-01-01 00:00:00

Source: Authors’ construct

First, the reliability of the Curve Fit Forecast model is demonstrated through RMSE metrics, validating the model’s predictive strength across diverse national contexts.

Second, the fitted curve typologies show that more than half of the countries follow exponential growth, signaling an accelerating energy transition. Others display linear, S-shaped, or parabolic trends, suggesting more gradual or constrained evolution. Third, outlier detection identifies abnormal deviations, primarily concentrated in 2020, highlighting the sensitivity to exogenous shocks.

The fourth analytical layer reveals spatial disparities in solar production across Europe, with countries grouped into five levels of intensity. A complementary 3D visualization captures forecasted national values and long-term trends, showing an acceleration starting in 2007. Together, these representations expose differentiated velocities of transformation, enabling the identification of both leaders and laggards in the solar transition.

Finally, the trend confidence map confirms widespread statistical significance ($\geq 99\%$) of upward trajectories, reinforcing convergence toward solar expansion across the EU + .

The structured synthesis of results underscores not only the diversity of solar transition patterns across Europe but also the methodological novelty of using a digital, automated, geostatistical, and predictive instrument. This space–time forecasting model aligns naturally with the data-driven digital transformation agenda, offering a robust framework for analyzing complex energy dynamics at multiple scales.

Overall, the model provides a digitally driven, interpretable, and scalable solution that aligns with the goals of Europe’s green and digital transition.

The values obtained for forecast RMSE and validation RMSE confirm the capability of the Curve Fit Forecast models to estimate the trend of solar energy production (Table 3).

Table 3 Summary of accuracy across locations (MW/year)

Category	Min	Max	Mean	Median	SD
Forecast RMSE	0.00	3879.85	450.25	44.20	915.95
Validation RMSE	0.00	8761.62	1101.32	87.96	2051.78

Source: Research results

Table 4 Summary of selected curve type

Curve type	Number of locations	% of locations
Linear	7	18.92
Parabolic	4	10.81
Exponential	20	54.05
S-shaped (Gompertz)	6	16.22

Source: Research results

Table 5 Summary of time series outliers

Item	Value
Number of locations containing outliers	15
Percent of locations containing outliers	40.54
Number of outliers by location (Min; Mean; Max)	0; 0.41; 1
Number of outliers by time step (Min; Mean; Max)	0; 0.45; 5
Time step containing largest number of outliers	After 2020-01-01 00:00:01 to on or before 2021-01-01 00:00:00

Source: Research results

A higher RMSE value indicates a larger discrepancy between forecasted and actual values. While most locations exhibit low-to-moderate RMSE scores (mean forecast RMSE = 450.25; mean validation RMSE = 1101.32), some outlier values (e.g., > 8000) reflect locations with abrupt changes, possible data anomalies, or structural breaks (such as policy shifts or unusual climatic events). These outliers do not invalidate the model but highlight areas that may require separate policy attention or data refinement [57, 58].

At the same time, the proposed method identified the curve type and equation that best fits the raw data for solar energy production, showing that 54% of the locations are explained with exponential curves, 19% by linear, 16% by S-shape, and only 11% by parabolic (Table 4).

Moreover, 15 locations contain outliers, and a thorough analysis of these locations could provide significant insights into unexpected situations, influencing factors, and risks that need to be addressed (Table 5). Also, it can be seen that the largest number of outliers was registered for 2020. It has to

Table 6 Overall trends (MW/year)

Trend direction	Increasing
<i>Overall data trend—MEGAWATTS_N_SUM_ZEROS</i>	
Trend statistic	8.1656
Trend <i>p</i> value	0.0000
<i>Overall data trend—TEMPORAL_AGGREGATION_COUNT</i>	
Trend statistic	4.7304
Trend <i>p</i> value	0.0000

Source: Research results

be corroborated with the weather information to validate the influence factor or to look for other aspects to explain the anomaly.

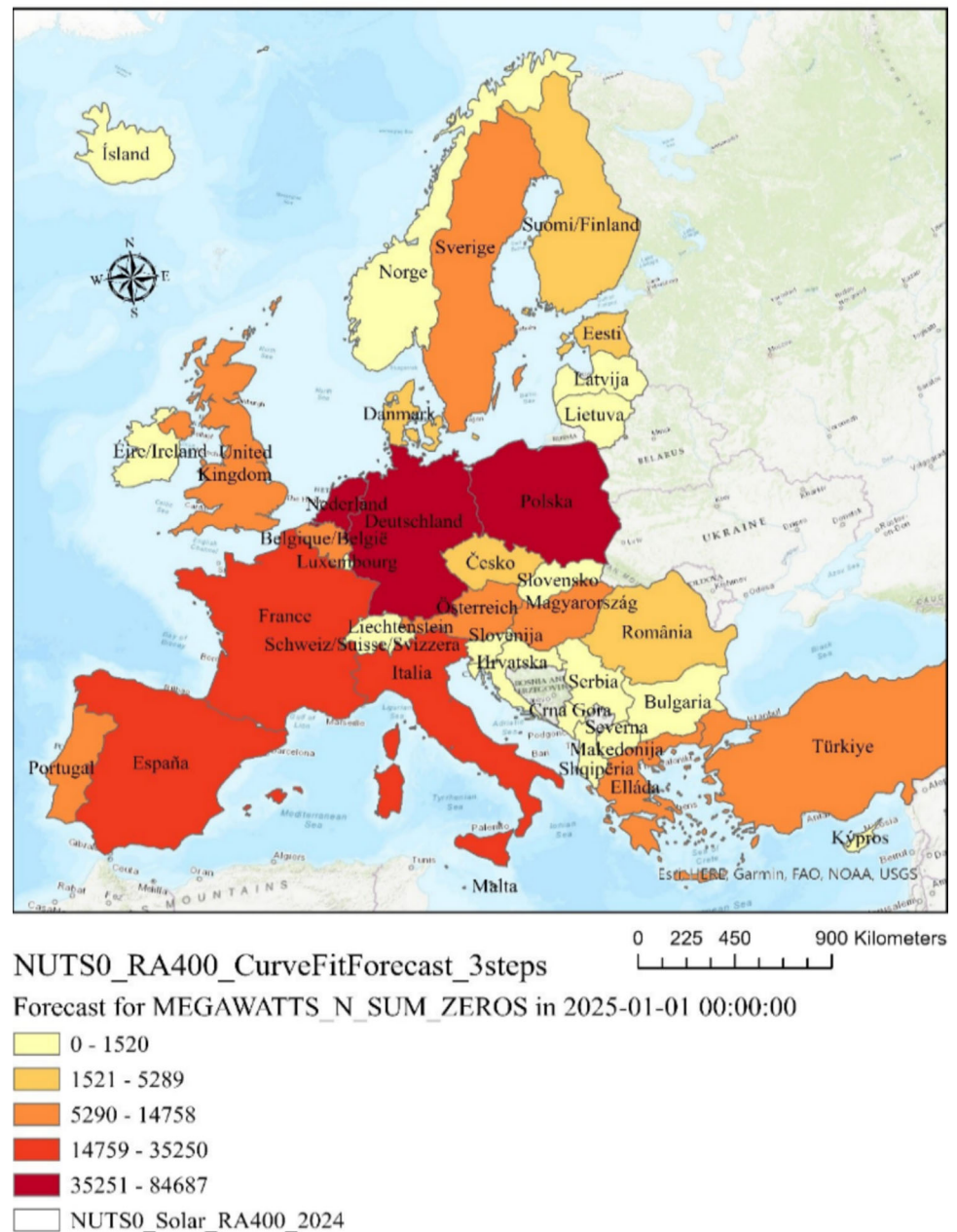
The proposed model's most important result is the overall trends confirming the significant exponential evolution of solar energy production (Table 6).

The trend differs from country to country, with Poland, Germany, and the Netherlands having the highest solar production, followed by France, Spain, and Italy. Figure 1 presents a 2D representation of the expected solar production for the 37 studied locations based on the Curve Fit Forecast model. We can observe five types of counties, categorized by their solar energy production levels: very high, high, medium, low, and very low.

High-performing countries such as Germany and Spain benefit from long-standing policy frameworks, generous feed-in tariffs, and substantial investments in grid infrastructure, which have accelerated solar adoption and stabilized market growth [2, 8, 30]. These countries also enjoy favorable irradiance conditions (especially in Southern Europe), combined with mature manufacturing and financing ecosystems. By contrast, several Eastern European countries (e.g., Romania, Bulgaria, Serbia) remain low-performing, where adoption has been constrained by limited infrastructure investments, weaker policy incentives, and slower integration of renewables into national grids [21, 29]. These structural differences explain the observed disparities in solar capacity, underscoring the importance of targeted policies and infrastructure support to foster convergence across the EU.

The lower solar exposition justifies the lower solar energy levels in Nordic countries (Iceland, Norway, Finland, Denmark, etc.). Still, less infrastructure and technology can

Fig. 1 Curve Fit Forecast for solar energy production at NUTS0, 3 Steps 2025—2D representation. Source: Research results captured in ArcGIS Pro 3.3



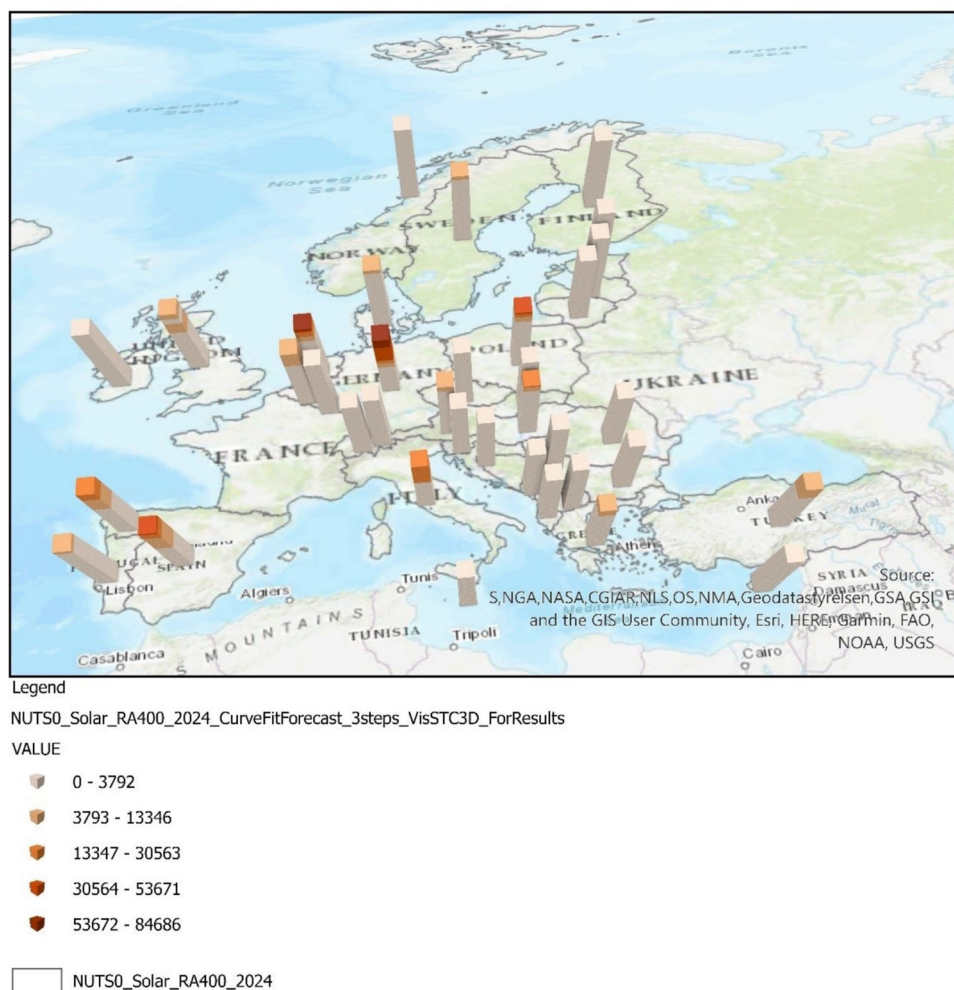
explain it for countries from Eastern Europe (Slovenia, Romania, Serbia, Bulgaria).

Figure 2 presents a 3D geospatial and temporal visualization of forecasted solar energy production across European countries (NUTS0 level) for the year 2025. The data were modeled using a curve-fitting technique in a three-step forecasting approach and displayed using ArcGIS Pro 3.3. Vertical bars represent country-level production values, color-coded by intensity, with darker shades indicating higher projected outputs. The five-tier legend categorizes forecast values ranging from 0 to 84,886. The lower panel illustrates the aggregated time series trend (1989–2024),

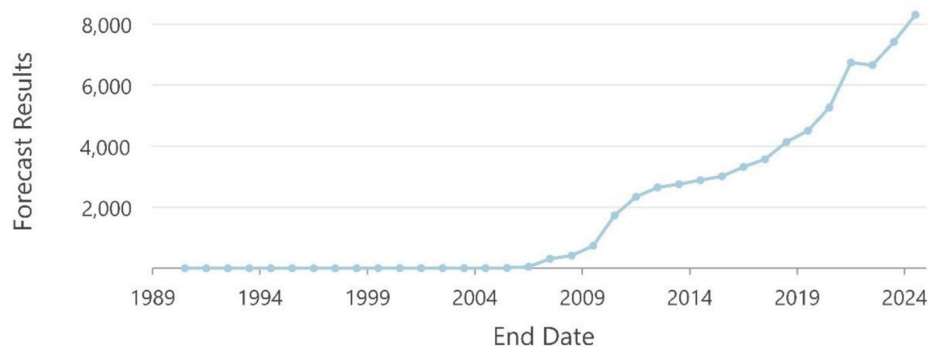
showing a sharp increase in solar energy production starting around 2007, with consistent exponential growth through 2024. This dual representation supports spatial-temporal analysis for energy planning, highlighting national disparities and trends in solar adoption across Europe.

This 3D visualization presents the results of a curve-fitting-based production forecast for solar energy carried out on the NUTS0 level in Europe in 2024, made with ArcGIS Pro 3.3. Each bar in the graph represents a country's predicted solar energy production, expressed in five quantile ranges: 0 to 84,886. The red–brown colors darken with increasing values, highlighting countries poised to make greater solar energy contributions.

Fig. 2 Time series chart for Curve Fit Forecast for solar energy production at NUTS0, 3 Steps 2025—3D representations. Source: Research results captured in ArcGIS Pro 3.3



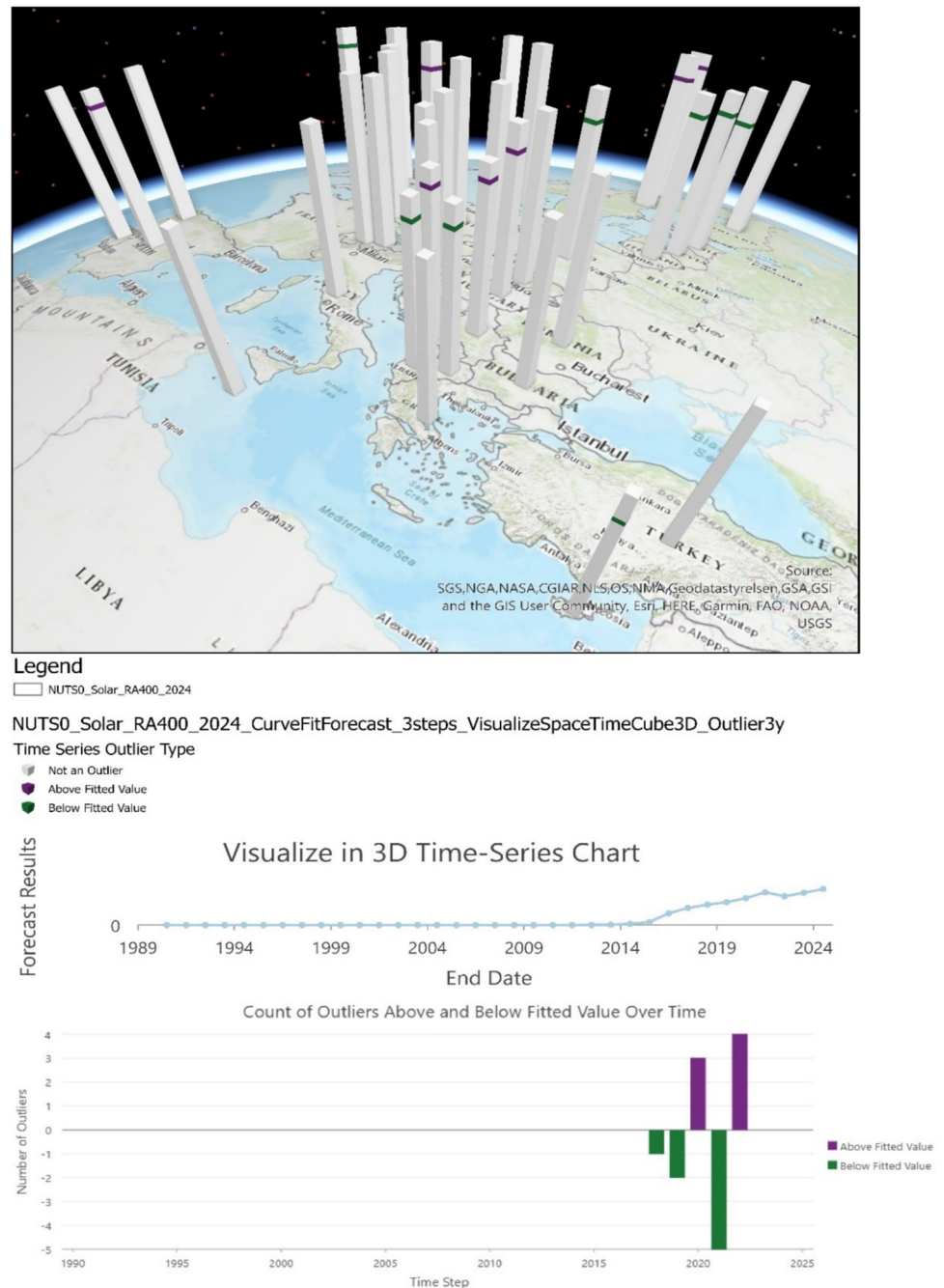
Visualize in 3D Time-Series Chart



This is evident in the map, where some regions are seen to be rising, with Germany and Spain leading other central and western European countries in the best solar energy production forecast sectors. These results may be attributed to established infrastructure, supportive policies, and favorable solar irradiance conditions.

The accompanying time series chart shows the general forecasted development between 1989 and 2024. From 2007, a significant acceleration in the upward trend is evident, which continues until 2024. This trend reflects the increased adoption of solar energy technologies in the EU, associated with greater investments, supportive policies, and decreasing technology costs.

Fig. 3 The Curve Fit Forecast for solar energy production outliers—3D representations. Source: Research results captured in ArcGIS Pro 3.3



Through the synthesis of both spatial and temporal information, the analysis provides a comprehensive evaluation of solar energy trends, promoting comparison among regions and energy planning. With the aid of a three-step curve-fitting model within ArcGIS Pro 3.3, Fig. 3 presents a 3D spatial-temporal analysis of solar energy production forecasts in NUTS0 regions. The upper panel displays separate country forecasts as vertical columns, and outlier markers indicate each forecast's deviation from projections. Purple-colored points denote values that are mostly higher than the curve, while green points indicate values that are significantly lower

than anticipated. The observed anomalies evidence regional disparities in solar efficiency as compared to anticipated scenarios.

In the lower table, the frequency and direction of outliers are monitored over consecutive periods. Between 2019 and 2024, a high surge of outlier phenomena is identified, with countries deviating above or below the model's projections. Such alterations in the frequency of outliers may indicate the potential impact of emerging technologies, new policies, or an unforeseen shift in the environment, which the model has not yet considered.

An interesting result of the analysis is the concentration of the outliers in 2020, which warrants further investigation. In 2020, unprecedented events that disrupted energy systems took place across Europe and globally. At the top of them was the COVID-19 pandemic that contributed to lockdowns, decreased industrial production, and massive drops in energy demand. Electricity generation and total electricity declined, but the proportion of the renewable output could grow, particularly in solar power, as it has priority access to the grid and is cheaper to run [9]. These shifts might have resulted in abnormal changes in production data that bring about abnormal disparity in the production pattern.

Also, promoting its role was the abnormal weather in 2020. Several European areas reported aberrant solar irradiance because some places in Central and Northern Europe received more sunshine than average, whereas Southern regions received less than average [26]. Such meteorological abnormalities would have directly impacted solar output and accounted for the geographically inconsistent outliers in the data. 2020 was associated with massive policy and market dislocation. Some EU nations changed feed-in tariffs or offered new tenders in renewable energy that either temporarily slowed or accelerated expansion [2]. Disruptions to photovoltaic equipment supply chains because of the pandemic added imbalances to the rates of installation. In total, these drivers also generated structural breaks in otherwise stable trends of solar deployment.

Thus, the outliers in 2020 can be viewed as the result of the unusual combination of pandemic-induced demand pressure and unusual weather conditions, as well as transitional policy. Instead of weakening the model, such interpolations actually demonstrate the informational value of the Curve Fit Forecast in showing when exogenous shocks suppress structural growth tendencies. Future studies could be improved by the inclusion of exogenous factors, such as weather data and government policies, to provide a more real-life context of such an oddity.

The visualization emphasizes significant discrepancies present in terms of time and space, which can enhance the analysis of variability in solar energy production forecasts. Such observations support the updating of regional forecasts and enable a developmental study of what drives the event of outliers.

Figure 4 illustrates spatial trend binning results derived from a three-step Curve Fit Forecast model applied over 3 years (2023–2025), visualized through a 2D Space–Time Cube in ArcGIS Pro 3.3. Each NUTS0 region is color-coded according to the direction and statistical confidence of its forecast trend in solar energy production.

The map reveals a uniform upward trend with 99% statistical confidence (dark purple) across nearly all European countries, indicating strong and consistent projected growth in solar energy output through 2025. No regions display

statistically significant downward trends, and no areas fall into the “no significant trend” category, underscoring the robustness and convergence of solar development trajectories across the continent.

This highly consistent spatial trend suggests the widespread effectiveness of EU-level renewable energy directives, funding mechanisms, and national policy alignment. It also validates the forecast model’s capacity to detect sustained growth patterns with high confidence.

Such results can guide energy planners and policymakers by highlighting the resilience and scalability of solar expansion throughout Europe.

5 Discussions

This study addresses a methodological gap by merging spatial–temporal visualization with classical statistical forecasting, providing a platform for both policy evaluation and strategic foresight.

5.1 Hypotheses confirmation

Most locations are forecasted using exponential curves (54%), while the rest are forecasted using linear, S-shape (Gompertz), and parabolic models, validating H1. The Curve Fit Forecast model is performant in determining the trends of solar energy for the studied locations, with a 95% confidence rate validating H2. It can be added to the other confirmed models, creating a large base of forecasting tools for solar energy.

The model findings provide insight into EU policies that support solar energy technology innovation and promote capacity building, particularly in countries with a high solar potential but limited infrastructure. A detailed analysis of the 3-year forecast, trends, and outliers will offer more information for decision-makers.

The findings of the Curve Fit Forecast model verified the appropriateness of each of the proposed hypotheses. Hypothesis 1, which claimed constant estimations to produce solar energy through Curve Fit Forecast models from 1990 to 2022, received support from robust accuracy scores from 37 European countries. It was noted that the robustness of the forecast RMSE and validation RMSE was confirmed, as their mean values were 450.25 and 1101.32, respectively. These results indicate that the model can work reliably in a wide range of climatic and infrastructural configurations.

The results also confirmed Hypothesis 2, which hypothesized the continuous growth of solar energies across Europe. In line with the idea of conducting trend analyses, approximately 54% of trend analyses depicted exponential curves, indicating an accelerating adoption trend. Notably, no significant difference was observed across all regions, as shown

Fig. 4 The Curve Fit Forecast for solar energy production confidence Rate—2D representations. Source: Research results captured in ArcGIS Pro 3.3

Visualize STC for 3 year forecast 2023 2D Trends BIN



Legend

□ NUTS0_Solar_RA400_2024

NUTS0_Solar_RA400_2024_CurveFitForecast_3steps_VisualizeSpaceTimeCube2D TREND_BIN

- Up Trend - 99% Confidence
- Up Trend - 95% Confidence
- Up Trend - 90% Confidence
- No Significant Trend
- Down Trend - 90% Confidence
- Down Trend - 95% Confidence
- Down Trend - 99% Confidence

<all other values>

by the 99% confidence interval for nearly all European countries in Fig. 4. This confirms the EU's ambitions to increase renewable energy and reiterates the model's role in making informed plans.

A high fraction of exponential trends suggests rainfall has continued to be boosted by favorable legislation, technological progress, and market competitiveness [2, 8]. Recognized anomalies at specific time steps, especially in 2020, indicate

that external circumstances such as the COVID-19 pandemic or climatic situations may have influenced the captured data. However, the model stayed constant in its overall direction with the variation.

5.2 Comparison with similar studies

The findings of the forecasting confirm previous empirical studies. Other research that utilizes ARIMA and machine learning has also shown that solar deployment is on the rise, partly due to supportive policies and a reduction in technology costs [4, 5]. Unlike opaque approaches such as deep learning, the application of curve fitting enables a transparent understanding of trends and typologies, ranging from linear to exponential and Gompertz curves, thereby facilitating communication with policymakers to inform decisions.

In contrast to works using neural networks, such as Buturache and Stancu [38] or Jamil et al. [48], the current paper proves to have a superior balance in nature of both simplicity and precision. At the highest level of accuracy, deep learning models show a slight improvement, albeit at the cost of intense reliance on computationally intensive technology and the high cost of data collection. Although curve fitting offers clarity and simplicity, it also meets the needs of stakeholders, including policymakers and urban planners.

Using spatial–temporal models, such as Space–Time Cubes in ArcGIS, which allow for additional analytical depth, the study aligns with those who support the inclusion of renewable energy forecasting in national policies, as suggested by Sweeney et al. [53]. Furthermore, the observed differences in solar adoption within regions—notably in Central and Eastern Europe—resonate with those reported by Kabir et al. [21] and Vakulchuk et al. [29], who also emphasize the importance of infrastructure and institutional support.

Basurto et al. [44] and Blaga et al. [43] studies provide fundamental support for this work, as they demonstrate the feasibility of ensuring accurate forecasting with hybrid and curve-based models in conditions of irregular data and anomalous weather. Identifying outliers, particularly in 2020 and 2021, conforms to the research of Juliano et al. [26].

6 Conclusions

This paper discussed the spatial and temporal patterns of solar electricity generation in European countries, and it found that there exist significant regional variations in deployment trajectories of solar electricity generation and factors influencing such regional disparities. With Curve Fit Forecast methodology, it is possible to capture long-term growth dynamics as well as short-term anomalies. Findings reflect the broad trend of solar capacity growth, with some countries showing a more rapid penetration associated with favorable policy preconditions and conditions available to them in nature. As it happens simultaneously, the presence of outliers, including those in 2020, serves as a reminder of the

sensitivity of renewable deployment to exogenous disruptions, not least the COVID-19 pandemic, weather anomalies, and transitional policy changes. These results highlight how structural tendencies and short-term shocks should be taken into attention when one needs to interpret the data about renewable energy. They also indicate the importance of using quantitative forecasting and contextual policy and environment analyses to explain deviations and increase reliability.

6.1 Theoretical and practical contributions

This paper contributes to the body of works by modifying the research methodology in the application of the Curve Fit Forecast within a geospatial and time-based setting, a procedure that remains untapped in Europe. By using Space–Time Cubes that respect the NetCDF-based Space–Time Cube to model regional solar energy trends over a 30-year period, the study goes beyond the standard single-point forecasting models. Such methodological improvement increases realism and factual syllabus accuracy to provide a more informative knowledge of the subject matter in relation to long-term renewable energy. It shows how spatially specific forecasting can identify regional disparities in addition to time oddities that are necessarily missed by using the standard treatments.

The practical significance of the work is manifold. The forecasting results are helpful in every aspect by offering critical information on the 37 countries, comprising all the EU members and adjoining nations, to make credible evidence for national energy plans. The exponential curve patterns identified in Germany, Spain, and Poland point to prospects of expanding the solar capacity at a low financial risk.

Second, the embedded outlier detection capacity would assist in the formation of early warning systems. By identifying anomalies, the model helps stakeholders identify potential drivers of anomalies, including weather-related disruptions, grid instabilities, or errors in reporting that have the potential to unravel policies or operational decisions. This changes the tool not just as a model of prediction but as a diagnostic and planning tool as well.

Lastly, the utilization of publicly available Eurostat data and research conducted using open-source approaches supports greater replicability and research transparency, which favors a broader adoption of the measures and methods by other researchers, utilities, municipalities, and NGOs. The relatively low amounts of computing needed to run the model would mean the model can be used at the local and pilot project levels, where the detailed outputs can be used to make intervention decisions. This type of output can inform selective subsidy programs, geographic region economic plans, and technology plans that can target areas differently, all of which are highly important, given solar exposures, policy, and infrastructure differences in the continent.

Based on the model's findings, several practical policy implications can be highlighted. First, in countries following exponential trajectories (e.g., Germany, Spain, Poland), maintaining momentum requires further investments in grid modernization and storage systems to ensure stability and minimize curtailment [2, 8]. Second, in regions showing linear or parabolic trends (e.g., several Eastern European states), targeted incentives such as revised feed-in tariffs, dedicated EU cohesion funds for renewable infrastructure, and capacity-building programs for local utilities could help accelerate deployment [21, 29]. Third, given the identified spatial disparities, the European Commission and national governments may prioritize differentiated policy support—channeling resources to lagging regions where solar potential remains underutilized. Finally, the adoption of early warning and anomaly detection tools, as suggested by our outlier analysis, can guide adaptive policymaking by anticipating disruptions due to climate shocks, regulatory shifts, or market volatility [26].

6.2 Study limits

The Curve Fit Forecast model provides practical information, but it is not entirely devoid of limitations.

First, the model's performance depends strongly on the quality and completeness of the Eurostat dataset. Approximately 6% of the records were missing or interpolated, which may affect the reliability of the fitted curves and forecast outputs. Such data gaps can introduce artificial continuity or smooth out real variability, potentially biasing the choice of the best-fitting curve. Although the use of RMSE validation mitigates part of this risk, forecasts for countries with larger data gaps should be interpreted with caution [56, 58].

Second, the model primarily identifies past production patterns, which potentially leave a gap in considering contemporary or anticipated changes in policy, technology (e.g., perovskite solar cells), or unexpected events (e.g., war and pandemics). Outliers reveal some patterns but do not provide information about their causes.

Third, the limitation to four curve types (linear, parabolic, exponential, and S-shaped) implies an implicit understanding of predictable mathematical trajectories for solar developments. While this makes interpretation less obtrusive, it is likely to overlook sophisticated, nonlinear growth diagrams that adaptive machine learning models are better placed to understand [39, 48].

Fourth, the analysis consolidates solar deployment data only at a country or NUTS0 level. Such analysis overlooks variations at regional levels in countries like France, Germany, and Turkey, which have non-uniform solar development across the nation. To increase the accuracy of the findings, future research could further apply this methodology to regional levels, such as NUTS2 or NUTS3.

Additionally, the model also does not take into consideration the aspect of feed-in tariffs, the cost of solar panels, or grid expansion metrics. Once these elements are included, it would be possible to make causal inference more accurate and scenario-based forecasting more feasible.

6.3 Further developments

Based on this investigation, several promising areas for future research are identified. Future studies can add to the analysis by including more renewable sources to provide a more comprehensive understanding of the energy transition. Also, a combination of meteorological factors, policy input, and socioeconomic data might assist in improving models and better comprehension of causality behind the anomaly. The other direction is to use the framework at finer regional scales, in which regional dynamics might vary from the national trends.

Incorporating both scenario planning and curve-fitting techniques enables dynamic simulations across a range of policy, investment, and cost scenarios for technology. A combination of the curve fit model and artificial intelligence techniques, such as random forest or LSTM networks, may improve accuracy without compromising the transparency of results. By combining different model classes, one may increase strengths in prediction accuracy. One of the premises for acting on forecasts at subnational levels (NUTS2/NUTS3, for example) is to identify regional differences and assist policymakers with the targeted distribution of resources. By integrating solar irradiance, temperature, and cloud coverage into model inputs, forecasts can become more accurate, facilitating better climate-sensitive decision-making. The opening of solar forecasts using real-time dashboards based on ArcGIS or open-source technology may encourage governments and businesses to make informed decisions.

Additionally, the model's scope could be expanded to discuss solar energy's role in integrating with agricultural systems, industrial landscapes, or the expansion of electric mobility. By projecting the model into specific regions, such as the Middle East and North Africa (MENA), Southeast Asia, and Sub-Saharan Africa, we can assess its applicability and gain comparative perspectives on policy approaches.

In conclusion, the Curve Fit Forecast model presented in this study not only validates the exponential growth of solar energy across Europe but also offers a practical, interpretable, and adaptable tool for planning the next phase of the continent's energy transition. The findings reinforce the need for localized planning, continuous model refinement, and integrated forecasting approaches in meeting Europe's renewable energy goals. In all, the paper will add value to the body of research evidence on the solar energy transition

in Europe and provide recommendations to the methodological context of making future research closer to evidence and policy-relevant.

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Data availability No datasets were generated or analyzed during the current study.

Declarations

Competing Interests The authors declare no competing interests.

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