Energy 333 (2025) 137266

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

Integrating machine learning and econometric models to uncover macroeconomic determinants of renewable energy production in the selected European countries

Atif Maqbool Khan, Artur Wyrwa *

Faculty of Energy and Fuels, AGH University of Krakow, A. Mickiewicza 30, 30–059, Kraków, Poland

ARTICLE INFO

Handling editor: Wojciech Stanek

Keywords:
Renewable energy
Forecasting
Deep learning
Machine learning
Macroeconomic determinants

ABSTRACT

The transition to renewable energy is a strategic priority across Europe, yet limited attention has been paid to the macroeconomic and institutional determinants of renewable energy production (REP). Understanding these factors is essential for crafting effective and resilient energy policies, particularly in a region characterized by diverse economic and governance contexts. This study investigates the drivers of REP in 26 European countries from 1995 to 2022, integrating panel econometric analysis with machine learning forecasting. Driscoll-Kraay Standard Errors (DKSE) and Fixed Effects (FE) models are compared, with DKSE preferred due to its ability to address heteroskedasticity, autocorrelation, and cross-sectional dependence. In addition, five machine learning models—including Random Forest, Support Vector Machine, CNN-BiLSTM-AR, LSTM, and ARIMA—are used to evaluate forecasting accuracy. The results identify research and development (R&D) expenditure as a dominant positive driver of REP, while political instability and weak rule of law significantly hinder progress. Macroeconomic variables such as GDP, inflation, population, and financial development also influence REP to varying degrees. Among forecasting models, Random Forest achieves the highest predictive accuracy across most countries, validating the role of data-driven approaches in energy planning. These findings underscore the importance of stable governance, targeted innovation support, and macroeconomic stability in promoting renewable energy production, providing policymakers in Europe with timely insights for achieving sustainable energy transitions.

1. Introduction

1.1. Background information

The availability of sustainable energy is widely recognized for its significant influence on public health, economic development, energy security, and environmental sustainability [1]. Renewable energy production (REP) has become a key pillar in pursuing low-carbon and ecologically responsible growth. Countries worldwide are increasingly adopting renewable energy technologies to reduce carbon emissions and address the challenges of climate change. Although earlier studies have emphasized the role of the financial sector in the energy transition, they have often overlooked its specific impact on the deployment of renewable energy. At the same time, renewable energy has garnered increasing attention from researchers, policymakers, and international organizations, particularly in the context of developing economies [2–4]. REP is now widely seen as a key component of energy supply at both national and regional levels, with co-benefits including lower air pollution and enhanced resilience against fossil fuel price shocks [5–7]. For this reason, many countries have integrated renewable energy objectives into their policy agendas, recognizing their importance for environmental protection, climate mitigation, and social welfare [8,9]. Long-term projections underscore the growing global relevance of renewable energy. According to the International Renewable Energy Agency (IREA), over two-thirds of the world's energy supply will come from renewables by 2050 [10]. Meanwhile, the International Energy Agency (IEA) emphasizes that global REP must increase significantly to meet the Sustainable Development Goals (SDGs), particularly the target of generating 50 % of the world's energy from renewables by 2030 and ensuring universal access to affordable, reliable, and modern energy

This article is part of a special issue entitled: ICCET 2024 published in Energy.

* Corresponding author.
E-mail address: awyrwa@agh.edu.pl (A. Wyrwa).

https://doi.org/10.1016/j.energy.2025.137266
Received 17 April 2025; Received in revised form 28 May 2025; Accepted 21 June 2025
Available online 24 June 2025

(SDG 7) [11]. In this context, renewable energy contributes to environmental and social objectives and is crucial in supporting economic growth and generating public revenue [12].

Global renewable electricity production surged from 2278.61 TWh in 1990 to 8559.23 TWh in 2022 (Fig. 1), reflecting a sustained upward trajectory (EIA, 2025). Growth accelerated post-2000, doubling from 2829.63 TWh (2001) to 7504.07 TWh (2020), driven by climate initiatives and policy support. The 2010s witnessed rapid expansion, rising from 3758.57 TWh in 2008 to 7504.07 TWh in 2020, driven by investments in renewable technologies. A sharp increase to 8559.23 TWh by 2022 highlights technological advancements, cost reductions, and stronger policy frameworks. These trends underscore a decisive global shift toward renewable energy. (https://www.eia.gov/international/data/world, (accessed on 15.01.2025)).

While global renewable electricity production (REP) exhibits clear growth, regional disparities persist (see Fig. 2). Asia & Oceania dominate growth, surging from 560.5 TWh (2000) to 4220.8 TWh (2023), driven by industrialization, population expansion, and economic development. North America and Europe show steady increases, rising from 765.4 TWh to 1458.1 TWh and 666.3 TWh to 1734.0 TWh, respectively. Central & South America exhibit moderate growth (565.7 TWh to 1019.9 TWh). In comparison, Africa and the Middle East lag significantly in absolute terms: Africa's REP grows from 77.0 TWh to 222.8 TWh, and the Middle East fluctuates between 8.1 TWh and 47.7 TWh (2000–2023). These contrasts highlight the uneven adoption of renewable energy, despite the global momentum.

Due to their pioneering role in institutionalizing renewable energy transitions through binding supranational policies, this study focuses on EU member states, offering critical insights into the interplay of governance and implementation. Since the 1990s, EU countries have adopted rigorous climate frameworks, driven by growing concerns over global warming and greenhouse gas (GHG) emissions. Early support schemes (e.g., REFIT, RPS) evolved into legally binding EU-wide targets under the Renewable Energy Directives (RED I: 20 % by 2020; RED II: 32 % by 2030). The European Green Deal (2019) and European Climate Law (2021) further solidified the bloc's commitment, mandating climate neutrality by 2050. These policies reflect both urgency—aligning with global imperatives to limit warming to 1.5°C—and rationality, as the EU's diverse economic and energy landscapes provide a representative microcosm of global challenges. By analyzing EU nations, this study leverages a region where policy ambition, regulatory bindingness, and regional heterogeneity converge, enabling actionable lessons for the scalable adoption of renewable energy worldwide [13,14].

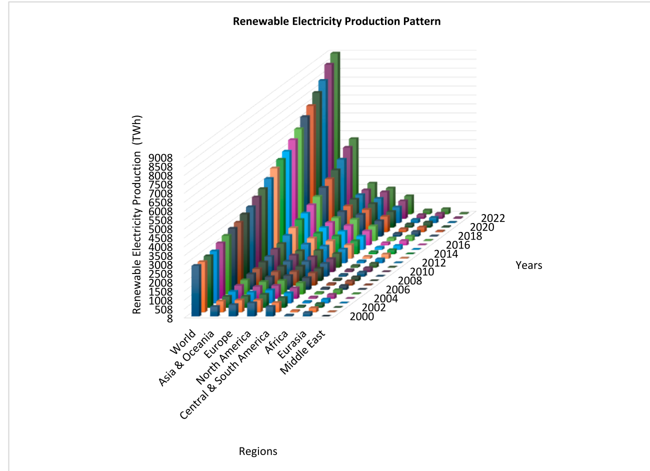

Fig. 2. Dynamic Renewable electricity production pattern in 2000–2023 in the eight regions.

Additionally, the European Green Deal set a GHG reduction target for 2030 of at least a 55 % net reduction in greenhouse gas emissions compared to 1990. To align EU policies with this target, the "Fit for 55″ package [15], a set of legislative proposals was introduced, including the revised Renewable Energy Directive (RED III). RED III established an overall renewable energy target of at least 42.5 %, binding at the EU level by 2030, with an aspirational goal of 45 %. Fig. 3 illustrates the extent to which EU climate and energy policies have influenced the share of renewables in electricity generation across member states between 2005 and 2023. Countries such as Finland, Austria, and Ireland exhibit substantial increases from 2005 to 2023, indicating marked improvements in their respective metrics.

In contrast, countries like Sweden and Denmark maintain consistently high percentages across both years, reflecting a level of stability in their performance. Cyprus was in third place, with its generation mainly based on solar and wind energy. The share of RES in electricity in the EU increased from approximately 16.5 % to over 45 % between 2005 and 2023. Additionally, the chart reveals considerable variability among other nations, with some experiencing increased percentages by 2023 while others show minimal changes. This variability may suggest the

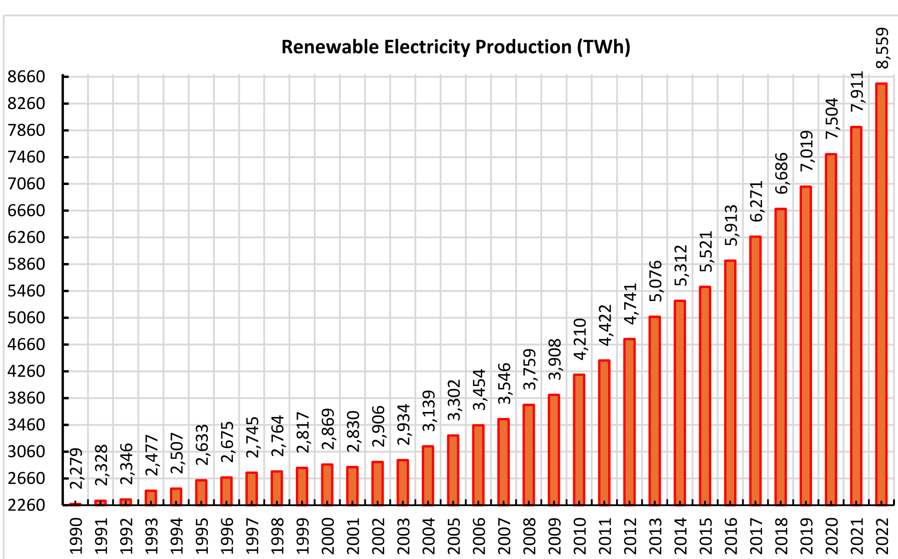

Fig. 1. Global renewable electricity production for 1990–2022.

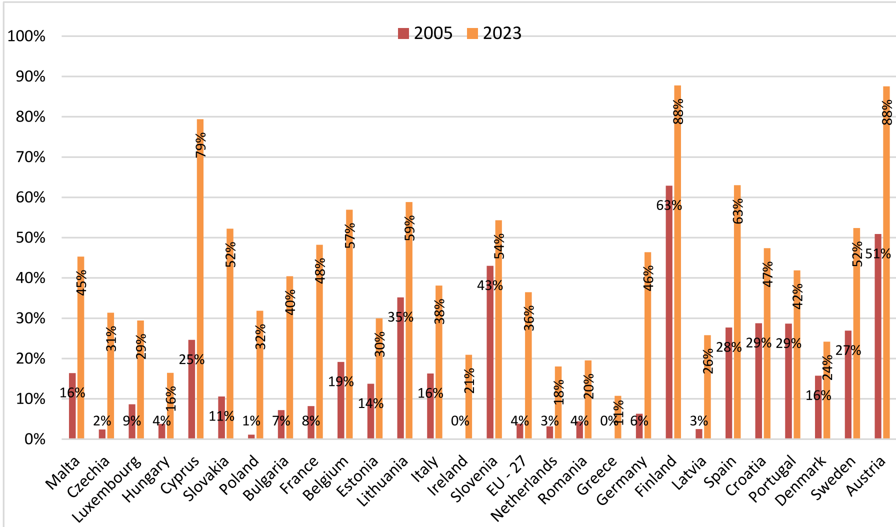

Fig. 3. Share of energy from renewable sources in electricity in 2005 and 2023.

influence of differing economic or social factors as well as the natural resource potential of each country. Overall, these findings underscore the dynamic nature of REP and provide a foundation for further investigation into the underlying causes of these trends. The data on the share of renewable energy is extracted from https://ec.europa.eu/eurostat/databrowser/product/page/nrg_ind_ren, accessed on January 19, 2025.

Numerous previous studies (e.g., Refs. [2,10–14]) have employed quantitative methods to examine the drivers of REP. However, most of this research has focused on a narrow set of variables, often overlooking the broader macroeconomic and institutional context. Only a limited number of empirical studies [7,8,16–18] have examined how macro-level factors, such as governance quality, financial development, or external economic conditions, influence the deployment of renewable energy across countries. In particular, existing research rarely considers the combined effect of key variables such as GDP, inflation, unemployment, financial development, FDI, and energy imports, alongside governance-related factors like political stability, rule of law, and control of corruption. This study addresses this gap by offering a systematic and comprehensive assessment of 16 explanatory variables grouped into four categories. First, macroeconomic fundamentals encompass the general economic and demographic environment that influences energy demand and policy space. This group includes GDP, population, inflation, unemployment, and government debt. Second, financial and external economic linkages encompass indicators of capital availability, trade exposure, and resource dependence, such as financial development, foreign direct investment, energy imports, oil prices, and natural resource rents. Third, institutional and governance quality reflect the broader political and regulatory environment that shapes investor confidence and the implementation of policy. This includes political stability (measured inversely via PSA), the rule of law, and control of corruption. Finally, innovation and energy system transformation comprise variables that directly influence technological progress and system decarbonization, most notably R&D expenditures and CO_2 emissions, which serve as a proxy for the decarbonization challenge.

The current study addresses a critical issue in Europe's ongoing energy transition, which has become increasingly urgent due to geopolitical, environmental, and economic challenges. Rising concerns over energy security, amplified by geopolitical instability such as the Russia–Ukraine conflict, volatile fossil fuel prices, and heightened climate obligations under the EU Green Deal, underscore the necessity of accelerating renewable energy production (REP). In this context, understanding the macroeconomic and institutional determinants of REP is crucial for designing effective policies that are adaptable to evolving regional and global pressures.

Regarding methodology, the current study distinguishes itself from earlier contributions by integrating econometric rigor with advanced forecasting techniques. While prior works often rely exclusively on conventional econometric models or apply machine learning (ML) in narrow contexts, this study employs a hybrid approach that combines Driscoll-Kraay standard errors (DKSE) with cutting-edge ML algorithms, including Random Forest (RF) and Convolutional Neural Network-Bidirectional Long Short-Term Memory-AutoRegressive (CNN-BiLSTM-AR). DKSE addresses panel-specific issues such as heteroskedasticity and cross-sectional dependence, enhancing the robustness of the estimated effects. Meanwhile, ML models benchmark predictive accuracy across countries with diverse regional economic patterns (REP dynamics). This combination allows for both causal interpretation and high-resolution forecasting. Compared to existing studies, which tend to focus on single-country analyses or rely on basic linear models, such as ARIMA, the current study offers broader applicability and more granular insights into policy drivers across the European continent.

Building on this structure, the analysis pursues two interconnected objectives to deepen the understanding of renewable REP dynamics in selected European countries. First, the study employs a robust panel framework to investigate the macroeconomic and institutional determinants of REP. By employing Fixed Effects and Driscoll-Kraay estimators, the analysis accounts for heteroskedasticity, autocorrelation, and cross-sectional dependence, which are common in macro-panel data. While the linear framework applied in this study ensures clarity and tractability, future research could benefit from exploring potential asymmetries in the response of macroeconomic variables to external shocks, as suggested in the literature [19,20].

Second, the study pioneers a comparative evaluation of advanced machine learning (ML) models, including CNN-BiLSTM-AR, Support Vector Machine (SVM), Random Forest (RF), and Long Short-Term Memory (LSTM), for forecasting REP. This dual-method approach identifies the drivers of renewable energy adoption and quantifies their predictive power, enabling the design of robust policies.

1.2. Theoretical framework

This study's selection of explanatory variables is grounded in established macroeconomic and institutional theories. From the perspective of endogenous growth theory [21], innovation, typically measured through research and development (R&D) expenditure, serves as a key engine of long-term productivity growth and transition toward clean technologies.

Institutional theory emphasizes that governance quality, reflected in indicators such as the rule of law and political stability, shapes investment certainty, transaction costs, and the effectiveness of policy implementation [22]. Weak institutions and political unrest create barriers to private investment in capital-intensive renewable energy infrastructure.

Additionally, the role of financial development is dual-faceted. While it provides liquidity and access to capital, post-Keynesian theory [23,24] cautions that unregulated or excessive credit expansion may lead to resource misallocation, speculation, or macroeconomic instability, particularly in the absence of strong institutional checks.

This theoretical integration informs the inclusion of variables such as GDP, inflation, CO_2 emissions, unemployment, financial development, and institutional quality in our model. It provides a structured rationale for understanding the multifactorial determinants of renewable energy production and their interaction across European economies.

1.3. Research gap and contribution

Our research makes three significant contributions. Methodologically, we advance the renewable energy economics literature by integrating robust panel econometric techniques with machine learning–based forecasting. This novel combination links causal inference with predictive analytics. We apply the Driscoll-Kraay estimator, which is rarely used in this context, to address key statistical challenges in macro-panel data, such as heteroskedasticity and cross-sectional dependence. This enhances inference reliability and uncovers relationships often overlooked in conventional fixed-effects models. Empirically, we find that R&D investment is the most influential determinant of REP, surpassing the effects of traditional macroeconomic drivers, including GDP and population growth. At the same time, we demonstrate that institutional quality, as measured by political stability and the rule of law, plays a crucial role in shaping the outcomes of renewable energy. These findings emphasize that, beyond economic fundamentals, the broader governance environment is a critical enabler or barrier to large-scale RES deployment across Europe.

Practically, the current study benchmarks five machine learning models to forecast REP and shows that RF consistently delivers the highest accuracy across countries. This model outperforms traditional tools such as ARIMA and offers a reliable and scalable solution for anticipating energy transitions. Combined with scenario-based planning, this predictive toolkit can help policymakers align infrastructure investments, enhance system integration, and mitigate uncertainty surrounding climate and energy targets. Based on these empirical findings, the study proposes policy recommendations to support the effective, innovative-driven, and institutionally grounded expansion of renewable energy sources (RES) across European countries.

1.4. Study objectives and research questions

Building upon the theoretical rationale and empirical gaps outlined above, this study aims to explore the macroeconomic and institutional determinants of renewable energy production (REP) across selected European countries from 1995 to 2022.

The primary research question is:

What are the key macroeconomic and institutional factors influencing REP in Europe, and how can machine learning methods improve forecasting accuracy compared to traditional econometric models?

Accordingly, the study sets out the following objectives.

1. To empirically assess the impact of variables such as GDP, R&D, inflation, population, institutional quality, and CO_2 emissions on REP using panel data econometrics.
2. To compare the forecasting performance of conventional models (e.g., ARIMA) with advanced machine learning techniques (e.g., RF, LSTM, CNN-BiLSTM-AR).
3. To derive policy recommendations tailored to different country contexts based on the combined insights from explanatory and predictive models.

2. Literature review

The literature on renewable energy has grown significantly, with many studies examining the drivers of renewable energy consumption (REC). At the same time, few have explicitly focused on renewable energy production (REP) despite its central role in achieving energy transition goals. The distinction is particularly relevant in interconnected markets, such as the European Union (EU), where production and consumption may occur in different countries. Previous research has identified a range of determinants for renewable energy, including economic growth, energy imports, fossil fuel dependency, and environmental pressures [25,26].

While prior studies have highlighted the importance of institutional frameworks and financial support in fostering renewable energy deployment, the cross-national spillover effects of renewable energy policies remain underexplored. Ref. [27] demonstrates that international policy interactions significantly affect national-level renewable energy outcomes, reinforcing the need for multi-country empirical designs such as the one employed in this study. Furthermore, recent advances in artificial intelligence are increasingly shaping energy modeling and forecasting. Ref. [28] provides global evidence of AI's role in transforming energy security and system resilience, aligning with the present study's application of machine learning methods to forecast REP across Europe.

Numerous studies have confirmed a positive relationship between per capita GDP and renewable energy development, underscoring the role of economic growth in facilitating investments in renewable infrastructure and innovation [29–31]. In line with this, Ref. [32] emphasizes that economic development, typically measured by GDP per capita, can further support the expansion of renewable energy by facilitating necessary investments in infrastructure and technological progress. This is also corroborated by Ref. [33], which found a sustained correlation between GDP and renewable energy production. Similarly, Ref. [34] showed a positive relationship between GDP and renewable energy generation in African nations. Ref. [35] reported a consistent association with per capita GDP. The contribution of GDP to REP is demonstrated by the fact that higher per capita GDP allows the state to allocate a more significant portion of its budget toward renewable energy projects, highlighting the significance of GDP in REP. These financial resources can be leveraged to establish renewable energy facilities, promote clean energy technologies, and develop favorable regulations and incentives that encourage the adoption of renewable energy. This aligns with the findings of [36,37]. As economies grow, nations gain the capacity to fund initiatives that enhance the affordability and efficiency of renewable energy technologies. This financial support fosters innovation and facilitates the integration of renewable energy sources into existing conventional energy systems. For further insights, refer to the works of [38,39]. Economic growth, reflected in rising GDP rates, enables the construction of essential infrastructure such as wind farms, solar parks, hydroelectric power plants, and investments in smart grids. These developments enhance the effective management and distribution of renewable energy [40,41].

Ref. [31] used real GDP, CO_2 emissions, and oil prices to determine renewable energy for six emerging nations between 1980 and 2006. The long-term panel results suggest that real GDP and CO_2 emissions have a positive impact on the dependent variable. For seven Central American countries between 1980 and 2010, Apergis and Payne [42] investigated the relationship between GDP per capita, CO_2 emissions, real oil prices, real coal prices, and the amount of renewable energy consumed per capita. All of the coefficients are estimated to be positive. Ref. [43] uses identical models, but real coal prices are not included. According to their FMOLS results, there is a positive and substantial correlation between the per capita consumption of renewable energy and all dependent variables.

Ref. [44] examines several variables influencing renewable energy in 64 countries. By dividing the nations into three smaller groups based on income levels from 1990 to 2011, they examined the problem. The empirical findings show that the global group and all three subpanels use more renewable energy when CO_2 emissions per capita rise. Real oil prices reduce the usage of renewable energy by middle-income subpanels and the global panel. The use of renewable energy in high- and middle-income nations is influenced by GDP per capita. All groups, except the high-income subpanel, use more renewable energy when trade opens.

The relationship between CO_2 emissions per capita, real oil prices, GDP per capita, trade openness, and the use of renewable energy in 64 nations is examined by Ref. [45]. The time frame spans from 1990 to 2011. They classify the nations into global panels and low-, middle-, and high-income national groups. The empirical study shows that, except for the low-income nation panel, all panel groups' GDP and CO_2 emissions per capita elasticity estimates have positive signs. However, only the worldwide panel group benefits from higher oil prices when using renewable energy. Ref. [46] examines how several institutional, political, and economic aspects affect the use of renewable energy for specific country groups between 1995 and 2011. The economic elements under investigation are oil prices, education, and per capita income. They have proven to have significant and favorable benefits. According to Ref. [47], the primary factors influencing renewable energy in African nations that produce oil are real income per capita, carbon emissions per capita, energy consumption per capita, and energy prices.

Ref. [48] researched the Balkan nations. The independent variables are CO_2 emissions, GDP per capita, trade openness, and natural gas and oil rents. The findings indicate that GDP per capita has a negative impact on renewable energy. Conversely, trade and natural gas rents have a favorable effect on the use of renewable energy. The study by Ref. [49] empirically analyzes 22 African nations between 1990 and 2011. When renewable energy consumption is the dependent variable and non-renewable energy consumption, CO_2 emissions, and GDP per capita are the independent variables, the long-term results indicate that GDP per capita is not significant, non-renewable energy consumption has a positive sign, and CO_2 emissions have a negative sign. Ref. [50] examines how several factors affect a few independent variables for 12 Commonwealth of Independent States (Russian Commonwealth) nations between 1992 and 2015. Factors influencing renewable energy include composite trade intensity, non-renewable energy consumption, real GDP, CO_2 emissions, and financial openness. Except for the coefficient of non-renewable energy use, all estimated coefficients are positive.

Coal prices, crude oil prices, natural gas prices, CO_2 emissions per capita, GDP per capita, population growth, energy consumption, the proportion of electricity imported to consume, and the Kyoto Protocol's confirmation (a dummy variable) are all used by Ref. [25] to determine the proportion of renewable energy in the production of electricity. They conducted empirical analyses of 17 nations in Sub-Saharan Africa between 1990 and 2014. The results show that while the population growth rate reduces the share of renewable energy in power production, GDP per capita and energy demand rise. The effects of oil prices, CO_2 emissions, GDP per capita, and high technology exports on renewable energy development in industrialized and developing nations are examined [51]. Their results show that GDP per capita has a beneficial impact on the output of renewable energy in both groups of countries. Nonetheless, the elasticity estimate of CO_2 emissions is anticipated to be positive for emerging nations and negative for rich nations. High oil prices and technological exports have a good effect on generating renewable energy for both nations.

Ref. [52] examines the association between several economic and social factors and the proportion of energy consumed by renewable sources in 21 African nations between 1990 and 2013. Economic indicators include GDP per capita, trade openness, and Foreign Direct Investment (FDI); social indicators include the Human Development Index and the Democracy Index. According to empirical research, foreign direct investment, GDP per capita, and the Human Development Index (HDI) have a negative impact on the proportion of renewable energy.

One hundred and seven nations are grouped [53] based on their level of development. The empirical analysis spans the period from 1990 to 2013, with real GDP, CO2 emissions, and oil prices driving both renewable and non-renewable energy consumption. According to the study, real GDP has a negative effect on the use of renewable energy in low-income nations, while CO_2 emissions have a favorable effect. However, for high-income countries, the use of renewable energy is positively impacted by real GDP and negatively by CO_2 emissions. Using panel data from 29 countries from 2000 to 2015, Ref. [54] seeks to measure the effectiveness of seven aggregate and twelve individual renewable energy public programs. The effects of trade openness, economic growth, and technological advancement on the use of renewable energy for 25 OECD nations between 1970 and 2012 are examined in the work by Ref. [55]. One indicator of technical advancement is the quantity of patents. The long-term findings show that every element examined has a favorable and significant impact on the utilization of renewable energy.

Building on these global insights, it is essential to examine how similar dynamics unfold within the EU, where unique institutional, socio-economic, and policy factors shape energy transition processes. Decision-making processes at the EU level have been supported for many years by model-based analyses conducted using interconnected tools, with the PRIMES model playing a central role [56]. PRIMES is used to prepare scenarios for developing the EU energy system and to conduct Impact Assessments. It is a partial equilibrium modeling framework representing the energy market equilibrium within the EU and its Member States. For each sector, representative agents optimize an economic objective function. The results of the PRIMES model present future renewable energy production under predefined conditions in scenarios. Therefore, the approach used by PRIMES differs from the one applied in this study.

Approaches related to the one applied in this study include a panel vector autoregressive model, which was employed in Ref. [57] to test dynamic relationships between 1990 and 2015 among several institutional and socio-technical variables affecting renewable energy production in 18 European Union (EU) member states. The results showed that environmental policy stringency does not influence REP, while income and education have a negative impact. The study highlighted the substantial heterogeneity among EU countries in their energy transition processes, which is influenced by differing starting points in terms of installed capacity, energy security, and energy imports. An increase in GDP has a negative effect on renewable electricity output, defined as a percentage of total electricity production. Economic growth is associated with increased energy demand, and the development of renewable energy sources often fails to meet this higher demand. There was also a negative causal relationship between REP and CO_2 emissions. The analysis reveals that countries with varying initial installed capacity conditions require tailored transition policies. Historically, high- and low-energy-importing countries have maintained their status.

This paper focuses on the electricity sector rather than the primary RES energy supply. A particularly relevant study is Ref. [58], which presents an econometric analysis of the factors motivating the use of renewable energy (excluding hydropower) in electricity production using panel data from EU Member States from 2000 to 2015. The explanatory variables included oil price, gas price, coal price, interconnection, fossil fuel share, nuclear share, hydropower share, population growth, GDP per capita, emissions, foreign direct investment, and growth in the share of taxes in electricity prices. The results suggest that renewable energy is viewed as a substitute for oil, but not necessarily for natural gas, in the production of electricity. In many countries, gas complements renewables, as it is used to fill gaps in the availability of renewable energy sources (RES).

Contrary to expectations, a rise in coal prices discourages long-term use of renewable energy, suggesting a complementary relationship between the two. Electricity grid interconnection has a positive impact on the incorporation of renewable energy into electricity production, suggesting that enhancing grid interconnection between countries is crucial for maximizing the potential of renewable energy. The ability of a country to export excess renewable electricity during periods of high supply and import electricity during periods of low supply increases its capacity to integrate renewable energy. Additionally, GDP per capita has a significant positive impact on the deployment of renewable energy sources (RES).

3. Data sources

This section provides a detailed analysis of the study's findings on renewable energy production (REP) in European countries from 1995 to 2022, focusing on data sources, methodology, and interpretation of results in alignment with prior literature. The study integrates panel econometric models—DKSE and Fixed Effects (FE)—with advanced machine learning techniques for REP forecasting. Comparative references are made to studies conducted on Jordan, WAEMU countries, transition economies, and Egypt.

The study employs a balanced panel dataset with annual observations to investigate REP across Europe. For the forecasting component, the dataset spans from 1995 to 2022 and includes all 26 European countries listed in Table 1, providing a robust foundation for developing and evaluating machine learning models. This 28-year panel ensures sufficient temporal depth to capture long-term trends and dynamics in renewable energy production.

In contrast, for analyzing the macroeconomic determinants of REP, the study focuses on a subset of the data from 1999 to 2022, comprising 23 countries, excluding the United Kingdom, Norway, and Switzerland. This selection focuses on EU member states to ensure greater consistency in policy and institutional frameworks that affect REP. Additionally, this subset aligns with the structural requirements of the Fixed Effects model, which benefits from panel dimensions where the number of periods (T) and cross-sectional units (N) remain below 25. From 1999 to 2022, $T = 24$ and $N = 23$, enabling statistically robust and methodologically sound estimation while reflecting EU-specific energy dynamics.

The analysis includes nine core explanatory variables: GDP, inflation (INF), population (POP), unemployment (UNE), political stability absence (PSA), CO_2 emissions, financial development (FD), research and development expenditure (RDE), and rule of law (RL). These are employed in the DKSE and FE models. In contrast, machine learning models—SVM, RF, CNN-BiLSTM-AR, LSTM, and ARIMA—are used for REP forecasting. The results highlight the significance of R&D investment, political stability, and the predictive superiority of Random Forest, with actionable policy recommendations for enhancing renewable energy deployment.

Descriptions of all variables, proxies, and data sources used in this study are presented in Table 2.

4. Methodology

This paper used CNN-BiLSTM-AR, SVM, RF, LSTM, and ARIMA models. All models utilize monitored machine learning models, which analyze data using training data and then create a data prediction function. The accuracy of the six models is determined by their performance in predicting renewable energy production, as well as in extracting the main determinants of the value of renewable energy production. The machine learning algorithms used in this study were written in Python using the scikit-learn package.

4.1. Random forest model

A random forest consists of many distinct decision trees. The study

Table 2
Descriptions, sources, and proxies of macroeconomic and institutional variables used in the analysis.

No.	Variable Abbreviation	Variable name	Proxy/Scale of measurement	Data source
1	GDP	GDP	constant 2015 US$	WDI
2	POP	Population	Total Population	WDI
3	CO_2	CO_2 emissions	Metric tons	WDI
4	PSA	Political stability and absence of violation	Index (−2.5 to 2.5)	WGI
5	CCUR	Control of corruption	Index (−2.5 to 2.5)	WGI
6	RL	The rule of law	Index (−2.5 to 2.5)	WGI
7	OP	Oil price	Spot crude oil price (US dollars per barrel)	BP
8	EI	Energy imports	Net Energy imports (% of energy use)	OWD
9	FD	Financial Development	Domestic credit to the private sector (% of GDP)	WDI
10	FDI	Foreign Direct Investment	Net inflows (current US $, millions)	WDI
11	GD	Government Debt	Government debt (% of GDP)	WDI
12	UNE	Unemployment	Total Unemployment (% of total labor force)	WDI
13	INF	Inflations	Consumer price index (annual %)	WDI
14	REP	Renewable Energy Production	Renewable electricity production (terawatt-hours, TWh)	EIA
15	RDE	Research and Development Expenditures	% of GDP	WDI
16	RNR	Rents from Natural Resources	Total natural resources rents (% of GDP)	WDI

Notes: WGI: Worldwide Governance Indicators (scale: −2.5 to +2.5, where higher values indicate better governance). WDI: World Development Indicators (World Bank). EIA: U.S. Energy Information Administration. BP Statistics 861 Review: Annual energy market report by BP.Our World in Data (OWD): Open-access platform for global development data.

Table 1
List of 26 European countries included in forecasting analysis (1995–2022).

Countries	Codes	Countries	Codes	Countries	Codes	Countries	Codes
Austria	AUT	Germany	DEU	Luxembourg	LUX	Slovenia	SVN
Belgium	BEL	Greece	GRC	Netherlands	NLD	Spain	ESP
Czech Republic	CZE	Hungary	HUN	Norway	NOR	Sweden	SWE
Denmark	DNK	Ireland	IRL	Poland	POL	Switzerland	CHE
Estonia	EST	Italy	ITA	Portugal	PRT	United Kingdom	GBR
Finland	FIN	Latvia	LVA	Romania	ROU	–	–
France	FRA	Lithuania	LTU	Slovak Republic	SVK	–	–

employs a classification-style decision tree to forecast a binary outcome variable, rather than using a serial number. These two kinds of decision trees similarly split the data into two groups at each decision point. At every node, a yes or no choice is taken. After that, further explanatory variables are added, and the data is again divided. The first one selected is the explanatory variable that can explain the most significant data separation. The mean value of the separated bucket of data is what the model predicts for that smaller bucket. When a decision tree has too many partitions, overfitting can cause the model to perform poorly in out-of-sample predictions, as it was trained too closely to the in-sample data. When out-of-sample prediction is a significant issue, it is recommended to restrict the number of variables and decision nodes [59].

Without reducing the number of allowed divisions or trimming the tree, the random forest methodology seeks to prevent overfitting by creating many trees for different subsets of the data. The results of the trees are averaged to lessen forecast variance. To further divide the data at each node, the random forest chooses a variable from a random subsample of the variables. Consequently, each tree's nodes cannot access the same variables.

Overfitting the in-sample data is generally not an issue [60]. The following equation represents the fundamental random forest model [60]:

$$F_0(z) = \frac{1}{m}\sum_{j=1}^{m}\left(v_j - \widehat{v}_j\right)^2 \tag{1}$$

Where $\widehat{v}_j$ indicates the expected value, v_j indicates the observed value, and m is the number of trees.

4.2. Convolutional Neural Network-bidirectional long short-term memory-auto regressive model

The Convolutional Neural Network-Bidirectional Long Short-Term Memory-Auto Regressive (CNN-BiLSTM-AR) model is a hybrid deep learning framework designed for day-ahead electricity price forecasting [61]. The model integrates three key components: a Convolutional Neural Network (CNN) for feature extraction, a Bidirectional Long-Short-Term Memory (BiLSTM) network for capturing long-term temporal dependencies, and an Auto-Regressive (AR) model for addressing local scaling issues and enhancing prediction accuracy.

The hybrid model combines the CNN-BiLSTM block with an AR model to address local scaling issues and enhance prediction accuracy. The AR model captures short-term linear dependencies, while the CNN-BiLSTM block captures spatial and long-range temporal patterns. The final prediction is obtained by combining the outputs of the CNN-BiLSTM and AR models:

$$\widehat{Z}_{T+k} = \widehat{Z}^{C}_{T+k} + \widehat{Z}^{A}_{T+k} \tag{2}$$

where $\widehat{Z}^{C}_{T+k}$ is the prediction from the CNN-BiLSTM block and $\widehat{Z}^{A}_{T+k}$ is the prediction from the AR model. The model is trained using the Adam optimizer and the Mean Squared Error (MSE) loss function, and dropout layers are employed to prevent overfitting.

4.3. Support vector machine model

Classification applications employing a unique machine learning approach have an independent and identically distributed (iid) training dataset. This discriminating function is capable of accurately predicting new occurrence labels. An algorithm for categorization discrimination is modified to include a new data point x. It assigns it to one of the many classes in classification problems, as opposed to generative approaches to machine learning, such as calculating probability distributions. Particularly in multidimensional areas, discriminatory techniques that are less effective and frequently used when outlines are necessary need fewer resources. Finding a multidimensional surface equation that best distinguishes numerous classes is required when only later opportunities are available. SVM always provides the same optimal space value as convex optimization problems solved analytically, unlike evolutionary algorithms, which are commonly employed in machine learning classification, such as perceptrons. Perceptrons have significant initialization and termination requirements [62].

In 1995, Vapnik introduced the SVM regression model as a non-parametric method. This is how the SVM linear function appears:

$$f(z) = \langle u, z \rangle + c \tag{3}$$

u represents the weight vector, z signifies the input or feature vector, and c indicates the bias, aiming to maintain the function as flat as possible, i. e., a minimal u. One method to achieve this is by minimizing the conventional u [63]. Characterized the function as a convex optimization problem [63]:

$$0.5\|u\|^2 + D\sum_{j=1}^{n}\left|\left(v_j - f(z_j)\right)\right|_{\eta} \tag{4}$$

LSSVM, a machine learning technique introduced by Ref. [64], transforms quadratic programming into linear equations by employing equality constraints rather than inequality constraints. $y = \psi^{\top}\phi(z) + c$, where ψ^{T} represents the weight, $\phi^{(z)}$ denotes the nonlinear function that maps the input into a high-dimensional feature space, and c signifies the bias. For a given training set $\left\{(z_j, v_j) \,|\, j = 1, 2, \cdots, z_j \in R^n, z_j \in R^n\right\}$, in which z_j is the input, v_j is the output corresponding to z_{jt} is the size of the training set, LSSVM is defined as follows [65]:

$$\min J(\psi, c, e) = \frac{1}{2}\|\psi\|^2 + \frac{\delta}{2}\sum\nolimits_{j=1}^{n} e_j^2 \tag{5}$$

$$v_j = \psi^T\phi(z_j) + c + e_j, j = 1, 2, \ldots, n$$

where $\psi \in R_n$, error $e_j \in R$, regularization $\delta > 0$. By introducing the Lagrange multiplier, we may derive [65]:

$$L(\psi, c, e, b) = Q(\psi, c, e) - \sum_{j=1}^{n} b_j\left[\psi^T\phi(z_j) + c + e_j - v_j\right] \tag{6}$$

where α_j denotes the Lagrange multiplier. Based on the Karush-Kuhn-Tucker criteria, the following is obtained [65]:

$$\begin{cases} \dfrac{\partial L}{\partial \psi} = 0 \Rightarrow \psi - \displaystyle\sum_{j=1}^{n} b_j\phi(z_j) = 0 \\ \dfrac{\partial L}{\partial c} = 0 \Rightarrow \displaystyle\sum_{j=1}^{n} b_j = 0 \\ \dfrac{\partial L}{\partial e_j} = 0 \Rightarrow \delta e_j - b_j = 0 \\ \dfrac{\partial L}{\partial b_j} = 0 \Rightarrow \psi^T\phi(z_j) + c + e_j - v_j = 0 \end{cases}$$

The linear equations are derived using elimination [65]:

$$\begin{bmatrix} 0 & 1_v^T \\ 1_v & \Omega + \delta^{-1}I \end{bmatrix}\begin{bmatrix} c \\ b \end{bmatrix} = \begin{bmatrix} 0 \\ v \end{bmatrix}$$

where $v = [v_1, v_2, \cdots v_1]^{\top}$, $1_v = [1, 1, \cdots 1]^{\top}$, $b = [b_1, b_2, \cdots b_n]^{\top}$, and/is a first-order unit matrix. Ω is a nonnegative definite matrix of $/ \times 1$, which meets the Mercer condition that $\Phi_{jk} = K(z_j, z_k) = \phi(z_j)$ $T\phi(z_j), j, k = 1, 2, \cdots 1, \mathrm{K}(\cdot)$ is a kernel function. After obtaining, the LSSVM predictor is defined as follows [65]:

$$f(z) = \sum\nolimits_{j=1}^{n} b_j K(z, z_k) + c \tag{7}$$

4.4. Long-short-term memory model

Hochreiter and Schmidhuber introduced long short-term memory (LSTM) [66], a specialized type of recurrent neural network (RNN) designed to address the issues of gradient vanishing and gradient explosion during training of extended sequences. LSTM effectively preserves the sequence's long-term fluctuation pattern within the parameters [67], making it ideal for illustrating the long-term increase in carbon prices post-2017.

The long-period mode following VMD decomposition exhibits a distinct trend component [68]. LSTM can capture this long-term trend more effectively than other artificial intelligence systems, such as support vector machines (SVM). Furthermore, the carbon price series' long-term trend exhibits significant non-linearity and non-stationarity, rendering it inappropriate for application with conventional econometric models.

An LSTM unit comprises two hidden states, h_t and d_t, designated for the retention of short-term and long-term information, respectively. Three control gates are introduced: the forget gate, the input gate, and the output gate. The forget gate p_t regulates the extent of information retained from the preceding state d_{t-1}. The forget gate at time t is

$$p_t = \sigma\left(U_p \cdot [g_{t-1}, Z_t] + c_p\right) \tag{8}$$

where $\sigma(\cdot)$ denotes the sigmoid activation function, and Z_t signifies the input of the prediction model, specifically historical carbon pricing data. f_t denotes the forget gate vector at time t; g_{t-1} signifies the output vector at time $t-1$ (also, the state g vector); U_p and c_p represent the weight matrix and bias of the forget gate, respectively; [•] indicates a vector concatenation operator.

The input gate q_t regulates the extent of current information to be incorporated for generating the current state $c_t.q_t$. It is computed as follows:

$$q_t = \sigma\left(U_q \cdot [g_{t-1}, Z_t] + c_q\right) \tag{9}$$

U_q and c_q denote the weight matrix and bias of the input gate, respectively. It is noted that q_t and p_t have a comparable structure, with both gates being influenced by g_{t-1} and Z_t.

The present hidden state d_t is derived by summing the information regulated by the two gates pt and q_t. Long-term information is governed by pt, while short-term information is governed by q_t :

$$d_t = \tanh(\boldsymbol{U}_d \cdot [g_{t-1}, Z_t] + c_d) \tag{10}$$

$$d_t = p_t{}^* d_{t-1} + q_t^* d_t$$

Where tanh $(\cdot)$ represents the tanh activation function, $\boldsymbol{U}_d$ and c_d signify the weight matrix and bias of the current state, and the operator * indicates the element-wise product, represented as $\begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} * \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix} = \begin{bmatrix} a_{11}c_{11} & a_{12}c_{12} \\ a_{21}c_{21} & a_{22}c_{22} \end{bmatrix}$

The final function of the LSTM unit is to determine the quantity of information to be produced, executed by the output gate r_t :

$$r_t = \sigma(\boldsymbol{U}_o \cdot [g_{t-1}, Z_t] + c_o) \tag{11}$$

The ultimate output of the LSTM unit is

$$g_t = r_t{}^* \tanh(d_t) \tag{12}$$

4.5. Autoregressive Integrated Moving Average model

The ARIMA model is the most recognized representation of nonstationary time series, expressed as:

$$\psi(L)(1-L)^d(Wt - \nu t) = \eta(L)\epsilon_t \tag{13}$$

Where $\psi(L)$, and $\eta(L)$ are lag operator polynomials, L is defined as $L^n x_t = x_{t-n}$, denoting the unconditional mean, d signifies the order of integer differencing, and ϵ_t is an independently and identically distributed normally distributed process (for further information, see Refs. [69]). This model is called an ARIMA(p, d, q) due to the p and q delays of the AR and MA terms, respectively, while d represents the differencing integer. The maximum likelihood approach is advised for estimating the parameters of the ARIMA model. The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are employed for the selection of models for the lag parameters p and q [70].

The ARIMA(p, d, q) model pertains to an integrated time series that achieves stationarity following d instances of differencing. The Augmented Dickey-Fuller test is often used to determine the stationarity of a time series [71]. The null hypothesis says that the time series is nonstationary of order one (I (1)), while the alternative hypothesis claims stationarity (I (0)). If the null hypothesis cannot be rejected, an alternative set of hypotheses must be evaluated, namely I (2) against I (1). The $ARMA(p, q)$ model is applicable when the time series exhibits stationarity.

4.6. Fixed effects model

The Fixed Effects (FE) model is one of the most widely used methods in panel data analysis, particularly for controlling unobserved heterogeneity that varies across groups but remains constant over time. The Fixed Effects model, proposed by Mundlak [72], controls unobserved heterogeneity and is ideal for analyzing persistence. The general equation for the FE model is given by

$$Y_{it} = \alpha_i + \beta_1 X_{it} + u_{it} \tag{14}$$

Where, Y_{it} for group i, time t, is the outcome, α_i is the individual effect, β_1 represents the Coefficients of the independent variables, X_{it} is the predictor, and u_{it} is the error.

Fixed-effects models are extensively employed in panel data analysis to mitigate unobserved heterogeneity that could distort estimates. These models account for time-invariant traits by eliminating individual-specific fixed effects, usually by demeaning the data. This method is especially advantageous when omitted variables remain constant throughout time yet differ among individuals, such as inherent ability or cultural influences. FE models are adaptable and resilient, effectively accommodating non-random sampling or imbalanced panels while imposing no stringent assumptions regarding the distribution of fixed effects. They concentrate on intra-group variance, deriving coefficients based on temporal changes rather than inter-group differences. Nonetheless, fixed-effect models possess certain drawbacks. They cannot estimate coefficients for time-invariant variables, such as gender or race, and require adequate periods to identify the model. Furthermore, they presuppose stringent exogeneity, indicating that independent variables must be uncorrelated with the error term. Notwithstanding these limitations, fixed-effects models remain an effective instrument for examining panel data, particularly where it is essential to account for unobserved heterogeneity.

4.7. Driscoll-Kraay Standard Errors model

Driscoll-Kraay standard errors (DKSE) were developed to address two common issues in panel data: cross-sectional dependence and heteroskedasticity. DKSE, introduced by Ref. [73], provides robustness to cross-sectional dependence and heteroskedasticity, making it indispensable for large panels. Driscoll-Kraay ensures reliable inference even in the presence of correlated shocks across groups by providing robust standard errors. The DKSE model is essential because it can address several significant problems in panel data analysis. Initially, it considers arbitrary types of autocorrelations and heteroskedasticity in each person's time series, ensuring that the standard errors remain reliable even in the presence of these complications. Second, unlike conventional clustered standard errors, the DKSE method allows for cross-sectional dependence, which is typically assumed to be absent in conventional clustered standard errors. This is especially important in domains such as finance or macroeconomics, where shocks like policy changes or economic crises can simultaneously impact multiple firms. Third, the model is adaptable and applicable without imposing restrictive assumptions regarding the structure of the error terms, as it employs a nonparametric approach with kernel-based weighting functions. Fourth, the Driscoll-Kraay estimator is perfect for contemporary datasets with many observations because it works incredibly well in large panels, where many individuals (N) and periods (T). Lastly, the DKSE offers more dependable inference than alternative techniques by concurrently resolving heteroskedasticity, autocorrelation, and cross-sectional dependence, ensuring that researchers can make appropriate inferences from their investigations. These characteristics highlight the Driscoll-Kraay model's resilience and adaptability in econometric applications.

Let X_{it} be the vector of explanatory variables, and let y_{it} be the dependent variable for individual i at time t. The following is an expression for the linear panel data model:

$$y_{it} = X_{it}'\beta + u_{it} \tag{15}$$

Where, $i = 1, 2, \ldots\ldots, N; t = 1, 2, \ldots\ldots, T$,

β is the vector of coefficients to be estimated. u_{it} is the error term that may exhibit heteroscedasticity, autocorrelation, and cross-sectional dependence.

The key idea is to construct a robust covariance matrix estimator that accounts for both serial correlation within individuals and cross-sectional dependence across individuals. However, instead of relying on traditional standard errors, Driscoll-Kraay adjusts the covariance matrix estimator to account for cross-sectional dependence using the formula:

The covariance matrix of the OLS estimator $\widehat{\beta}$ is given by:

$$VAR(\beta) = (X'X)^{-1}\Omega(X'X)^{-1} \tag{16}$$

Where X is the matrix of regressors and Ω is the covariance matrix of the residuals.

The Driscoll-Kraay estimator adjusts Ω as follows:

$$\widehat{\Omega}_{DK} = \frac{1}{NT}\sum_{t=1}^{T}\sum_{S=1}^{T}\omega(|t-s|)\widehat{u}_t\widehat{u}_s' \tag{17}$$

Where: $\widehat{u}_t = (\widehat{u}_{1t}, \widehat{u}_{2t}, \ldots.., \widehat{u}_{Nt})'$ is the vector of residuals for all individuals at time t.

$\omega(|t-s|)$ is a weighting function that depends on the lag $|t-s|$. A common choice is the Bartlett kernel:

$$w(k) = \begin{cases} 1 - \dfrac{k}{M} & \text{if } k \le M, \\ 0 & \text{otherwise}, \end{cases} \tag{18}$$

Where M is the bandwidth parameter that controls the number of lags considered.

4.8. Forecasting accuracy measures

The most widely used method for determining forecast accuracy is calculating forecast errors. Mean square error (MSE), mean absolute percentage error (MAPE), and root mean square error (RMSE) are the most common examples of such measurements [74]. The MSE, MAPE, and RMSE are expressed in Eqs. 19–21, where $x^{(0)}(k)$ and $\widehat{x}^{(0)}(k)$ are the actual values at the time k and the corresponding prediction, respectively.

$$MSE = \frac{1}{n}\sum_{k=1}^{n}\left(x^{(0)}(k) - \widehat{x}^{(0)}(k)\right)^2 \tag{19}$$

$$MAPE = \frac{1}{n}\sum_{k=1}^{n}\left|\frac{x^{(0)}(k) - \widehat{x}^{(0)}(k)}{x^{(0)}(k)}\right| \times 100\% \tag{20}$$

$$RMSE = \sqrt{\frac{\sum_{k=1}^{n}\left(x^{(0)}(k) - \widehat{x}^{(0)}(k)\right)^2}{n}} \times 100\% \tag{21}$$

Their utility is limited to displaying disparities in the accuracy of generated forecasts while saying nothing about the forecasting process.

Apart from the defined indicators, the current study uses the NRMSE [75,76]. There are different versions of NRMSE, depending on the problem's requirements and the nature of the data.

The RMSE can be normalized by:

The mean: $NRMSE = \frac{RMSE}{\overline{X}}$

The difference between maximum and minimum: $NRMSE = \frac{RMSE}{\mathrm{Xmax} - \mathrm{Xmin}}$

The standard deviation: $NRMSE = \frac{RMSE}{\sigma}$

The interquartile range; $NRMSE = \frac{RMSE}{Q1 - Q3}$ i.e., the difference between the 25th and 75th percentile.

If the data set is homogeneous, each measure can be used. If the data is highly dispersed, skipping the maximum and minimum values and using the interquartile range is preferred.

[77] developed a testing approach with equivalent prediction accuracy. Under the null hypothesis, the alternative procedures (models) are assumed to be equally accurate on average. Diebold and Mariano's test is based on time series, which include actual and predicted values, say y_t and $\widehat{y}_{it}$.

The loss function may take many forms, which is discussed further in this part. What we compare is a loss differential between the two forecasts, coming from two competing models of the form:

$$h(y_t, \widehat{y}_{it}) = h(\widehat{y}_{it} - y_t) = h(e_{it}) \tag{22}$$

The loss function can take various shapes. Typically, mean square error (MSE) or mean absolute error (MAE) is used. The loss differential between the two forecasts, derived from two competing models, takes the form.

$$d(t) = h(e_{1t}) - h(e_{2t}) \tag{23}$$

The forecasting methods are equally accurate if $E(d(t)) = 0$, which is assumed under the null hypothesis.

This paper applied the Diebold-Mariano test to compare several machine learning methods (SVM, RF, CNN-BiLSTM-AR, LSTM, and ARIMA) models estimated. The loss function based on the MSE was selected for comparison because the differences between forecast errors were relatively low.

5. Empirical results

The descriptive statistics provided summarize the distribution of 16 variables—REP, GDP, INF, POP, UNE, OP, PSA, CCUR, CO_2, EI, FD, FDI, GD, RDE, RL, and RNR—for a panel dataset covering 23 countries from 1999 to 2022, with 552 observations. These statistics are presented in Table 3 and serve as a foundational diagnostic to examine variable scales, dispersion, and potential anomalies prior to econometric modeling.

These variables, spanning economic, governance, and environmental domains, are characterized by their mean, standard deviation, minimum, maximum, 1st and 99th percentiles, skewness, and kurtosis, offering insights into their central tendencies, variability, and distributional shapes. This interpretation focuses solely on the table's statistics, elucidating the characteristics of each variable and their implications for understanding the dataset's structure across 23 countries

Table 3
Descriptive statistics of time series variables across 23 countries.

Variables	Obs	Mean	Std. Dev.	Min	Max	p1	p99	Skew.	Kurt.
REP	552	29.516	41.435	0.017	257.962	0.06	221.457	2.394	10.222
GDP	552	31594.163	21765.015	4451.762	112000	6005.917	107000	1.602	6.192
INF	552	2.951	4.193	−4.448	45.804	−1.134	19.398	5.501	48.393
POP	552	18600000	22400000	430475	83797985	458095	82657002	1.593	4.301
UNE	552	8.407	4.3	1.805	27.686	2.345	24.731	1.567	6.008
OP	552	81.357	33.688	32.6	143.402	32.6	143.402	0.417	1.958
PSA	552	0.807	0.405	−0.475	1.759	−0.236	1.677	−0.325	3.142
CCUR	552	1.116	0.82	−0.58	3.553	−0.381	2.899	0.181	2.144
CO_2	552	133000	173000	6928.3	848000	7282.3	821000	2.295	8.341
EI	552	47.903	54.07	−596.898	98.29	−145.527	97.956	−7.208	72.901
FD	552	78.905	37.732	0.186	201.259	10.09	182.096	0.601	3.121
FDI	552	2.30E+10	6.29E+10	−3.59E+11	7.34E+11	−8.33E+10	2.76E+11	3.673	41.835
GD	552	64.794	39.181	3.811	253.226	4.944	198.957	1.282	5.332
RDE	552	1.626	0.883	0.352	3.874	0.389	3.618	0.572	2.288
RL	552	1.157	0.571	−0.266	2.125	−0.154	2.021	−0.212	2.001
RNR	552	0.562	0.732	0.005	5.714	0.01	3.461	2.469	11.158

Note: Min = Minimum; Max = Maximum; Std.Dev. = Standard deviation; Kurt = Kurtosis; Skew = Skewness; Obs = Observations; p1 = 1st percentile; p99 = 99th percentile. The names of the variables corresponding to the abbreviations are provided in Table 2.

over the specified period.

Economic indicators such as GDP and UNE exhibit significant disparity and skewness, with GDP ranging from $4451.762 to $112,000 and UNE from 1.805 % to 27.686 %. These distributions highlight global economic inequality and labor market heterogeneity. Governance metrics, such as PSA and CCUR, exhibit near-symmetric distributions, suggesting balanced governance challenges across the panel. INF and EI display extreme skewness and kurtosis, indicating rare hyperinflation and significant variability in energy imports, respectively. The variable REP has a mean of 29.516 and a standard deviation of 41.435, indicating substantial variation across countries. It ranges from 0.017 to 257.962, with a highly positively skewed distribution (skewness = 2.394) and heavy tails (kurtosis = 10.222). This suggests that most countries have low to moderate REP values, while a few exhibit extremely high values, which may be outliers. POP shows a mean of 18.6 million and a standard deviation of 22.4 million, with positive skewness (1.593) and moderate kurtosis (4.301), indicating diverse demographic profiles across the panel.

Environmental and resource-related variables, such as CO_2 and RNR, also exhibit substantial skewness and kurtosis, with CO_2 emissions ranging from 6928.3 to 848,000 and RNR from 0.005 % to 5.714 % of GDP. These distributions reflect the influence of industrial activity and resource dependence in a few countries. Financial metrics such as financial development and foreign direct investment demonstrate varying levels of financial development and investment inflows, with FDI showing significant positive outliers. OP has a mean of 81.357 and a standard deviation of 33.688, with low skewness (0.417) and kurtosis (1.958), suggesting a relatively balanced distribution. RDE has a mean of 1.626 % of GDP and a standard deviation of 0.883, with low skewness (0.572) and kurtosis (2.288), indicating consistent R&D efforts. RL shows a mean of 1.157 and a standard deviation of 0.571, with slight negative skewness (−0.212) and low kurtosis (2.001), suggesting a near-symmetric distribution.

The descriptive statistics reveal a complex interplay of economics, governance, and environmental dynamics. The significant variation and skewness in many variables highlight the need for nuanced analysis when examining cross-country differences and trends over the specified period. This detailed dataset characterization provides a foundation for further investigation into the underlying factors driving these disparities and their implications for policy and development.

The regression results in Table 4 compare two-panel data models—DKSE and FE—estimating the impact of nine explanatory variables (GDP, INF, POP, UNE, PSA, CO_2, FD, RDE, RL) and a constant term on a dependent variable, likely an economic outcome such as growth, investment, or productivity. Each model reports coefficients, p-values (with significance denoted by *** for $p < 0.01$, ** for $p < 0.05$, * for $p < 0.1$), and R^2 values. Given that PSA represents the absence of political stability and the lack of violence (i.e., political instability), the results reflect how economic, environmental, and governance factors interact with instability. The study interprets each variable in detail using the DKSE model, which was identified as the best due to its robustness. It compares it with FE to explain why DKSE is superior.

Table 4
Regression results for fixed effects (FE) and Driscoll-Kraay standard errors (DKSE) models.

	Driscoll-Kraay SE		Fixed Effects (FE)	
Variable	**Coeff.**	**p-value**	**Coeff.**	**p-value**
GDP	0.001	0.001***	0.001	0.019**
INF	−0.394	0.000***	−0.394	0.068*
POP	0	0.001***	0	0.000***
UNE	−0.62	0.014**	−0.62	0.284
PSA	−10.449	0.002***	−10.449	0.292
CO2	0	0.004**	0	0.005**
FD	−0.081	0.002***	−0.081	0.402
RDE	7.583	0.000***	7.583	0.128
RL	−7.73	0.002***	−7.73	0.236
CONS	−69.496	0.11	−69.496	0.118
R^2	0.5035		0.9397	

Note: Significance levels: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

In the DKSE model, GDP has a coefficient of 0.001 with a p-value of 0.001***, indicating that a 1-unit increase in GDP (likely in billions) raises the dependent variable by 0.001 units, with high significance. This suggests that higher economic output modestly boosts outcomes such as investment or consumption, although the small effect implies mediation through factors like employment. The correlation matrix shows GDP's positive links with the rule of law (0.724, p = 0.000) and R&D expenditure (0.471, p = 0.000), suggesting that wealthier economies foster stability and innovation, reinforcing this effect. DKSE's robust standard errors ensure reliability, even in the presence of heteroskedasticity or cross-sectional dependence, making this estimate trustworthy. The positive link between GDP and REP aligns with Salim & Rafiq [78] and Wesseh & Lin [4], confirming that economic growth supports renewable energy development.

Political stability absence (PSA) has a coefficient of −10.449 with a p-value of 0.002*** in DKSE, meaning a 1-unit increase in instability reduces the dependent variable by 10.449 units. This significant effect highlights how political unrest disrupts activity, deters investment, and undermines confidence, severely impacting outcomes. The correlation matrix's positive correlations with control of corruption (r = 0.607, p = 0.000) and rule of law (r = 0.605, p = 0.000) suggest that instability coexists with weaker governance, thereby amplifying the damage. DKSE's design for cross-sectional dependence ensures the reliability of this estimate, making PSA a key policy focus. This aligns with Ref. [4], which identified governance challenges as barriers to renewable energy adoption in Africa but extends their findings by quantifying the outsized impact of instability in European contexts.

CO_2 emissions show a coefficient of 0 with a p-value of 0.004** in DKSE, implying a small positive effect (likely <0.001). A 1-unit increase (e.g., metric tons per capita) slightly raises the dependent variable, possibly reflecting industrial activity driving short-term output. The correlation matrix's link with the population (0.929, p = 0.000) and negative link with PSA (−0.222, p = 0.000) suggest that emissions scale with economic size but may decline with instability. DKSE's significance confirms CO_2's nuanced role, which is robust to autocorrelation. This finding is supported by York [79], who identified a modest positive relationship between CO_2 emissions and economic output.

Financial development (FD) has a coefficient of −0.081 with a p-value of 0.002*** in DKSE, indicating a 1-unit increase reduces the dependent variable by 0.081 units. This suggests excessive credit or financialization may cause instability, harming outcomes through debt or bubbles. The correlation matrix's positive links with GDP (0.417, p = 0.000) and the rule of law (0.554, p = 0.000) indicate that financial development accompanies economic strength; however, its negative effect highlights potential risks. DKSE's robust errors ensure this estimate's accuracy. This contrasts with Ref. [1], which viewed financial development as a facilitator of energy access, underscoring the need to differentiate between productive finance and speculative growth. This aligns with Svirydzenka [24], who introduced a comprehensive index of financial development and emphasized that rapid, unregulated credit growth can undermine economic stability.

Research and Development expenditure (RDE) shows a coefficient of 7.583 with a p-value of 0.000*** in DKSE, meaning a 1-unit increase (e.g., % of GDP) boosts the dependent variable by 7.583 units. This significant effect highlights the crucial role of innovation in driving productivity and growth, even in the face of instability. The correlation matrix's links with GDP (0.471, p = 0.000) and rule of law (0.767, p = 0.000) suggest innovation thrives in supportive settings. DKSE's strong significance confirms the importance of R&D as a policy lever. This supports Ref. [80], which found that R&D expenditure is a key driver in transition economies, but contrasts with Ref. [2], which emphasized financial incentives over innovation in Greece. Our results highlight RDE as a universal policy lever across Europe. This result is consistent with Li et al. [81], who identified eco-innovation and R&D investment as critical drivers of renewable energy consumption and energy productivity in OECD countries.

The rule of law (RL) has a coefficient of −7.73 with a p-value of 0.002*** in DKSE, indicating that a 1-unit improvement reduces the dependent variable by 7.73 units. This counterintuitive effect may reflect regulatory costs hindering short-term outcomes in unstable contexts. The correlation matrix's positive links with GDP (0.724, p = 0.000) and PSA (0.605, p = 0.000) suggest that the rules of law support stability, making this negative effect context-specific, possibly due to over-regulation. DKSE's robust errors confirm the reliability, warranting further study. This result is consistent with Ozpolat et al. [82], who found that the rule of law does not always yield uniform growth benefits, especially in developing or institutionally weak settings. Further investigation is needed to unpack this relationship in the renewable energy context.

The constant term (CONS) is −69.496, with an insignificant p-value of 0.11 in DKSE. This suggests that the baseline dependent variable level isn't reliably estimated when predictors are zero, which is common in panel data. DKSE's R^2 of 0.5035 indicates that 50.35 % of the variation is explained, which is reasonable for panel data given unobserved heterogeneity.

The FE model shares identical coefficients but differs in terms of significance and the R-squared value. FE's R^2 is 0.9397, explaining 93.97 % of the variation, but only GDP (0.001, p = 0.019**), POP (0, p = 0.000***), and CO_2 (0, p = 0.005**) are significant. INF (−0.394, p = 0.068*), UNE, PSA, FD, RDE, and RL are insignificant, reducing interpretability. For example, PSA's −10.449 (p = 0.292) and RDE's 7.583 (p = 0.128) lack significance, potentially missing key effects. FE's high R^2 reflects control for time-invariant heterogeneity, but its standard errors assume no heteroskedasticity or autocorrelation, leading to inflated p-values.

DKSE is the better model because it finds eight variables significant versus FE's three, indicating greater precision due to standard errors adjusted for heteroskedasticity, autocorrelation, and cross-sectional dependence. For instance, PSA's significance (p = 0.002 vs. FE's p = 0.292) shows that DKSE detects instability's impact reliably. DKSE's design for panel data ensures robustness, which is critical for variables such as GDP and CO_2, which are correlated across countries. Its R^2 (0.5035) balances fitness and significance, unlike FE's inflated 0.9397, which sacrifices precision for explanatory power. The correlation matrix supports DKSE, with PSA's links to unemployment (−0.454, p = 0.000) and RDE's to GDP (0.471, p = 0.000) aligning with its significant effects, unlike FE's misses.

In conclusion, DKSE provides robust insights, demonstrating that GDP, POP, CO_2, and RDE have a positive influence on the dependent variable, with RDE's significant effect (7.583) highlighting the impact of innovation. INF, UNE, PSA, FD, and RL negatively impact outcomes, with PSA's −10.449 underscoring instability's toll. RL's negative effect suggests regulatory burdens that require further exploration. Policymakers should reduce instability (PSA), control inflation (INF) and unemployment (UNE), invest in R&D (RDE), and monitor financial development (FD). DKSE's superiority—due to more significant coefficients, robust errors, and balanced fit—makes it ideal for guiding policy, while FE's limited significance and overstated R^2 reduce its reliability.

The results of Table A2 evaluate the forecasting accuracy of various machine learning models (SVM, RF, CNN-BiLSTM-AR, LSTM, and ARIMA) for REP across 26 European countries. The MAPE contextualized using Table A2's accuracy ranges (≤10 % = High, 10–20 % = Good, 20–50 % = Feasible, ≥50 % = Low) provides critical insights into model performance. The evaluation metrics include MSE, MAE, RMSE, NRMSE, and MAPE, all of which are essential for assessing predictive accuracy. All MAPE values are expressed as percentages after being multiplied by 100.

The forecasting accuracy results presented in Table A1 evaluate the performance of five models—SVM, RF, CNN-BiLSTM-AR, LSTM, and AutoRegressive Integrated Moving Average (ARIMA)—in predicting REP across 26 European countries. The analysis focuses on the MAPE, expressed as percentages, to assess model accuracy and identify cross-model and cross-country trends. The MAPE values reveal significant variations in performance both between models and across countries. For example, SVM exhibited a wide MAPE range of 4 %–139 %, with Switzerland and Norway achieving the lowest errors (4 % and 5 %, respectively), while Estonia and Hungary showed the highest errors (139 % and 35 %, respectively), Switzerland's low MAPE (3–7 %) suggests stable REP trends due to robust policy frameworks, consistent with IEA reports [83]. In contrast, RF demonstrated superior consistency, maintaining the lowest MAPE values across most countries, ranging from 3 % in Switzerland to 14 % in Estonia. CNN-BiLSTM-AR and LSTM performed moderately, with MAPE ranges of 4 %–34 % and 6 %–60 %, respectively, indicating their ability to handle complex REP patterns but not as effectively as RF. ARIMA consistently underperformed, with a narrow yet high MAPE range of 23 %–38 %, underscoring its limitations in modeling non-stationary REP data.

RF emerged as the most robust model, achieving the lowest MAPE values in several countries, including 3 % in Switzerland, 4 % in Norway, and 11 % in the UK. This highlights RF's strength in capturing nonlinear relationships within REP data. Conversely, ARIMA's poor performance, with MAPE values consistently above 23 %, suggests it is ill-suited for forecasting REP due to its reliance on linear and stationary assumptions. This validates RF's ability to capture nonlinear REP patterns, as noted in Ref. [84] for wind energy forecasting. SVM displayed mixed results, excelling in Switzerland (4 %) but failing significantly in Estonia (139 %), likely due to overfitting or issues related to data scaling. The deep learning models, CNN-BiLSTM-AR and LSTM, performed moderately, often bridging the gap between RF and ARIMA in terms of accuracy, albeit at a higher computational cost. Certain countries consistently achieved lower MAPE values across all models, notably Switzerland, Norway, Finland, and Ireland, with MAPEs ranging from 3 % to 11 %. These countries are likely to exhibit stable REP patterns, which are easier to forecast. On the other hand, Estonia, Greece, Hungary, and Portugal experienced the highest MAPE values (14 %–139 %), possibly due to volatile REP trends or insufficient training data. Notably, Germany and the United Kingdom demonstrated substantial improvements when using RF compared to SVM, with MAPE reductions from 21 % to 6 % in Germany and 40 %–11 % in the UK, highlighting RF's adaptability to complex energy systems.

Several key insights emerge from this analysis. RF's consistently low MAPE values (3 %–14 %) indicate its effectiveness in capturing nonlinear REP patterns, making it the most reliable model for REP forecasting. ARIMA's high MAPE values (23 %–38 %) reflect its inability to model complex, non-stationary REP data, limiting its applicability in this context. SVM's extreme MAPE in Estonia (139 %) underscores its sensitivity to outliers or scaling issues, suggesting caution in its application. While CNN-BiLSTM-AR and LSTM outperform ARIMA, their higher computational requirements may not justify their marginal gains over RF. The variability in MAPE values across countries (e.g., Estonia vs. Switzerland) suggests that REP forecasting requires localized model tuning to address the unique data characteristics of each country. Based on these findings, it is recommended to prioritize RF for REP forecasting due to its balance of accuracy and computational efficiency. For countries with more complex temporal patterns, such as Germany and France, hybrid models like CNN-BiLSTM-AR may be considered despite their higher computational demands. ARIMA should be avoided unless the data strictly adheres to linear and stationary assumptions.

Additionally, efforts should be made to investigate data quality and scaling issues in high-MAPE countries, such as Estonia and Greece, to improve model performance. This analysis emphasizes the importance of tailoring model selection to country-specific REP dynamics and highlights the superiority of machine learning approaches, particularly Random Forest, over traditional econometric methods, such as ARIMA. A detailed comparison of forecast performance across all models and countries is presented in Appendix Table A1. Visual comparisons of MAPE values across countries and models are presented in Appendix Figure A1.

Figure A1 presents a horizontal bar chart comparing the Mean Absolute Percentage Error (MAPE) of five forecasting models across 26 countries. The models evaluated are SVM, RF, CNN-BiLSTM-AR, LSTM, and ARIMA. The MAPE values, represented as percentages, indicate the average magnitude of prediction errors, with lower values signifying higher forecasting accuracy. The chart uses a color-coded scheme to differentiate between the models: SVM is represented by blue bars, RF by green bars, CNN-BiLSTM-AR by orange bars, LSTM by red bars, and ARIMA by purple bars. The MAPE values are categorized into four accuracy levels: High Accuracy ($\leq$10 %), Good Accuracy (10–20 %), Feasible Accuracy (20–50 %), and Low Accuracy ($\geq$50 %).

Key observations from the chart include the consistently low MAPE values of RF across most countries, frequently falling into the High Accuracy category, such as 3.76 % for Austria and 3.46 % for the United Kingdom. CNN-BiLSTM-AR also performs well, with MAPE values often in the Good Accuracy range, including 6.13 % for Austria and 7.34 % for the United Kingdom. In contrast, ARIMA generally exhibits the highest MAPE values, often exceeding 30 % and falling into the Low Accuracy category for several countries, such as 138.84 % for Estonia. Country-specific insights reveal that Estonia has the highest overall MAPE values, with all models exceeding 30 %, while Austria and Norway show relatively low MAPE values across all models. Romania and the Slovak Republic exhibit mixed performance, with some models achieving Good Accuracy while others fall into Feasible Accuracy. The results highlight the superior performance of RF and CNN-BiLSTM-AR in forecasting tasks that require high accuracy. At the same time, ARIMA struggles significantly, particularly in countries with volatile or non-stationary time series data. Appendix Figures A2 to A6 present detailed error distributions and residual diagnostics for each machine learning model, supporting the evaluation of model-specific performance across countries.

The results of the Diebold-Mariano test, presented in Table A3, compare the forecast accuracy of ARIMA with that of four alternative models (SVM, RF, CNNBILSTMAR, and LSTM) across 26 countries. The p-values indicate whether the differences in predictive performance between ARIMA and the other models are statistically significant. For most countries, ARIMA and LSTM exhibit remarkably similar performance, with high p-values (e.g., Austria: 0.995, Italy: 0.991, Latvia: 0.945), suggesting no significant difference in forecast accuracy. Similarly, ARIMA and CNN-BILSTM-AR align strongly in countries such as Estonia ($p = 0.986$) and Switzerland ($p = 0.917$). However, exceptions exist, such as in Germany, where ARIMA significantly outperforms LSTM ($p = 0.299$), and in Finland, where CNNBILSTMAR underperforms relative to ARIMA ($p = 0.706$). SVM and RF models demonstrate weaker consistency than ARIMA, with lower p-values in countries such as Spain (ARIMA vs. RF: $p = 0.461$) and Switzerland (ARIMA vs. SVM: $p = 0.451$), suggesting potential performance gaps. Moderate p-values, such as Germany's ARIMA vs. LSTM ($p = 0.299$) or Switzerland's ARIMA vs. RF ($p = 0.400$), suggest marginal but inconclusive differences at the 5 % significance level. These results underscore the context-dependent nature of model performance, where geographic and economic heterogeneity likely influence the efficacy of forecasting. While high p-values dominate LSTM and CNNBILSTMAR, SVM and RF exhibit more significant variability, emphasizing the need for localized model selection. Table A3 highlights that statistical equivalence (high p-values) does not necessarily imply identical practical utility but reflects comparable error distributions under the Diebold-Mariano framework. ARIMA's statistical equivalence with LSTM/CNN-BiLSTM-AR in most countries (e.g., Austria, Italy) indicates shared limitations in modeling REP's complexity. However, RF's dominance (e.g., 6 % MAPE in Germany vs. ARIMA's 21 %) underscores the value of ensemble methods for heterogeneous European economies.

Our study uniquely combines econometric rigor and ML adaptability to address REP's macroeconomic drivers and forecasting challenges. By contextualizing these findings against prior work, we provide theoretical advancements (e.g., the outsized role of instability) and practical tools (RF-based forecasts) for European policymakers.

This study advances existing literature in three distinct ways. First, it introduces a hybrid methodological framework that combines DKSE for robust macroeconomic analysis with machine learning (ML) models for forecasting REP. Unlike single-method approaches, e.g., Refs. [2,80], this dual strategy bridges explanatory rigor (e.g., quantifying the impact of political instability) with predictive scalability (e.g., Random Forest forecasts), providing policymakers with both causal insights and actionable tools. The DKSE model's correction for cross-sectional dependence and heteroskedasticity ensures reliable inferences for critical variables like political instability (PSA), which exhibits a statistically significant coefficient (-10.449, $p = 0.002^{***}$) validated by Driscoll-Kraay errors—a level of precision absent in conventional fixed-effects models.

Second, the findings reveal policy-relevant innovations. While prior studies, e.g., Refs. [1,4], have emphasized income or financial development as drivers of REP, this research identifies political instability (PSA) as a pivotal barrier, with its size dwarfing that of GDP (0.001). Furthermore, financial development (FD) demonstrates a counterintuitive negative coefficient (-0.081, $p = 0.002^{***}$), suggesting excessive credit may divert resources from REP investments—a trade-off unaddressed in earlier work. These insights challenge assumptions about the universal benefits of financialization and underscore the need to prioritize stability for sustainable energy transitions.

Third, the study pioneers forecast innovations by demonstrating the scalability of ML models for REP. While Wang et al. [70] focused on single-energy sources, our RF model achieves MAPE values of 3–14 % across 26 European countries, outperforming ARIMA's 23–38 % and setting a benchmark for pan-European forecasting. Notably, the high

MAPE in Estonia and Greece highlights the necessity of localized data preprocessing—a practical insight often overlooked in broad-scale analyses, such as those conducted by the IEA [83]. Together, these contributions position our integrative framework as a transformative approach to analyzing REP, offering both theoretical depth and actionable policy guidance.

7. Conclusion and policy recommendations

This study integrates panel econometric models with machine learning techniques to examine the macroeconomic and institutional drivers of REP in 26 European countries between 1995 and 2022. By combining DKSE and forecasting models such as RF, the analysis provides both explanatory and predictive insights into the dynamics of REP.

A key finding is the substantial, positive impact of research and development expenditures (R&D expenditures) on REP, confirming that innovation is central to scaling renewable energy. R&D not only enhances the performance of renewable technologies but also facilitates critical system-wide advancements, including grid integration, energy storage, digitalization, and smart infrastructure. These innovations are crucial for managing the variability of renewable energy sources and ensuring reliability, efficiency, and flexibility in energy systems.

Institutional quality also plays a crucial role. Political instability and a weak rule of law significantly hinder the deployment of renewable energy, particularly in cases where capital-intensive projects rely on long-term policy stability. Governance-related risks reduce investor confidence and delay project implementation. The findings suggest that trust in regulatory institutions, transparency of legal frameworks, and consistent policy enforcement are as important as economic and technological conditions in facilitating energy transitions.

Macroeconomic variables such as GDP, inflation, unemployment, population, and financial development have statistically significant but relatively modest effects. In high-income European countries, the marginal influence of GDP may reflect mature infrastructure and a shift toward policy and institutional enablers. Financial and economic stability, while not primary drivers, shaped the investment environment for REP deployment.

From a methodological perspective, DKSE outperforms the fixed effects model by producing more significant estimates and correcting common macro-panel issues. In forecasting, Random Forest consistently achieves the highest accuracy, while deep learning models, such as CNN-BiLSTM-AR and LSTM, offer moderate improvements but come at a higher computational cost. ARIMA underperforms, validating the need for nonlinear models in REP forecasting.

Based on these findings, five key policy recommendations are proposed.

(1) Countries should prioritize sustained investment in research and development, particularly in areas that enhance system-level flexibility and integration. For high-income countries, this may involve direct public funding and partnerships for advanced storage systems, digital infrastructure, and the expansion of smart grids. For middle-income countries, targeted tax incentives and participation in international research and development collaborations may be more feasible.
(2) Governments must ensure legal and regulatory stability to foster investor confidence and accelerate project timelines. This includes creating transparent permitting procedures, maintaining consistency in support schemes, and avoiding abrupt policy reversals. Independent energy regulators and long-term legislation play a central role in achieving this.
(3) In countries with lower political stability, efforts should focus on minimizing policy uncertainty. Reforms should focus on enhancing institutional accountability, reducing administrative delays, and ensuring policy coherence. Stronger rule of law mechanisms, anti-corruption measures, and judicial efficiency contribute directly to a more secure environment for renewable energy investment.
(4) Policymakers and energy planners should adopt machine learning tools, particularly Random Forest models, for forecasting REP trends. These tools can inform real-time policy decisions and infrastructure planning. However, they should be complemented with scenario-based models that account for long-term uncertainties such as geopolitical shifts, technological disruptions, and climate events.
(5) Macroeconomic stability, while not a direct driver, should be treated as a necessary enabler of renewable energy investments. Policies that ensure low inflation, manageable unemployment, and financial system resilience contribute to a favorable investment climate and should be integrated into broader energy strategies.

This study has several limitations. It relies on secondary data, which may not fully capture post-2022 structural changes or emerging technologies. The analysis treats R&D as a composite variable and does not disaggregate by technology type (e.g., energy storage vs. grid digitalization), which could refine policy targeting. Additionally, while the study focuses on European countries with well-developed institutions and climate policies, the results may not generalize to developing economies with different institutional and market structures. Future research could extend the analysis globally, incorporating country-specific governance mechanisms and technology-specific R&D expenditures to deepen understanding of REP drivers across various contexts.

CRediT authorship contribution statement

Atif Maqbool Khan: Writing – original draft, Validation, Resources, Investigation, Data curation, Writing – review & editing, Visualization, Software, Methodology, Formal analysis, Conceptualization. **Artur Wyrwa:** Writing – original draft, Supervision, Project administration, Investigation, Conceptualization, Writing – review & editing, Validation, Resources, Methodology, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

This research was funded by the AGH University of Krakow, Faculty of Energy and Fuels (grant number 16.16.210.476) with the financial support of the “Excellence Initiative Research University” program.

Appendix A

Table A1
Forecasting Accuracy Metrics for REP Across 26 Countries Using Machine Learning and Econometric Models

Accuracy Metrics	AUT	BEL	CZE	DNK	EST	FIN	FRA	DEU	GRC	HUN	IRL	ITA	LVA	LTU	LUX	NLD	NOR	POL	PRT	ROU	SVK	SVN	ESP	SWE	CHE	GBR
SVM (MSE)	11.60	22.29	0.99	14.17	0.34	16.06	215.24	1238.16	14.50	2.63	9.11	68.38	0.11	0.12	0.06	123.42	60.23	25.99	7.93	3.86	0.20	0.14	200.37	132.74	4.95	890.69
SVM (MAE)	2.28	2.70	0.71	2.24	0.31	2.58	9.30	23.47	2.18	0.81	1.67	6.35	0.28	0.25	0.12	5.02	6.14	2.93	2.45	1.68	0.38	0.30	10.24	7.32	1.60	17.94
SVM (RMSE)	3.41	4.72	1.00	3.76	0.59	4.01	14.67	35.19	3.81	1.62	3.02	8.27	0.33	0.35	0.24	11.11	7.76	5.10	2.82	1.96	0.44	0.37	14.16	11.52	2.22	29.84
SVM (NRMSE-Mean)	0.08	0.52	0.17	0.28	0.63	0.15	0.18	0.29	0.40	0.66	0.61	0.11	0.12	0.31	0.59	0.81	0.06	0.41	0.14	0.10	0.09	0.09	0.20	0.14	0.06	0.61
SVM (NRMSE-SD)	0.59	0.59	0.29	0.48	0.57	0.69	0.70	0.44	0.65	0.78	0.70	0.29	0.60	0.39	0.81	0.94	0.54	0.48	0.36	0.44	0.48	0.43	0.45	0.71	0.65	0.64
SVM (NRMSE-Max-Min)	0.16	0.20	0.11	0.14	0.19	0.19	0.21	0.15	0.19	0.22	0.23	0.10	0.12	0.14	0.25	0.23	0.15	0.15	0.12	0.14	0.13	0.11	0.14	0.17	0.16	0.22
SVM (NRMSE-IQR)	0.41	0.35	0.14	0.31	0.36	0.45	0.49	0.24	0.38	0.53	0.46	0.15	0.82	0.24	0.79	1.05	0.36	0.27	0.21	0.24	0.33	0.28	0.24	0.58	0.50	0.40
SVM (MAPE)	0.05	0.35	0.12	0.15	1.39	0.09	0.09	0.21	0.19	0.35	0.32	0.08	0.10	0.30	0.19	0.23	0.05	0.32	0.13	0.09	0.07	0.07	0.13	0.08	0.04	0.40
RF (MSE)	8.35	10.48	0.19	6.67	0.18	7.43	127.22	484.50	7.03	1.59	4.55	24.44	0.12	0.05	0.04	85.19	43.37	13.56	4.74	1.43	0.09	0.19	76.35	77.14	3.79	461.19
RF (MAE)	1.82	1.54	0.29	1.30	0.20	1.73	6.79	11.50	1.47	0.57	1.07	3.53	0.25	0.12	0.09	3.83	4.86	1.64	1.78	0.97	0.23	0.32	6.18	5.16	1.33	10.81
RF (RMSE)	2.89	3.24	0.44	2.58	0.43	2.73	11.28	22.01	2.65	1.26	2.13	4.94	0.34	0.22	0.19	9.23	6.59	3.68	2.18	1.19	0.30	0.43	8.74	8.78	1.95	21.48
RF (NRMSE-Mean)	0.06	0.36	0.08	0.19	0.46	0.10	0.13	0.18	0.28	0.51	0.43	0.07	0.12	0.19	0.46	0.67	0.05	0.30	0.11	0.06	0.06	0.10	0.12	0.10	0.05	0.44
RF (NRMSE-SD)	0.50	0.41	0.13	0.33	0.42	0.47	0.54	0.27	0.45	0.60	0.49	0.17	0.62	0.24	0.64	0.78	0.46	0.35	0.28	0.27	0.33	0.50	0.28	0.54	0.56	0.46
RF (NRMSE-Max-Min)	0.14	0.14	0.05	0.09	0.14	0.13	0.16	0.10	0.13	0.17	0.16	0.06	0.13	0.09	0.20	0.19	0.12	0.11	0.09	0.09	0.09	0.12	0.09	0.13	0.14	0.16
RF (NRMSE-IQR)	0.35	0.24	0.06	0.21	0.27	0.30	0.38	0.15	0.27	0.41	0.33	0.09	0.85	0.15	0.63	0.87	0.30	0.19	0.16	0.14	0.22	0.33	0.15	0.44	0.44	0.29
RF (MAPE)	0.04	0.09	0.05	0.07	0.14	0.06	0.07	0.06	0.12	0.13	0.11	0.04	0.09	0.07	0.12	0.13	0.04	0.08	0.10	0.05	0.04	0.07	0.08	0.05	0.03	0.11
CNN-BiLSTM-AR (MSE)	12.76	0.81	0.22	1.12	0.04	6.13	80.04	250.59	3.87	0.58	0.49	93.36	0.30	0.13	0.02	19.00	134.79	2.63	16.15	8.75	0.29	0.33	130.09	71.65	9.30	127.49
CNN-BiLSTM-AR (MAE)	2.73	0.57	0.37	0.83	0.11	2.07	7.53	9.94	1.46	0.35	0.50	8.00	0.41	0.20	0.07	2.31	9.22	1.05	3.28	2.49	0.41	0.43	9.19	6.44	2.71	6.51
CNN-BiLSTM-AR (RMSE)	3.57	0.90	0.47	1.06	0.21	2.48	8.95	15.83	1.97	0.76	0.70	9.66	0.55	0.36	0.12	4.36	11.61	1.62	4.02	2.96	0.54	0.57	11.41	8.46	3.05	11.29
CNN-BiLSTM-AR (NRMSE-Mean)	0.08	0.10	0.08	0.08	0.22	0.09	0.11	0.13	0.20	0.31	0.14	0.13	0.19	0.31	0.30	0.32	0.09	0.13	0.20	0.15	0.10	0.14	0.16	0.10	0.08	0.23
CNN-BiLSTM-AR (NRMSE-SD)	0.62	0.11	0.14	0.14	0.20	0.43	0.43	0.20	0.34	0.36	0.16	0.33	1.00	0.40	0.42	0.37	0.80	0.15	0.51	0.66	0.59	0.66	0.36	0.53	0.89	0.24
CNN-BiLSTM-AR (NRMSE-Max-Min)	0.17	0.04	0.05	0.04	0.07	0.12	0.13	0.07	0.10	0.10	0.05	0.12	0.21	0.15	0.13	0.09	0.22	0.05	0.17	0.21	0.16	0.16	0.11	0.12	0.22	0.08
CNN-BiLSTM-AR (NRMSE-IQR)	0.43	0.07	0.07	0.09	0.13	0.28	0.30	0.11	0.20	0.25	0.11	0.17	1.37	0.25	0.41	0.41	0.54	0.09	0.30	0.36	0.40	0.44	0.20	0.43	0.69	0.15
CNN-BiLSTM-AR (MAPE)	0.06	0.07	0.09	0.06	0.34	0.08	0.09	0.07	0.15	0.09	0.11	0.10	0.14	0.12	0.11	0.12	0.07	0.09	0.18	0.13	0.08	0.10	0.14	0.08	0.07	0.10
LSTM (MSE)	14.38	1.01	0.20	1.36	0.06	8.21	96.62	74.67	3.24	0.69	0.68	69.43	0.22	0.15	0.00	42.76	134.10	3.00	17.87	8.83	0.39	0.51	109.71	109.44	8.37	119.46
LSTM (MAE)	3.06	0.59	0.38	0.94	0.16	2.48	8.15	6.37	1.43	0.54	0.61	6.35	0.37	0.23	0.04	3.17	9.84	1.00	3.42	2.30	0.43	0.57	8.51	7.44	2.33	5.73
LSTM (RMSE)	3.79	1.00	0.45	1.17	0.25	2.87	9.83	8.64	1.80	0.83	0.82	8.33	0.47	0.38	0.06	6.54	11.58	1.73	4.23	2.97	0.62	0.72	10.47	10.46	2.89	10.93
LSTM (NRMSE-Mean)	0.09	0.11	0.08	0.09	0.27	0.11	0.12	0.07	0.19	0.34	0.17	0.11	0.16	0.34	0.15	0.48	0.09	0.14	0.21	0.15	0.12	0.17	0.15	0.12	0.08	0.22
LSTM (NRMSE-SD)	0.66	0.13	0.13	0.15	0.25	0.49	0.47	0.11	0.31	0.40	0.19	0.29	0.85	0.42	0.20	0.55	0.80	0.16	0.54	0.66	0.68	0.83	0.33	0.65	0.84	0.23
LSTM (NRMSE-Max-Min)	0.18	0.04	0.05	0.04	0.08	0.14	0.14	0.04	0.09	0.11	0.06	0.10	0.18	0.16	0.06	0.14	0.22	0.05	0.18	0.21	0.19	0.21	0.10	0.15	0.20	0.08
LSTM (NRMSE-IQR)	0.46	0.07	0.07	0.10	0.16	0.32	0.33	0.06	0.18	0.27	0.13	0.15	1.17	0.27	0.20	0.62	0.54	0.09	0.31	0.36	0.46	0.55	0.18	0.53	0.66	0.15
LSTM (MAPE)	0.07	0.07	0.09	0.07	0.60	0.09	0.10	0.07	0.19	0.35	0.14	0.08	0.13	0.15	0.10	0.14	0.08	0.09	0.20	0.12	0.09	0.13	0.12	0.08	0.06	0.09
ARIMA (MSE)	552.72	88.33	18.96	114.19	1.23	252.39	2887.79	10726.84	68.78	6.56	28.20	2235.87	1.50	1.20	0.17	233.89	4645.58	151.23	174.87	127.98	8.69	5.46	2397.11	2491.07	296.06	3077.40
ARIMA (MAE)	12.70	4.36	2.25	5.14	0.53	9.31	31.14	49.79	4.64	1.22	2.56	25.31	0.80	0.55	0.20	6.77	41.47	5.80	8.91	6.84	1.80	1.51	28.69	30.40	8.92	26.07
ARIMA (RMSE)	23.51	9.40	4.35	10.69	1.11	15.89	53.74	103.57	8.29	2.56	5.31	47.28	1.22	1.09	0.41	15.29	68.16	12.30	13.22	11.31	2.95	2.34	48.96	49.91	17.21	55.47
ARIMA (NRMSE-Mean)	0.53	1.04	0.76	0.80	1.20	0.61	0.64	0.86	0.86	1.04	1.07	0.62	0.43	0.96	1.00	1.12	0.53	1.00	0.66	0.58	0.57	0.55	0.68	0.59	0.47	1.13
ARIMA (NRMSE-SD)	4.10	1.18	1.28	1.38	1.09	2.74	2.58	1.29	1.42	1.23	1.23	1.63	2.21	1.21	1.39	1.29	4.72	1.15	1.68	2.53	3.20	2.70	1.55	3.10	4.99	1.19
ARIMA (NRMSE-Max-Min)	1.11	0.40	0.49	0.38	0.37	0.75	0.77	0.45	0.42	0.35	0.40	0.59	0.46	0.45	0.43	0.32	1.28	0.36	0.55	0.82	0.88	0.67	0.49	0.73	1.21	0.40
ARIMA (NRMSE-IQR)	2.83	0.70	0.63	0.89	0.69	1.77	1.80	0.71	0.84	0.84	0.82	0.83	3.04	0.76	1.35	1.45	3.15	0.65	0.97	1.36	2.19	1.80	0.84	2.53	3.90	0.74
ARIMA (MAPE)	0.26	0.30	0.31	0.28	0.38	0.31	0.31	0.29	0.38	0.34	0.33	0.28	0.30	0.33	0.31	0.27	0.31	0.30	0.41	0.31	0.33	0.34	0.36	0.34	0.23	0.32

Note: Full Sample data considered from 1995 to 2022; the names of the countries corresponding to the codes are provided in Table 1.

Table A2
Classification of Forecasting Accuracy Based on MAPE Ranges (%)

S.no	Range of MAPE	Forecasting Accuracy
1	≤10 %	High
2	10–20 %	Good
3	20–50 %	Feasible
4	≥50 %	Low

Table A3
Diebold-Mariano Test Results: P-Values Comparing ARIMA Forecast Accuracy with SVM, RF, CNNBILSTMAR, and LSTM Across 26 Countries

Country	AUT	BEL	CZE	DNK	EST	FIN	FRA	DEU	GRC	HUN	IRL	ITA	LVA	LTU	LUX	NLD	NOR	POL	PRT	ROU	SVK	SVN	ESP	SWE	CHE	GBR
ARIMA vs. SVM	0.87	0.68	0.69	0.74	0.70	0.87	0.80	0.65	0.78	0.73	0.67	0.99	0.76	0.77	0.72	0.72	0.67	0.74	0.61	0.63	0.72	0.57	0.67	0.92	0.45	0.66
ARIMA vs. RF	0.69	0.68	0.84	0.77	0.73	0.93	0.92	0.72	0.94	0.74	0.68	0.62	0.70	0.69	0.67	0.72	0.57	0.77	0.51	0.53	0.56	0.58	0.46	0.84	0.40	0.66
ARIMA vs. CNNBILSTMAR	0.95	0.72	0.78	0.92	0.99	0.71	0.69	0.77	0.69	0.70	0.73	0.85	0.90	0.71	0.66	0.77	0.86	0.82	0.73	0.93	0.65	0.75	0.75	0.75	0.92	0.78
ARIMA vs. LSTM	1.00	0.69	0.76	0.94	0.84	0.93	0.78	0.30	0.72	0.83	0.87	0.99	0.95	0.75	0.85	0.83	0.88	0.85	0.76	0.89	0.82	0.95	0.63	0.98	0.76	0.80

Note: P-values below 0.05 indicate a statistically significant difference in forecast accuracy between ARIMA and the respective model at the 5 % significance level.

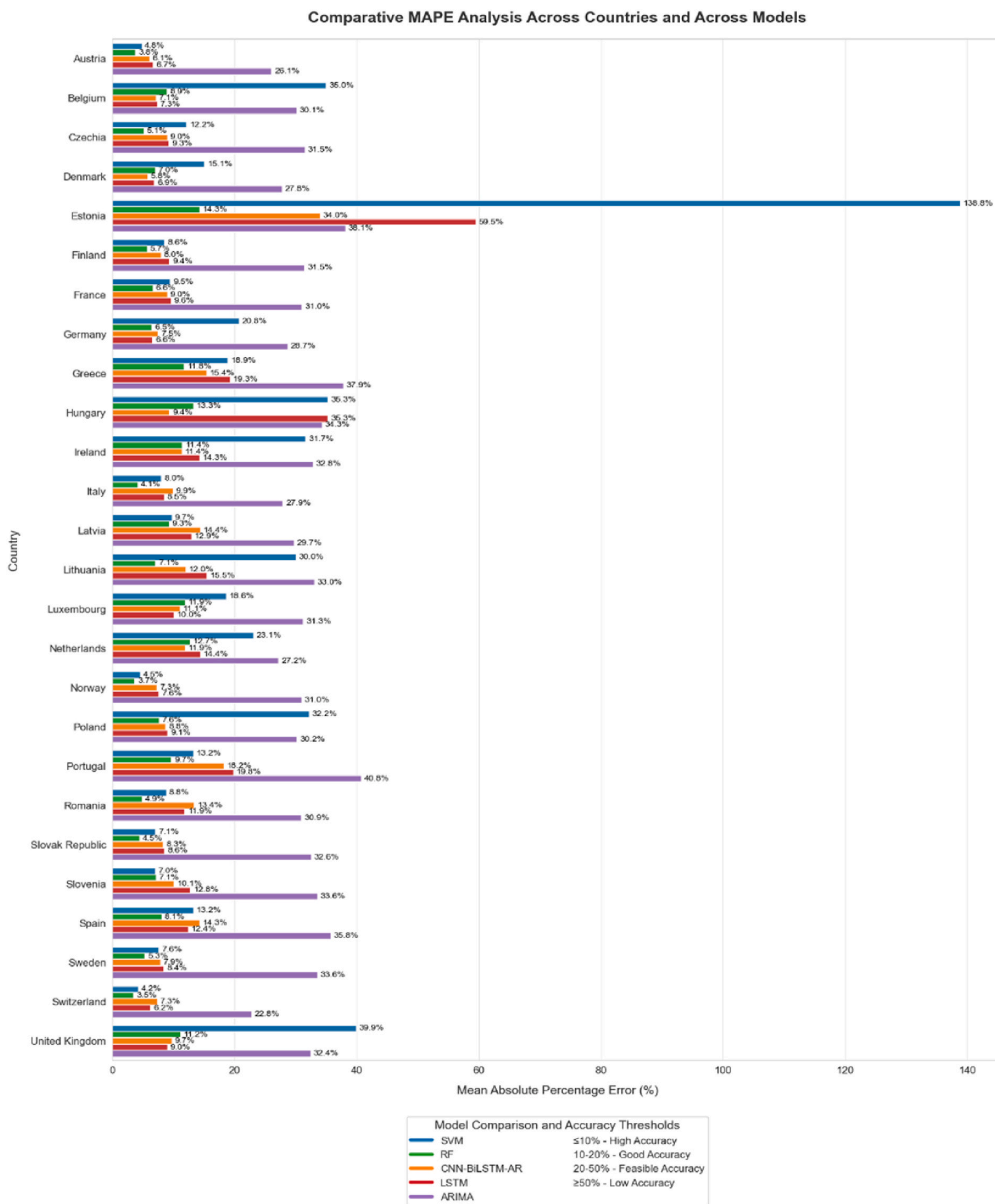

Fig. A1. Mean Absolute Percentage Error for REP Forecasts Across Models and 26 Countries

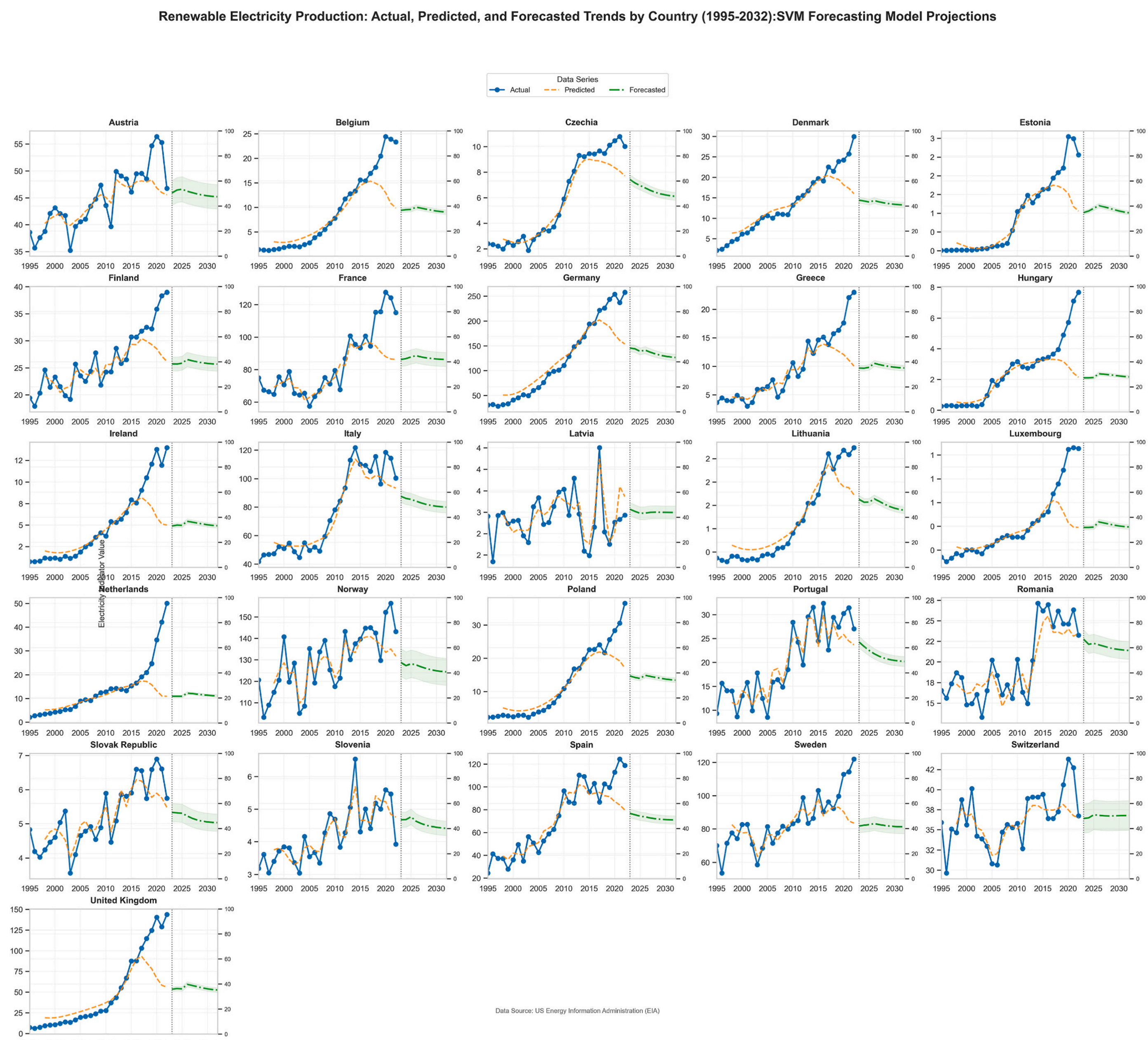

Fig. A2. Actual, Predicted, and Forecasted REP Trends Using the SVM Model

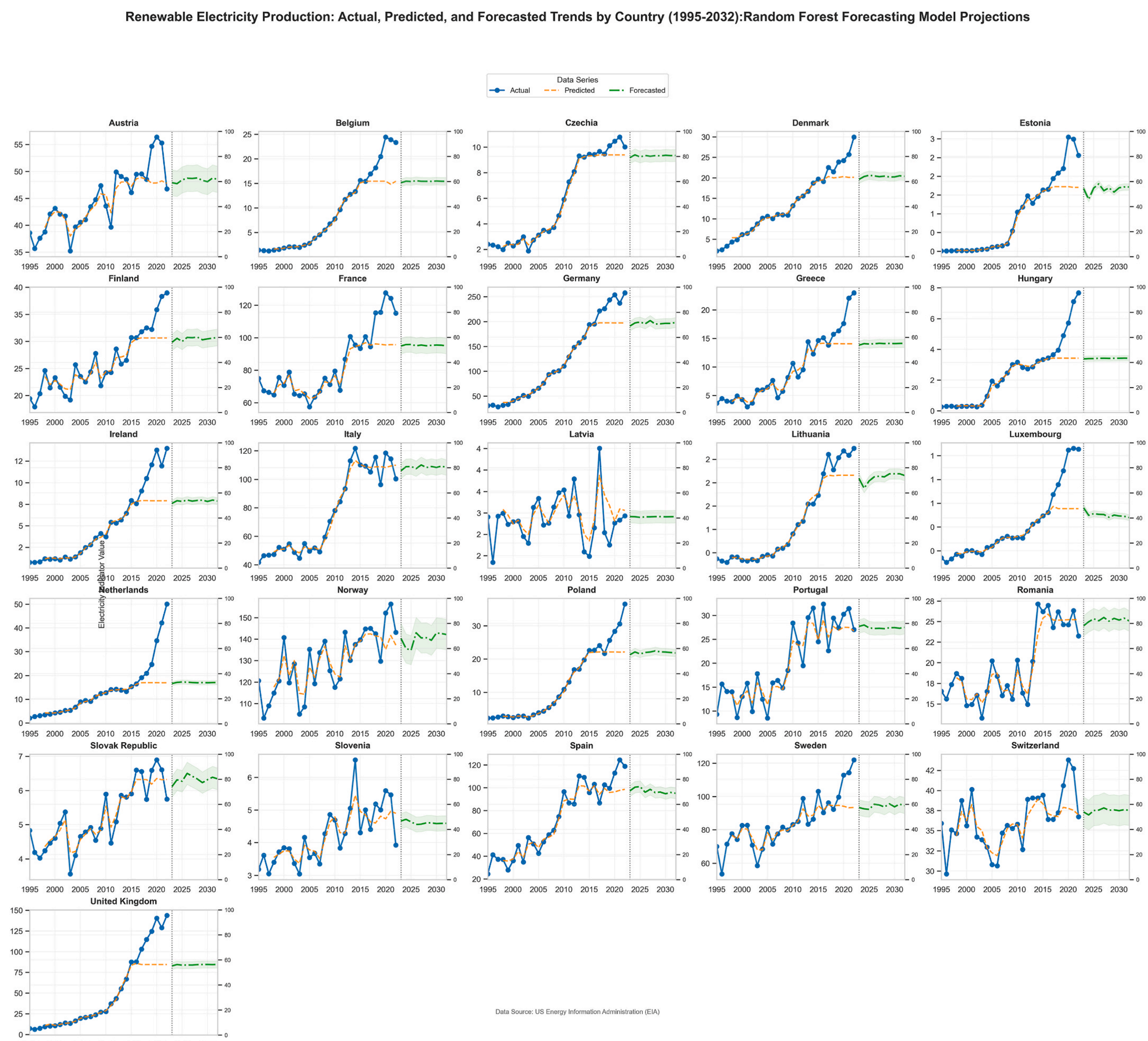

Fig. A3. Actual, Predicted, and Forecasted REP Trends Using the Random Forest Model

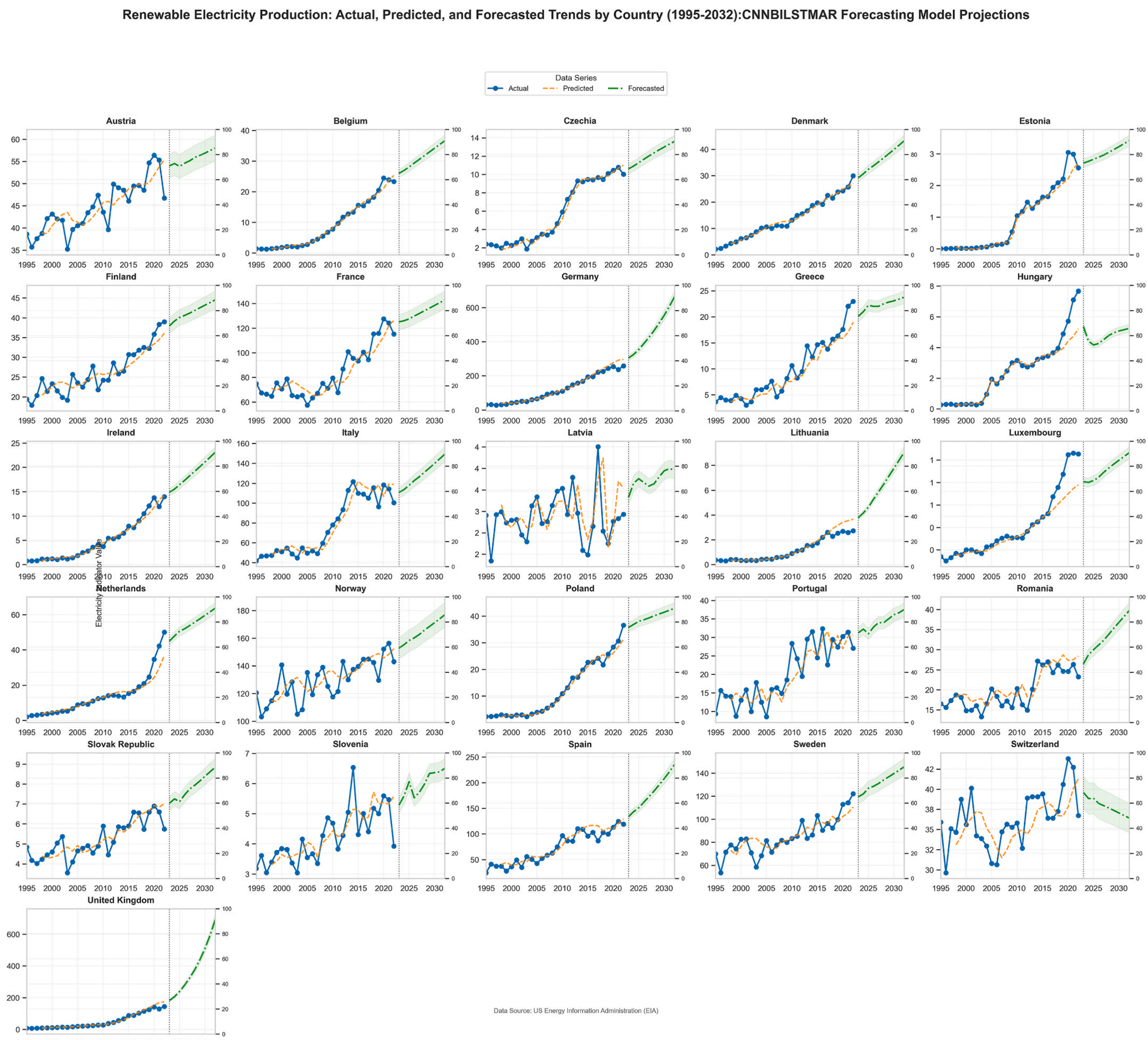

Fig. A4. Actual, Predicted, and Forecasted REP Trends Using the CNN-BiLSTM-AR Model

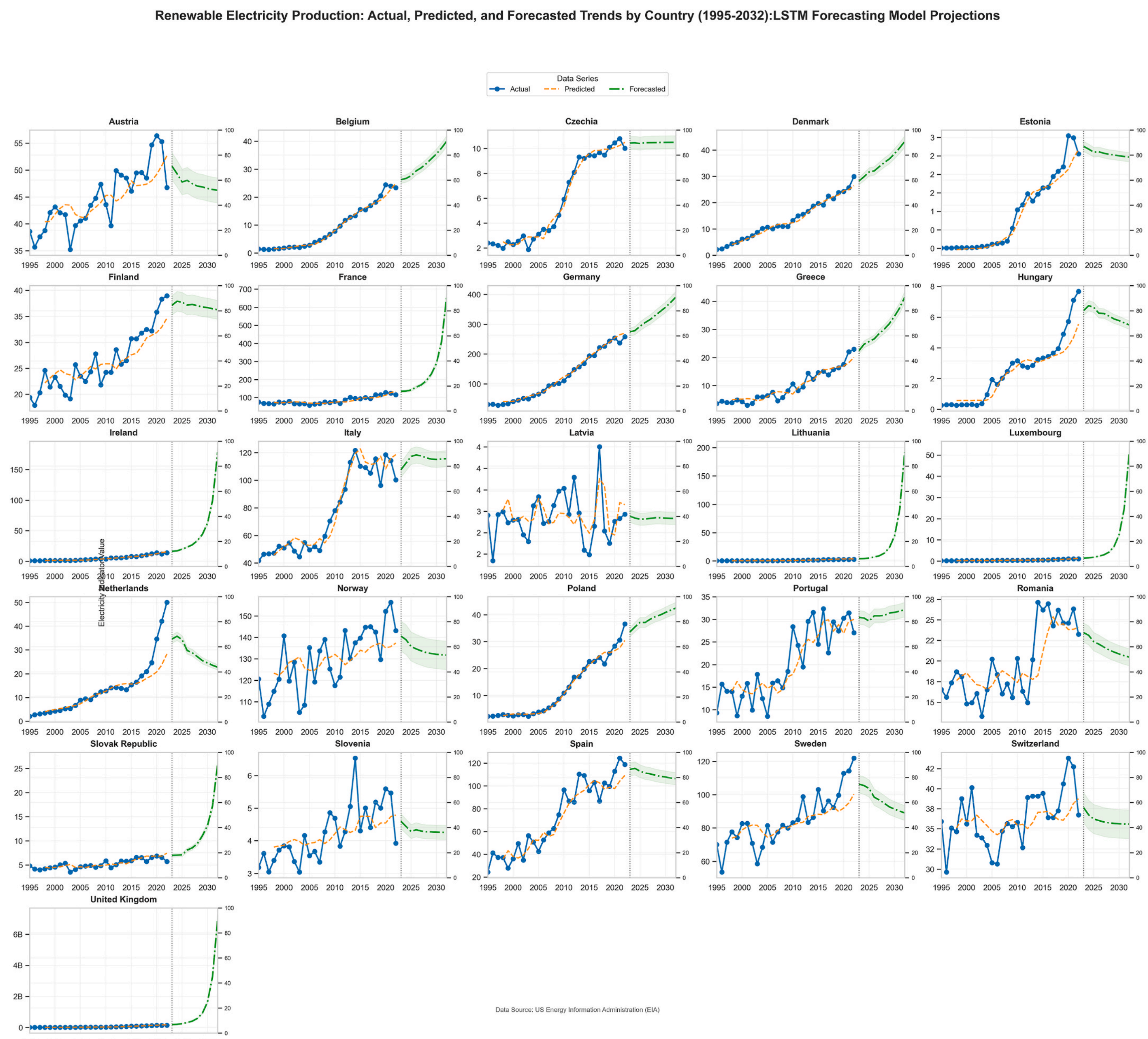

Fig. A5. Actual, Predicted, and Forecasted REP Trends Using the LSTM Model

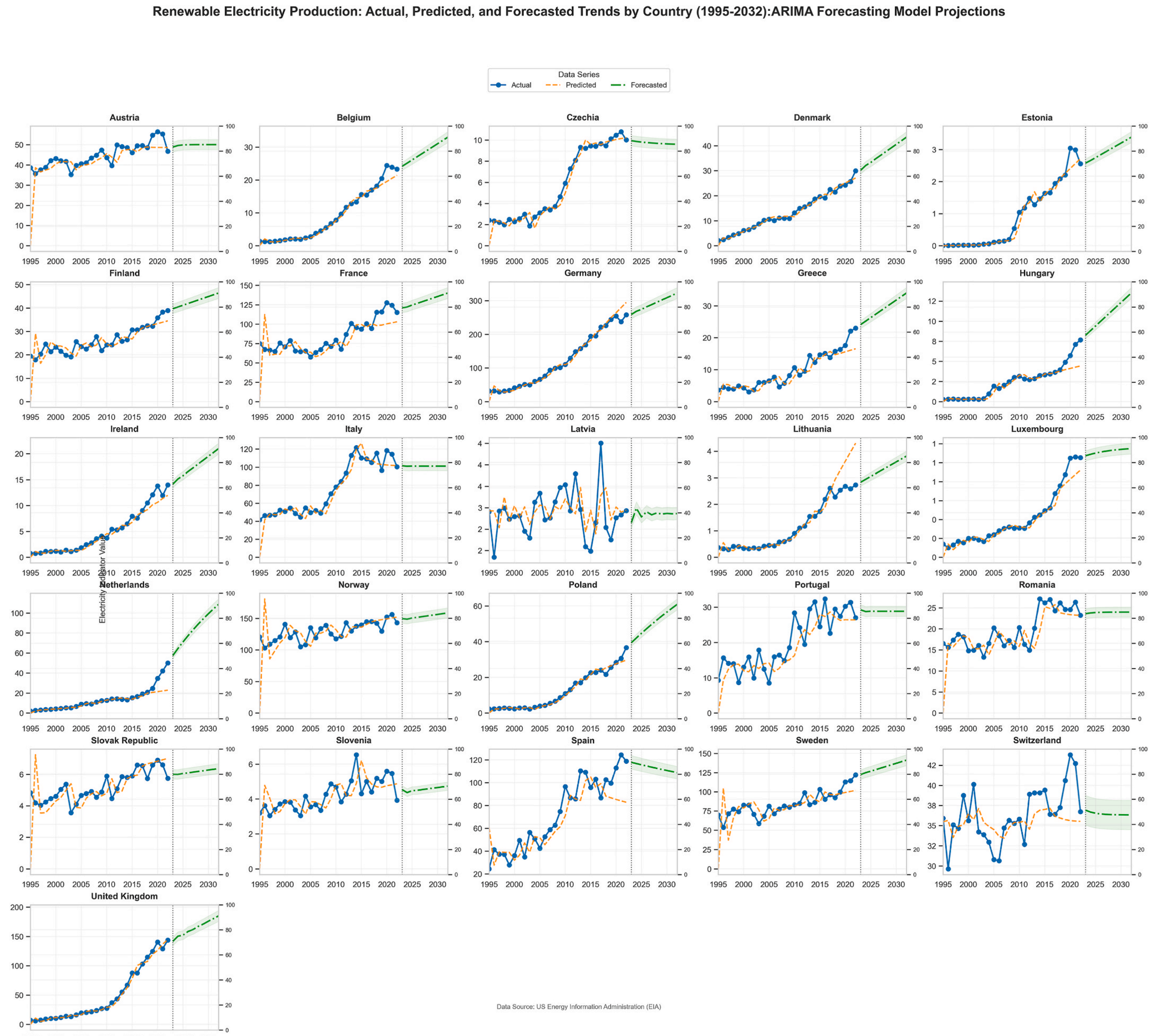

Fig. A6. Actual, Predicted, and Forecasted REP Trends Using the ARIMA Model

Data availability

Data will be made available on request.

References

[1] Bridge BA, Adhikari D, Fontenla M. Electricity, income, and quality of life. Soc Sci J 2016;53:33–9. https://doi.org/10.1016/j.soscij.2014.12.009.

[2] Frangou M, Aryblia M, Tournaki S, Tsoutsos T. Renewable energy performance contracting in the tertiary sector standardization to overcome barriers in Greece. Renew Energy 2018;125:829–39. https://doi.org/10.1016/j.renene.2018.03.001.

[3] Przychodzen W, Przychodzen J. Determinants of renewable energy production in transition economies: a panel data approach. Energy 2020;191:116583. https://doi.org/10.1016/j.energy.2019.116583.

[4] Wesseh PK, Lin B. Can African countries efficiently build their economies on renewable energy? Renew Sustain Energy Rev 2016;54:161–73. https://doi.org/10.1016/j.rser.2015.09.082.

[5] Heidari N, Pearce JM. A review of greenhouse gas emission liabilities as the value of renewable energy for mitigating lawsuits for climate change related damages. Renew Sustain Energy Rev 2016;55:899–908. https://doi.org/10.1016/j.rser.2015.11.025.

[6] Wolde-Rufael Y, Weldemeskel EM. Environmental policy stringency, renewable energy consumption and CO_2 emissions: panel cointegration analysis for BRIICTS countries. Int J Green Energy 2020;17:568–82. https://doi.org/10.1080/15435075.2020.1779073.

[7] Xu X, Wei Z, Ji Q, Wang C, Gao G. Global renewable energy development: influencing factors, trend predictions and countermeasures. Resour Policy 2019;63:101470. https://doi.org/10.1016/j.resourpol.2019.101470.

[8] Bourcet C. Empirical determinants of renewable energy deployment: a systematic literature review. Energy Econ 2020;85:104563. https://doi.org/10.1016/j.eneco.2019.104563.

[9] Sadiqa A, Gulagi A, Breyer C. Energy transition roadmap towards 100% renewable energy and role of storage technologies for Pakistan by 2050. Energy 2018;147:518–33. https://doi.org/10.1016/j.energy.2018.01.027.

[10] International Renewable Energy Agency. Global Energy Transformation: A Roadmap to 2050. 2018. Available at: Global Energy Transformation: A Roadmap to 2050.

[11] Gielen D, Boshell F, Saygin D, Bazilian MD, Wagner N, Gorini R. The role of renewable energy in the global energy transformation. Energy Strategy Reviews 2019;24:38–50. https://doi.org/10.1016/j.esr.2019.01.006.
[12] Bayale N, Ali E, Tchagnao A-F, Nakumuryango A. Determinants of renewable energy production in WAEMU countries: new empirical insights and policy implications. Int J Green Energy 2021;18:602–14. https://doi.org/10.1080/15435075.2021.1875467.
[13] Lauber V. REFIT and RPS: options for a harmonised community framework. Energy Policy 2004;32:1405–14. https://doi.org/10.1016/S0301-4215(03)00108-3.
[14] European Parliament and Council. European Climate Law (Regulation (EU) 2021/1119). 2021.
[15] European Commission. Fit for 55': delivering the EU's 2030 climate target on the way to climate neutrality. COM; 2021. 550 final) 2021.
[16] Carley S, Baldwin E, MacLean LM, Brass JN. Global expansion of renewable energy generation: an analysis of policy instruments. Environ Resour Econ 2017;68:397–440. https://doi.org/10.1007/s10640-016-0025-3.
[17] Lin B, Omoju OE. Focusing on the right targets: economic factors driving non-hydro renewable energy transition. Renew Energy 2017;113:52–63. https://doi.org/10.1016/j.renene.2017.05.067.
[18] Marques AC, Fuinhas JA, Pereira DS. The dynamics of the short and long-run effects of public policies supporting renewable energy: a comparative study of installed capacity and electricity generation. Econ Anal Pol 2019;63:188–206. https://doi.org/10.1016/j.eap.2019.06.004.
[19] Li Y, Zhang C, Li S, Usman A. Energy efficiency and green innovation and its asymmetric impact on CO2 emission in China: a new perspective. Environ Sci Pollut Res 2022;29:47810–7. https://doi.org/10.1007/s11356-022-19161-7.
[20] Ullah S, Ozturk I. Examining the asymmetric effects of stock markets and exchange rate volatility on Pakistan's environmental pollution. Environ Sci Pollut Res 2020;27:31211–20. https://doi.org/10.1007/s11356-020-09240-y.
[21] Romer PM. Endogenous technological change. J Polit Econ 1990;98:S71–102. https://doi.org/10.1086/261725.
[22] North DC. In: Institutions, institutional change and economic performance. first ed. Cambridge University Press; 1990. https://doi.org/10.1017/CBO9780511808678.
[23] Palley TI. Endogenous money and the business cycle. J Econ 1997;65:133–49. https://doi.org/10.1007/BF01226931.
[24] Svirydzenka K. Introducing a new broad-based index of financial development. IMF Working Papers 2016;16:1. https://doi.org/10.5089/9781513583709.001.
[25] Da Silva PP, Cerqueira PA, Ogbe W. Determinants of renewable energy growth in Sub-Saharan Africa: evidence from panel ARDL. Energy 2018;156:45–54. https://doi.org/10.1016/j.energy.2018.05.068.
[26] Sadorsky P, Renewable energy consumption. CO2 emissions and oil prices in the G7 countries. Energy Econ 2009;31:456–62. https://doi.org/10.1016/j.eneco.2008.12.010.
[27] Wang X, Jin W, Qin M, Su C-W, Umar M. Pushing forward the deployment of renewable energy: do cross-national spillovers of policy instruments matter? Energy 2024;301:131643. https://doi.org/10.1016/j.energy.2024.131643.
[28] Wang X, Wang K, Safi A, Umar M. How is artificial intelligence technology transforming energy security? New evidence from global supply chains 2025;2025:15–38. https://doi.org/10.24136/oc.3488. Oc.
[29] Lin B, Omoju OE, Okonkwo JU. Factors influencing renewable electricity consumption in China. Renew Sustain Energy Rev 2016;55:687–96. https://doi.org/10.1016/j.rser.2015.11.003.
[30] Marques AC, Fuinhas JA, Pires JR Manso. Motivations driving renewable energy in European countries: a panel data approach. Energy Policy 2010;38:6877–85. https://doi.org/10.1016/j.enpol.2010.07.003.
[31] Salim RA, Rafiq S. Why do some emerging economies proactively accelerate the adoption of renewable energy? Energy Econ 2012;34:1051–7. https://doi.org/10.1016/j.eneco.2011.08.015.
[32] Alhendawy HAA, Abdallah Mostafa MG, Elgohari MI, Mohamed IAA, Mahmoud NMA, Mater MAM. Determinants of renewable energy production in Egypt new approach: machine learning algorithms. IJEEP 2023;13:679–89. https://doi.org/10.32479/ijeep.14985.
[33] Elmassah S. Socioeconomic determinants of renewable energy production in emerging and developed countries. https://doi.org/10.21203/rs.3.rs-554269/v1; 2021.
[34] Abanda FH, Ng'ombe A, Keivani R, Tah JHM. The link between renewable energy production and gross domestic product in Africa: a comparative study between 1980 and 2008. Renew Sustain Energy Rev 2012;16:2147–53. https://doi.org/10.1016/j.rser.2012.01.005.
[35] Khoshnevis Yazdi S, Shakouri B. Renewable energy, nonrenewable energy consumption, and economic growth. Energy Sources B Energy Econ Plann 2017;12:1038–45. https://doi.org/10.1080/15567249.2017.1316795.
[36] Jamasb T, Pollitt M. Security of supply and regulation of energy networks. Energy Policy 2008;36:4584–9. https://doi.org/10.1016/j.enpol.2008.09.007.
[37] Neuhoff K. Large-Scale Deployment of Renewables for Electricity Generation. Oxford Review of Economic Policy 2005;21:88–110. https://doi.org/10.1093/oxrep/gri005.
[38] Vaona A. Granger non-causality tests between (non)renewable energy consumption and output in Italy since 1861: The (ir)relevance of structural breaks. Energy Policy 2012;45:226–36. https://doi.org/10.1016/j.enpol.2012.02.023.
[39] Yildirim E, Saraç Ş, Aslan A. Energy consumption and economic growth in the USA: Evidence from renewable energy. Renewable and Sustainable Energy Reviews 2012;16:6770–4. https://doi.org/10.1016/j.rser.2012.09.004.
[40] Mitrova T, Melnikov Y. Energy transition in Russia. Energy Transit 2019;3:73–80. https://doi.org/10.1007/s41825-019-00016-8.
[41] Wong VSH, El Massah S. Recent Evidence on the Oil Price Shocks on Gulf Cooperation Council Stock Markets. International Journal of the Economics of Business 2018;25;297–312. https://doi.org/10.1080/13571516.2017.1379216.
[42] Apergis N, Payne JE. Renewable energy, output, CO2 emissions, and fossil fuel prices in Central America: Evidence from a nonlinear panel smooth transition vector error correction model. Energy Economics 2014;42:226–32. https://doi.org/10.1016/j.eneco.2014.01.003.
[43] Apergis N, Payne JE. Renewable Energy, Output, Carbon Dioxide Emissions, and Oil Prices: Evidence from South America. Energy Sources, Part B: Economics, Planning, and Policy 2015;10:281–7. https://doi.org/10.1080/15567249.2013.853713.
[44] Omri A, Nguyen DK. On the determinants of renewable energy consumption: International evidence. Energy 2014;72:554–60. https://doi.org/10.1016/j.energy.2014.05.081.
[45] Omri A, Daly S, Nguyen DK. A robust analysis of the relationship between renewable energy consumption and its main drivers. Applied Economics 2015;47:2913–23. https://doi.org/10.1080/00036846.2015.1011312.
[46] Apergis N, Eleftheriou S. Renewable energy consumption, political and institutional factors: evidence from a group of European, Asian and Latin American countries. Singapore Econ Rev 2015;60:1550008. https://doi.org/10.1142/S0217590815500083.
[47] Ackah I, Kizys R. Green growth in oil producing African countries: A panel data analysis of renewable energy demand. Renewable and Sustainable Energy Reviews 2015;50:1157–66. https://doi.org/10.1016/j.rser.2015.05.030.
[48] Akar BG. The determinants of renewable energy consumption: an empirical analysis for the balkans. Eur Sci J ESJ 2016;12:594. https://doi.org/10.19044/esj.2016.v12n11p594.
[49] Attiaoui I, Toumi H, Ammouri B, Gargouri I. Causality links among renewable energy consumption, CO2 emissions, and economic growth in Africa: evidence from a panel ARDL-PMG approach. Environ Sci Pollut Res 2017;24:13036–48. https://doi.org/10.1007/s11356-017-8850-7.
[50] Rasoulinezhad E, Saboori B. Panel estimation for renewable and non-renewable energy consumption, economic growth, CO2 emissions, the composite trade intensity, and financial openness of the commonwealth of independent states. Environ Sci Pollut Res 2018;25:17354–70. https://doi.org/10.1007/s11356-018-1827-3.
[51] Bamati N, Raoofi A. Development level and the impact of technological factor on renewable energy production. Renewable Energy 2020;151:946–55. https://doi.org/10.1016/j.renene.2019.11.098.
[52] Ergun SJ, Owusu PA, Rivas MF. Determinants of renewable energy consumption in Africa. Environ Sci Pollut Res 2019;26:15390–405. https://doi.org/10.1007/s11356-019-04567-7.
[53] Nguyen KH, Kakinaka M. Renewable energy consumption, carbon emissions, and development stages: Some evidence from panel cointegration analysis. Renewable Energy 2019;132:1049–57. https://doi.org/10.1016/j.renene.2018.08.069.
[54] Liu W, Zhang X, Feng S. Does renewable energy policy work? Evidence from a panel data analysis. Renewable Energy 2019;135:635–42. https://doi.org/10.1016/j.renene.2018.12.037.
[55] Alam MdM, Murad MdW. The impacts of economic growth, trade openness and technological progress on renewable energy use in organization for economic co-operation and development countries. Renewable Energy 2020;145:382–90. https://doi.org/10.1016/j.renene.2019.06.054.
[56] Capros P, Mantzos L, Parousos L, Tasios N, Klaassen G, Van Ierland T. Analysis of the EU policy package on climate change and renewables. Energy Policy 2011;39:1476–85. https://doi.org/10.1016/j.enpol.2010.12.020.
[57] Marra A, Colantonio E. The institutional and socio-technical determinants of renewable energy production in the EU: implications for policy. J Ind Bus Econ 2022;49:267–99. https://doi.org/10.1007/s40812-022-00212-6.
[58] Mac Domhnaill C, Ryan L. Towards renewable electricity in Europe: Revisiting the determinants of renewable electricity in the European Union. Renewable Energy 2020;154:955–65. https://doi.org/10.1016/j.renene.2020.03.084.
[59] Rajkumar V. Predicting surprises to GDP : a comparison of econometric and machine learning techniques, 35. Massachusetts Institute of Technology; 2017.
[60] Tiffin A. Seeing in the Dark: A Machine-Learning Approach to Nowcasting in Lebanon. IMF Working Papers 2016. IMF Working Paper No. 16/56. Available at SSRN: https://ssrn.com/abstract=2770291.
[61] Mubarak H, Abdellatif A, Ahmad S, Zohurul Islam M, Muyeen SM, Abdul Mannan M, et al. Day-ahead electricity price forecasting using a CNN-BiLSTM model in conjunction with autoregressive modeling and hyperparameter optimization. International Journal of Electrical Power & Energy Systems 2024;161:110206. https://doi.org/10.1016/j.ijepes.2024.110206.
[62] Awad M, Khanna R. Efficient Learning Machines: Theories, Concepts, and Applications for Engineers and System Designers. ApressOpen; 2015.
[63] Richardson A, van Florenstein Mulder, Vehbi T. Nowcasting New Zealand GDP Using Machine Learning. Algorithms 2018.
[64] Suykens JAK, Vandewalle J. Multiclass least squares support vector machines. IJCNN'99. International Joint Conference on Neural Networks. In: Proceedings (Cat. No.99CH36339). 2. Washington, DC, USA: IEEE; 1999. p. 900–3. https://doi.org/10.1109/IJCNN.1999.831072.
[65] Zhu B, Ye S, Wang P, Chevallier J, Wei Y. Forecasting carbon price using a multi-objective least squares support vector machine with mixture kernels. Journal of Forecasting 2022;41:100–17. https://doi.org/10.1002/for.2784.
[66] Hochreiter S, Schmidhuber J. Long short-term memory. Neural Computation 1997;9:1735–80. https://doi.org/10.1162/neco.1997.9.8.1735.

[67] Wu Y-X, Wu Q-B, Zhu J-Q. Improved EEMD-based crude oil price forecasting using LSTM 1166 networks. Physica A: Statistical Mechanics and Its Applications 2019; 516:114–24. 1167 https://doi.org/10.1016/j.physa.2018.09.120.
[68] Wang Q, Dai X, Zhou D. Dynamic Correlation and Risk Contagion Between "Black" Futures in China: A Multi-scale Variational Mode Decomposition Approach. Comput Econ 2020;55:1117–50. https://doi.org/10.1007/s10614-018-9857-y.
[69] Box GE, Jenkins GE, Reinsel GC, Ljung GM. Time series analysis: Forecasting and Control 1976.
[70] Wang Y, Liu Q. Comparison of Akaike information criterion (AIC) and Bayesian information criterion (BIC) in selection of stock–recruitment relationships. Fisheries Research 2006;77:220–5. https://doi.org/10.1016/j.fishres.2005.08.011.
[71] Dickey DA, Fuller WA. Distribution of the Estimators for Autoregressive Time Series with a Unit Root. Journal of the American Statistical Association 1979;74: 427–31. https://doi.org/10.1080/01621459.1979.10482531.
[72] Mundlak Y. On the pooling of time series and cross section data. Econometrica 1978;46:69. https://doi.org/10.2307/1913646.
[73] Driscoll JC, Kraay AC. Consistent covariance matrix estimation with spatially dependent panel data. Rev Econ Stat 1998;80:549–60. https://doi.org/10.1162/003465398557825.
[74] Rachev R ST, Mittnik S, Fabozzi FrankJ, Focardi S, Jasic T. Financial econometrics: from basics to advanced modeling techniques. John Wiley & Sons; 2007.
[75] Ahmed R, Sreeram V, Mishra Y, Arif MD. A review and evaluation of the state-of-the-art in PV solar power forecasting: Techniques and optimization. Renewable and Sustainable Energy Reviews 2020;124:109792. https://doi.org/10.1016/j.rser.2020.109792.
[76] Otto SA, Kadin M, Casini M, Torres MA, Blenckner T. A quantitative framework for selecting and validating food web indicators. Ecological Indicators 2018;84: 619–31. https://doi.org/10.1016/j.ecolind.2017.05.045.
[77] Diebold FX, Mariano RS. Comparing Predictive Accuracy. Journal of Business & Economic Statistics 2002;20:134–44. https://doi.org/10.1198/073500102753410444.
[78] Salim RA, Rafiq S. Why do some emerging economies proactively accelerate the adoption of renewable energy? Energy Economics 2012;34:1051–7. https://doi.org/10.1016/j.eneco.2011.08.015.
[79] York R. Asymmetric effects of economic growth and decline on CO2 emissions. Nat Clim Change 2012;2:762–4. https://doi.org/10.1038/nclimate1699.
[80] Przychodzen W, Przychodzen J. Determinants of renewable energy production in transition economies: A panel data approach. Energy 2020;191:116583. https://doi.org/10.1016/j.energy.2019.116583.
[81] Li J, Zhang X, Ali S, Khan Z. Eco-innovation and energy productivity: New determinants of renewable energy consumption. Journal of Environmental Management 2020;271:111028. https://doi.org/10.1016/j.jenvman.2020.111028.
[82] Ozpolat A, Guven GG, Ozsoy FN, Bahar A. Does rule of law affect economic growth positively? RWE 2016;7:107. https://doi.org/10.5430/rwe.v7n1p107.
[83] Europe Energy Outlook. International Energy Agency (IEA) 2022. 2022.
[84] Wang C, Zhang S, Xiao L, Fu T. Wind speed forecasting based on multi-objective grey wolf optimisation algorithm, weighted information criterion, and wind energy conversion system: A case study in Eastern China. Energy Conversion and Management 2021;243:114402. https://doi.org/10.1016/j.enconman.2021.114402.