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Forecasting circular economy indicators: A Machine Learning study of European Union member states

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HIGHLIGHTS

- ML forecasting framework developed for EU Circular Economy indicators.
- Forecasting accuracy varies substantially across indicators and countries.
- Structural indicators show stronger forecasting performance than waste indicators.
- Limited training data constrains gains from additional predictive features.

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ABSTRACT

Accurate forecasting of Circular Economy (CE) indicators is essential for supporting evidence-based policy development and long-term strategic planning across the European Union (EU). Reliable projections enable policymakers to anticipate future resource needs, assess the impact of interventions and design measures that accelerate the transition towards a more circular economy. This study applies Machine Learning (ML) algorithms to predict official CE indicators published by Eurostat, covering four thematic areas: production and consumption, waste management, secondary raw materials and competitiveness. 25 member states of the EU are individually modelled, using country-specific time series data to train and evaluate five ML algorithms for regression: Ridge regression, Lasso regression, Random forest, XGBoost and support vector regression. A replicable framework for CE indicator forecasting is presented to support national and EU-level policy planning and early interventions. Best practice in ML-based forecasting is demonstrated, addressing challenges such as data sparsity, non-stationarity and model overfitting. No single model consistently outperforms others, though linear models tend to provide more reliable uncertainty estimates for structurally predictable indicators. Two features was determined optimal across models, as including additional features provided minimal improvement in MAE, reflecting the constraints imposed by the limited size of the training datasets. The results show the potential and limitations of current forecasting methodologies when applied to CE indicators, emphasising the importance of representative training data and careful uncertainty quantification in policy-relevant forecasts.

1. Introduction

To meet their environmental targets while maintaining economic competitiveness, European Union (EU) member states must fundamentally rethink how resources are utilised and managed (Baldassarre and Carrara, 2025). Current patterns of production and consumption are incompatible with long-term environmental and economic sustainability (Hartley et al., 2024). In response, the Circular Economy (CE) has become a cornerstone of EU sustainability and industrial policy through initiatives such as the 2015 Closing the Loop Action Plan (European Commission, 2015), European Green Deal (European Commission, 2019) and the Circular Economy Action Plan (CEAP) (European Commission, 2020). These policies underscore a growing recognition among EU policymakers that circularity is essential for achieving both climate and economic goals (European Commission, 2020).

To monitor the progress towards the CE, the European Commission launched the EU Circular Economy Monitoring Framework (CEMF) (European Commission, 2020). Introduced in 2018 and later updated in

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2023, the framework comprises 10 indicators and 27 sub-indicators structured around five thematic areas: production and consumption, waste management, secondary raw materials, competitiveness and innovation, and global sustainability and resilience (European Commission, 2023). International initiatives have advanced the conceptual and statistical foundations for CE monitoring; notably, the UNECE, OECD Guidelines for Measuring CE which establish a harmonised framework, including a headline definition, a conceptual model and a set of core indicators (United Nations Economic Commission for Europe (UNECE) and Organisation for Economic Co-operation and Development (OECD), 2023). While these guidelines provide an essential foundation for international comparability, the EU CEMF's consistent annual reporting allows for performance monitoring, making it a practical tool for policy evaluation and benchmarking across the EU.

Understanding past and current performance is essential for assessing progress, but policymakers also need tools that support forward-looking decision-making. Forecasting these indicators helps anticipate whether countries are on track to meet CE goals, identify future risks and better align investment and regulation with expected outcomes. It also supports scenario analysis, helping policymakers evaluate the potential impact of different policy or investment options. Resource prioritisation can also be facilitated, by identifying sectors or activities where interventions are likely to have the greatest effect, while enhancing transparency and accountability through evidence-based projections that inform long-term planning and policy evaluation. Forecasting has been widely applied in environmental fields such as emissions (Suganthi and Samuel, 2012), water resource management (Ahmed et al., 2024) and energy demand management (Ying et al., 2023); however, its application to the EU CEMF is yet to be explored.

Traditional time series methods such as ARIMA, exponential smoothing and vector autoregression have proven effective for forecasting environmental indicators (Zhong et al., 2024) with long, consistent time series and strong temporal autocorrelation (Su et al., 2018). However, their applicability for forecasting CE indicators from the EU CEMF is limited by the small number of data points in the time series and weak autocorrelation. In addition, these indicators are likely influenced by multiple factors exhibiting complex non-linear relationships. ML approaches offer greater adaptability to such constraints with ensemble methods, such as random forest having the ability to handle non-linear relationships and high-dimensional feature spaces. This allows for the consideration of socio-economic variables such as education, income, demographic composition and environmental regulation. These factors have been shown to influence CE performance across countries (Neves and Marques, 2022). Similarly, studies examining determinants of the circular economy in Europe highlight the importance of such socio-economic conditions (Robaina et al., 2020). As the Monitoring Framework grows, defining best practices for handling and forecasting its indicators becomes increasingly important to support accurate and reliable future analyses.

This study addresses this methodological gap by developing and evaluating a suite of ML models to forecast selected CE indicators using socio-economic and environmental predictors. Specifically, the study pursues the following objectives:

- Develop and compare ML-based forecasting models for CE indicators under conditions of limited time series length and weak temporal dependence.
- Determine the optimal feature set size and assess the relative importance of socio-economic and environmental features for predictive performance across indicators and countries.
- Assess model generalisation performance across EU Member States while accounting for national heterogeneity through country-specific modelling.
- Establish best practices for data preparation, feature selection, model validation and performance assessment in the context of CE indicator forecasting.

Five key indicators from the EU CEMF are modelled: *Resource Productivity*, *Municipal Waste generation per capita*, *Material Import Dependency*, *Private Investment in CE related sectors* and the *Recycling Rate of Municipal Waste*. Each EU Member State is modelled independently to capture structural and institutional differences affecting indicator dynamics.

The modelling approach combines multiple regression and tree-based algorithms, with a strong emphasis on best practices in data preparation, feature selection, model validation and performance assessment. Forecast uncertainty is explicitly quantified using bootstrap resampling, generating empirical prediction intervals that capture variability due to model estimation and limited data. By systematically evaluating the optimal number of features, assessing generalisation performance across countries and providing bootstrap-based confidence intervals for predictions, this study contributes to (i) advancing the methodological toolkit for CE monitoring and (ii) supporting evidence-based decision-making for national and EU-level policy.

Additionally, the study provides a benchmark for forecasting performance across multiple indicators and member states, identifying where predictive modelling is most robust and where indicator behaviour remains difficult to anticipate. By incorporating uncertainty quantification, the approach allows policymakers and researchers to interpret forecasts not only as point estimates but as ranges of plausible outcomes. This work lays the foundation for a replicable, policy-relevant forecasting framework tailored to the characteristics of European CE indicator data. The framework can be used by EU institutions and national statistical agencies to anticipate future trajectories, by policymakers to evaluate the prospective impact of interventions and by researchers to benchmark methodological advances in sustainability forecasting.

The remainder of the paper is organised as follows. Section 2 provides a literature review, highlighting prior empirical research on CE monitoring, methodological gaps in indicator measurement and the emerging application of machine learning for forecasting sustainability indicators. Section 3 presents the data and methodology used in this study, including model development, feature selection and uncertainty quantification. Section 4 presents the forecasting results, while Section 5 provides an in-depth discussion of their implications. Finally, Section 6 concludes with the main findings.

2. Literature review

While the concept of the CE has gained significant policy traction, its definition, operationalisation and measurement remain contested within academic circles (Murray et al., 2017). Scholars have questioned whether existing implementations adequately capture the systemic transformation envisioned by CE principles (Genovese and Pansera, 2021), or whether they reflect a narrower, efficiency-driven approach aligned with existing economic models (Hermann et al., 2022). Within this debate, the CEMF has provided a useful basis for comparative evaluation, but concerns persist that indicators related to food waste, green public procurement and eco-innovation remain underdeveloped. This has raised questions about the framework's ability to reflect the full scope of CE activities. Accordingly, several studies have called for an expansion of the indicator set, longer and more consistent time series (Pakuła et al., 2025) and the inclusion of qualitative or institutional dimensions into CE monitoring (Mazur-Wierzbicka, 2021b).

Beyond conceptual discussions, empirical research has drawn on the EU CEMF to assess CE performance across EU Member States, most notably through cross-national comparisons (Fura et al., 2020) and the construction of composite indices (Marino and Pariso, 2021). Analyses based on principal component analysis and clustering have revealed substantial heterogeneity among countries, with a persistent performance divide between EU-15 and EU-13 Member States (Mazur-Wierzbicka, 2021a). These findings highlight the policy relevance of the framework for benchmarking progress, yet applications remain largely

Table 1
Mapping of gaps in the CE literature across four dimensions.

Dimension	Description of gap	Implication
Methodological limitations	Use of parametric or aggregated models; weak handling of non-linear relationships	Limits accurate modelling of complex CE dynamics
Data limitations	Short time series, missing values, inconsistent cross-country coverage	Reduces reliability and generalisability of findings
Lack of predictive approaches	Most studies are descriptive; limited forecasting of CE indicators	Limits policy planning and anticipatory decision-making
Insufficient integration of socio-economic indicators	Focus on environmental indicators, neglecting demographic, economic, or institutional factors	Impedes understanding of social drivers of CE performance

retrospective. Current uses describe existing performance differences but do little to anticipate future trajectories, an important limitation if the framework is to inform proactive policymaking.

These limitations can be synthesised across four key dimensions: methodological limitations, data limitations, lack of predictive approaches and insufficient integration of socio-economic indicators. Table 1 summarises these gaps and their implications for research and policy.

These gaps highlight the need for predictive, methodologically robust approaches that integrate heterogeneous socio-economic and environmental data, which motivates the present study.

Although forecasting has not been explicitly applied to the CEMF, select component indicators have been examined in forecasting studies across wider sustainability contexts. Waste generation and management forecasting, for example, has been conducted at global, regional, national and urban scales, spanning diverse waste streams such as municipal solid waste, construction and demolition waste and electronic waste (Zhang et al., 2022; United Nations Environment Programme and United Nations Institute for Training and Research, 2023). Techniques such as neural networks, random forests and support vector machines have proven particularly effective in capturing non-linear dynamics and integrating heterogeneous datasets that include environmental, economic and socio-economic variables (Ayeleru et al., 2021). In comparison with traditional statistical time-series approaches such as ARIMA and VAR, machine learning methods offer several methodological advantages under complex, multi-variable conditions. Classical models typically assume linear relationships and stationarity and are often limited to univariate forecasting, whereas ML models can capture non-linear relationships and accommodate multiple predictors without restrictive parametric assumptions (Houssein et al., 2025). Empirical evidence from comparative studies shows that machine learning algorithms outperform traditional models in forecasting accuracy for complex systems, particularly when non-linearities or multiple interacting drivers are present (Abdeljaber et al., 2025; Golbaz et al., 2019). Simultaneously, traditional methods remain competitive in settings with simple, linear dynamics or very short series where they can be more interpretable and efficient (Kontopoulou et al., 2023). The advantages of ML-based forecasting observed in waste management, including the integration of heterogeneous socio-economic and infrastructural variables, the ability to capture complex dynamics and the generation of actionable insights, are transferable to other domains, provided that the data share similar complexity and multivariate structure. Collectively, these characteristics make ML-based forecasting a promising approach for supporting evidence-informed decision-making and strategic planning across multiple CE indicators.

ML-based forecasting has been applied in a variety of public policy-relevant domains, including energy demand management (Malka et al., 2023), urban planning (Chen and wan Zhang, 2024) and carbon emission trajectories (Chang et al., 2023). While many of these studies primarily focus on improving forecasting accuracy, they also generate outputs that are directly relevant for policy design and strategic planning. In the domain of waste and energy management, a machine learning-driven predictive analytics framework has been applied to forecast waste quantities and to inform decisions related to collection planning, energy utilisation and infrastructure optimisation, all of which are central to public waste and energy policy (Huang and Koroteev, 2021). Furthermore, recent research has demonstrated how ML methods can be systematically optimised to inform prediction-based public policies. Battiston et al. (2024) develop a framework that links prediction errors of any classification model to social welfare outcomes, allowing the ranking and selection of the optimal model for policy implementation. Their approach accounts for heterogeneous costs of type I and II errors and illustrates how ML-driven predictions can maximise policy effectiveness in contexts such as tax compliance. This study highlights that beyond accuracy, ML models can provide strategic, policy-relevant insights, identifying structural heterogeneity and informing decision-making in ways that directly enhance social and economic outcomes. Collectively, these applications demonstrate that ML-based forecasts can move beyond projections to support evidence-based and context-sensitive strategic planning, including in environmental and sustainability domains.

Within the EU, ML-based forecasting is increasingly being employed in public administration. Applications of predictive analytics to support decision-making, optimise operational processes and evaluate policy outcomes have commenced (European Commission and Joint Research Centre, 2020). These applications highlight the potential for ML-based for CE indicators, where socio-economic and environmental factors interact.

Despite these advances in related fields, no study has applied ML based forecasting to the EU CEMF. This absence is notable given the framework's central role in EU sustainability monitoring and its importance for comparative assessment. Extending forecasting to the framework could enable a transition from descriptive reporting to anticipatory analysis, equipping policymakers with reliable, interpretable and policy-relevant evidence to guide the transition towards circularity. To achieve this, forecasting approaches must be methodologically appropriate and statistically robust, ensuring that results are not only accurate but also transparent and credible for use within policy evaluation and strategic planning.

3. Materials and methods

This section describes the methodological steps taken in this study. The analysis begins with the selection of target and feature variables from the Eurostat database.[1] Data preprocessing, checks for stationarity and autocorrelation prepare the series for model training and determine whether lagged variables are required. Feature selection is then carried out using a two-step approach: Pearson correlation measures linear relationships, followed by Mutual Information ranking, which captures both linear and non-linear dependencies by estimating how much knowing one variable reduces uncertainty about another. Five machine learning models were developed and compared for each indicator and Member State, using the top one to four variables ranked by mutual information. To determine the optimal feature set size, a minimum threshold for improvement in MAE was applied. The specification with the lowest MAE in each case was selected as the best performing model.

[1] https://ec.europa.eu/eurostat/web/main/data/database.

Table 2
Selected CE indicators.

CE indicator	Unit	Time period
Resource productivity	euro per kilogram	2000–2022
Municipal waste generation	kilogram per capita	1995–2022
Material import dependency	percentage of domestic material input	1990–2021
Private investment and gross added value related to CE sectors	million euro	2005–2023
Recycling rate of municipal waste	kilogram per capita	1995–2023

3.1. Country-specific modelling rationale

The decision to develop separate forecasting models for each EU Member State is theoretically motivated by the structural heterogeneity underlying CE performance across countries. EU Member States differ substantially in economic structure, industrial composition, resource availability, institutional capacity, policy implementation and socio-demographic conditions (Cartone et al., 2021; Coelho et al., 2025). Empirical studies further show that the magnitude of associations between CE outcomes and their socio-economic development indicators differ significantly across Northern and Southern EU countries (Alnafrah et al., 2025), indicating that parameter homogeneity assumptions are systematically violated in multi-country CE analyses.

From a modelling perspective, pooling countries within a single global model would impose implicit assumptions of parameter stability and common functional relationships that are inconsistent with the institutional and structural diversity of the EU. Country-specific modelling therefore allows the estimation of relationships that are context-dependent, better reflecting national CE trajectories and policy environments. This approach is consistent with the objective of producing policy-relevant forecasts that are interpretable at the national level, where most CE interventions are designed and implemented.

Accordingly, each CE indicator is modelled independently for each member state, enabling the machine learning models to capture country-specific dynamics while avoiding bias arising from cross-country aggregation.

3.2. Data description

The time series data for forecasting targets were sourced from the EU CEMF,[2] while time series data for features were obtained from the broader Eurostat database. In this context, targets correspond to the CE indicator time series to be forecast, while features are other time series used as input variables in the models. The selected indicators span four of the five thematic areas of the EU CEMF, providing broad representation of the framework, and were chosen to ensure a sufficiently long and consistent time series (at least 19 years) for meaningful forecasting across countries with greater than 90% data completeness. Features were identified from the Eurostat database based on domain relevance, prior research and data availability; time series were only considered if their temporal coverage matched or exceeded that of the corresponding targets. Table 2 details the selected target indicators alongside its units and the time period for which data has been recorded. To illustrate the data preparation and modelling workflow, we use *Resource Productivity* for Ireland as a running example throughout the materials and methods, as well as the results and discussion.

[2] https://ec.europa.eu/eurostat/web/circular-economy/monitoring-framework.

3.2.1. Resource productivity

Resource productivity is calculated as the ratio of Gross Domestic Product (GDP) to the Domestic Material Consumption (DMC) of a specific year and is expressed in euros per kilogram.

$$\text{Resource Productivity} = \frac{\text{Gross Domestic Product}}{\text{Domestic Material Consumption}}$$

It is used as a proxy for the decoupling of economic growth from material resource use. As an economy develops, the shift from industry to services can lead to increased resource productivity, as services generally require fewer raw materials than manufacturing sectors (Cunha et al., 2024).

3.2.2. Generation of municipal waste per capita

Municipal waste generation is defined as the total quantity of waste, measured in kilograms per capita per year, that is collected by or on behalf of municipal authorities and managed through formal waste treatment systems. This indicator primarily captures waste originating from households, as well as from commercial and institutional sources that generate waste of a similar composition. It serves as a proxy for evaluating consumption patterns, societal behaviour and the operational effectiveness of municipal waste collection and management infrastructures.

3.2.3. Private Investment in CE related sectors

To measure the level of financial commitment by private entities in advancing CE activities, private investment related to CE sectors captures expenditures directed towards resource efficiency, waste management, recycling, repair, reuse and eco-innovation as a share of total GDP. It reflects the extent to which the private sector invests in infrastructures, technologies and processes that support sustainable resource use and circular business models. It includes both capital investments, such as machinery and facilities and operational investments like research and development and workforce training.

3.2.4. Material Import Dependency

The degree to which an economy depends on imported raw materials to meet its domestic material needs is captured by material import dependency. It is calculated as the ratio of net material imports to total DMC.

$$\text{Material Import Dependency} = \frac{\text{Imports} - \text{Exports}}{\text{Domestic Material Consumption}} \times 100\%$$

This indicator reflects the vulnerability of a country to external supply risks and its level of self-sufficiency regarding critical raw materials. High material import dependency may indicate exposure to geopolitical, economic, or supply chain disruptions and highlights the importance of resource efficiency, recycling and CE strategies to reduce reliance on external inputs.

3.2.5. Recycling rate of municipal waste

The recycling rate of municipal waste quantifies the proportion of municipal waste materials that are recovered through recycling relative to the total volume of municipal waste generated within a given year. This indicator encompasses the systematic collection, segregation and reprocessing of a broad spectrum of waste streams such as paper, plastics, glass, metals and organic matter primarily derived from household and similar sources.

3.3. Impact features

For each target indicator, a tailored set of socio-economic and environmental features was identified based on domain relevance, prior research and data availability. All features were sourced from the Eurostat database. To ensure temporal consistency in modelling, only those features with data coverage matching or exceeding the period of collection for the corresponding target indicator were considered. The considered features vary across indicators and are presented in Table 3.

Table 3
Impact features considered for each target indicator.

Target indicator	Feature	Units
Resource Productivity	Annual change in volume of mining	%
	Employment in knowledge-intensive activities	%
	Employment rate	%
	Government expenditure on environmental R&D	million euro
	Gross value added – primary sector	%
	Gross value added – secondary sector	%
	Household consumption expenditure	euro per capita
	Material import dependency	%
	Recycling rate of municipal waste	%
	Renewable share in energy consumption	%
	Tertiary educational attainment	%
Material Import Dependency	Annual change in volume of mining	%
	Employment rate	%
	Gross Domestic Product	euro per capita
	Gross value added - primary sector	%
	Gross value added - secondary sector	%
	Household consumption expenditure	euro per capita
	Population density	persons per km^2
	Resource productivity	euro per kg
	Tertiary educational attainment	%
Municipal Waste Generation	Dependency ratio	%
	Domestic material consumption	tonnes per capita
	Employment rate	%
	Gross Domestic Product	euro per capita
	Gross value added – services	%
	Household consumption expenditure	euro per capita
	Population density	persons per km^2
	Tertiary educational attainment	%
Private Investment in CE related sectors	Annual change in volume of mining	%
	Domestic extraction	tonnes per capita
	Domestic material consumption	tonnes per capita
	Employment rate	%
	Energy productivity	euro per kg
	Environmental taxes	euro per capita
	Gross Domestic Product	euro per capita
	Government expenditure on research	million euro
	Gross value added – primary sector	%
	Gross value added – secondary sector	%
	Household consumption expenditure	euro per capita
	Material import dependency	%
	Population density	persons per km^2
	Resource productivity	euro per kg
	Tertiary educational attainment	%
Recycling rate of municipal waste	Domestic material consumption	tonnes per capita
	Employment rate	%
	Gross Domestic Product	euro
	Government expenditure on environment	million euro
	Government expenditure on waste management	million euro
	Tertiary educational attainment	%

3.4. Data pre-processing

Missing data which accounted for at most, 2 data points per series was addressed using linear interpolation. The dataset was initially divided into training and testing subsets using an 80/20 split, preserving the chronological order of observations. The training set was used for stationarity assessment, autocorrelation analysis and feature selection, ensuring that no information from the test set was inadvertently incorporated.

3.5. Stationarity assessment

To test for stationarity, the Augmented Dickey–Fuller (ADF) test was utilised (Dickey and Fuller, 1979). The null hypothesis of the ADF test assumes the presence of a unit root (a non-stationary time series), while the alternative hypothesis indicates stationarity. A p-value < 0.05 was taken as evidence to reject the null hypothesis, confirming that the series is stationary. For series found to be non-stationary, first-order differencing was applied only for models that cannot extrapolate trends from non-stationary data. This transformation allows such models to focus on predicting the annual change in the indicator, rather than its absolute value, while preserving the original series for models capable of handling non-stationary patterns.

3.6. Autocorrelation analysis

Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots were generated up to six lags using the statsmodels library[3] in Python. The ACF plot captures both direct and indirect correlations across lags, while the PACF plot isolates the direct effect of each lag, controlling for the influence of shorter lags. Lags were considered statistically significant if their autocorrelation coefficients fell outside the 95% confidence interval around zero. Significant lags where present, were considered as additional features in the modelling process.

[3] https://www.statsmodels.org/stable/index.html.

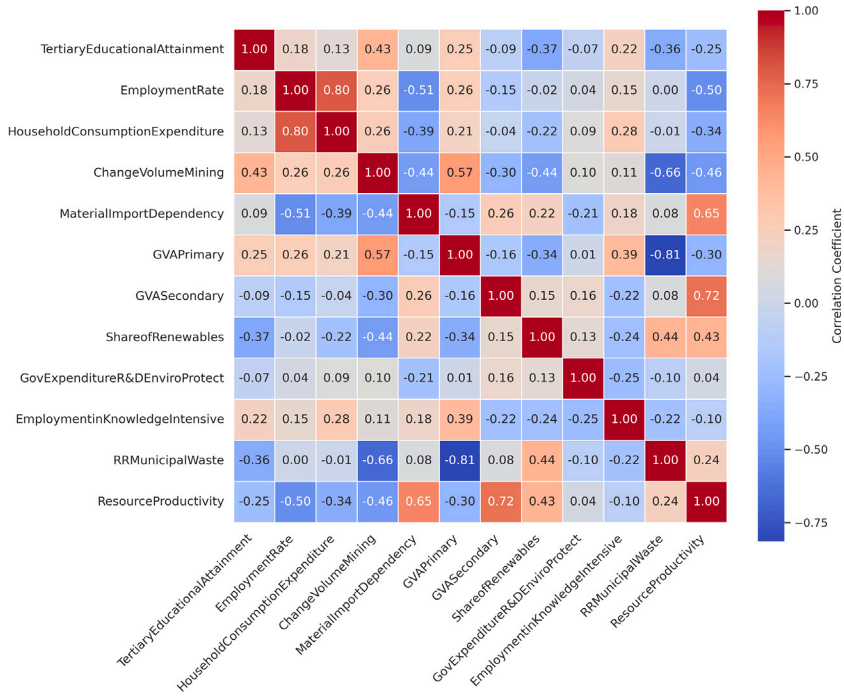

Fig. 1. Pearson's correlation matrix for Resource Productivity in Ireland.

3.7. Feature selection

3.7.1. Correlation analysis

Pearson correlation was used to assess the linear relationship between potential features and the target variable and to identify multicollinearity among features as shown for Ireland's *Resource Productivity* in Fig. 1. Multicollinearity occurs when two or more predictor variables are highly correlated with each other, resulting in redundant information that can distort regression coefficient estimates, inflate standard errors and reduce model interpretability. To mitigate these issues, features exhibiting high pairwise correlations ($|r| > 0.8$) were considered collinear. In such cases, the feature with the lower absolute correlation to the target variable was removed.

3.7.2. Mutual information

Mutual information (MI) is an information-theoretic measure that quantifies the amount of information shared between two random variables X and Y irrespective of whether their relationship is linear or non-linear. It is defined by the following equation:

$$I(X;Y) = \sum_{x\in\mathcal{X}} \sum_{y\in\mathcal{Y}} p(x,y) \log \left(\frac{p(x,y)}{p(x)p(y)} \right)$$

For each target indicator, MI scores were computed between the target and each potential feature. Features were then ranked by their MI score as presented in Table 4, where higher values indicate stronger dependency between the feature and the target.

3.8. Machine learning algorithm selection

The chosen ML models had to (i) perform well with limited training data, (ii) capture non-linear relationships between indicators and drivers and (iii) offer a degree of interpretability for policy-relevant insights. Five approaches were selected based on their ability to generalise under these constraints.

Table 4
Mutual information scores for Resource Productivity in Ireland.

Feature	MI score
Annual change in volume of mining	0.218
Material import dependency	0.211
Share of renewables in total energy consumption	0.071
Employment rate	0.052
Tertiary educational attainment	0.028
Gross value added of secondary activities	0.013
Recycling rate of municipal waste	0.000
Government expenditure on environmental protection research	0.000
Gross value added of primary activities	0.000
Household consumption expenditure	0.000
Employment in knowledge-intensive activities	0.000

3.8.1. Penalised regression methods

Polynomial regression models the relationship between independent and dependent variables as an nth-degree polynomial (Pedregosa et al., 2025) using OLS to minimise residual error. Higher order polynomials can overfit, so penalised regression adds a penalty to the loss function to limit large coefficients. The penalty strength λ controls the bias–variance trade-off, while α adjusts the number of variable selected. In this study, ridge (Hoerl and Kennard, 1970) and Lasso regression (Tibshirani, 2018) are the two primary penalisation approaches applied:

1. Ridge regression ($\lambda > 0, \alpha = 0$) uses an L2 penalty that shrinks coefficients continuously but does not set them to zero.
2. Lasso regression ($\lambda > 0, \alpha = 1$) uses an L1 penalty capable of shrinking coefficients to exactly zero.

3.8.2. Random forest

Random forest is an ensemble learning method that builds multiple decision trees during training and combines their predictions to improve accuracy and reduce overfitting (Breiman, 2001). Each tree is trained on a random subset of the data and considers a random subset of features when making splits. The final prediction of the random forest is obtained by averaging the outputs of all individual trees capturing complex, non-linear relationships and interactions between features without requiring strong assumptions about the underlying data distribution.

3.8.3. XGBoost

XGBoost regression is a gradient boosting algorithm that builds an ensemble of decision trees sequentially, where each new tree is trained to correct the errors of the previous trees (Chen and Guestrin, 2016). It optimises a differentiable loss function using gradient descent, which helps to improve prediction accuracy over time. To prevent overfitting and control model complexity, the objective function is augmented with an additional regularisation term. The importance of each feature is calculated by dividing the total gain accumulated across all trees by the total number of splits. The contribution of each feature increases proportionally to the number of splits where it is used. The gain at each split is computed as:

$$\text{Gain} = \frac{1}{2}\left[\frac{\left(\sum_{i\in S_L} g_i\right)^2}{\sum_{i\in S_L} h_i + \lambda} + \frac{\left(\sum_{i\in S_R} g_i\right)^2}{\sum_{i\in S_R} h_i + \lambda} - \frac{\left(\sum_{i\in S} g_i\right)^2}{\sum_{i\in S} h_i + \lambda}\right] - \gamma$$

where g_i and h_i represent the first and second-order gradients of the loss function with respect to the prediction for sample i, respectively. The sets S, S_L and S_R correspond to the samples in the parent node before the split and the left and right child nodes after the split, respectively. The parameter λ denotes the L2 regularisation term on leaf weights to control model complexity, while γ is the minimum loss reduction required to justify further partitioning (splitting) of the tree.

3.8.4. Support vector regression

Support vector regression (SVR) is an extension of the Support Vector Machine algorithm tailored for regression problems (Cortes and Vapnik, 1995). SVR seeks to estimate a continuous target variable by constructing a function that deviates from the observed data points by no more than a predefined threshold (ϵ), thereby creating an ϵ -insensitive tube around the predicted values. Only observations lying outside this tube, known as support vectors, influence the determination of the regression function. The use of kernel functions enables SVR to model complex, non-linear relationships by implicitly mapping input data into high-dimensional feature spaces, enhancing its flexibility and predictive capability.

3.9. Model development

For each country, a separate predictive model was developed for each target indicator. Models were implemented using Scikit-learn[4] in Python 3.11. Non-stationary time series were handled differently depending on the model class. For linear models (Ridge, Lasso, SVR), the raw series were used with an additional time index feature to allow the models to capture and extrapolate trend. For tree-based models (Random Forest, XGBoost), first-order differencing was applied to remove trend, as these models rely on partitioning the feature space and cannot extrapolate beyond the observed range. This approach ensures that each model type receives data appropriate for its learning assumptions, improving predictive performance while respecting the structural limitations of each algorithm. Differencing transforms the series so that model predictions are in terms of period-to-period changes rather than absolute levels. Consequently, interpretation shifts from absolute indicator values to short-term dynamics. While differencing can introduce error propagation when forecasts are iterated over multiple steps, such propagation does not arise in this study, as all predictions are generated one year ahead at each step. A standard scaler was fitted on the training data and subsequently applied to the test set to ensure consistent feature scaling across all folds. Hyperparameters were selected via a grid search over predefined parameter ranges. For each hyperparameter combination, model performance was evaluated using a one step ahead rolling-origin forecasting procedure, and the configuration minimising the root mean squared error across these forecasts was selected. Parameter ranges were constrained to prevent overfitting, which is particularly important given the limited sample size. The hyperparameter search spaces for each algorithm are detailed in Table 5.

Table 5
Hyperparameter grids for each model.

Model	Hyperparameters
Ridge regression	Degree: {1, 2} α: {0.5, 1, 10}
Lasso regression	Degree: {1, 2} α: {0.5, 1, 10}
Support Vector Regression	kernel: {'linear'} C: {0.01, 0.1, 1.0} epsilon: {0.1, 0.5, 1}
Random Forest	n_estimators: {20, 50, 100} max_depth: {5, 10, 20} min_samples_split: {2, 5} min_samples_leaf: {1, 2}
XGBoost	n_estimators: {20, 40, 60, 80} max_depth: {3, 5, 7} learning_rate: {0.02, 0.05, 0.1} subsample: {0.6, 0.8} colsample_bytree: {0.6, 0.8}

To investigate the effect of feature complexity, each model was trained four times using the top 1, 2, 3 and 4 features ranked by mutual information scores. The optimal feature count for each country-model pair was determined by examining the change in mean absolute error (MAE) on the test set as features were added in order of importance. A minimal improvement threshold of 2% in MAE was applied:

$$\frac{\text{MAE}_{k-1} - \text{MAE}_k}{\text{MAE}_{k-1}} \geq \delta$$

where:

- MAE_k is the mean squared error using k features,
- MAE_{k-1} is the mean squared error using $k-1$ features,
- $\delta = 0.02$ is the minimal improvement threshold (2%).

The kth feature is only added if it reduces the MAE by at least 2% compared to the previous number of features to avoid unnecessary model complexity and potential overfitting.

3.10. Model evaluation

To evaluate predictive performance, a one step ahead rolling-origin was implemented (Tashman, 2000). Rolling-origin evaluation is particularly suitable in this context because it generates multiple out-of-sample forecasts despite having limited historical observations, providing a more robust and reliable estimate of predictive performance rather than relying on a single train-test split that could be unrepresentative. For each country, the initial training set comprised 80% of the available observations (17–22 time points, depending on the series). At each iteration, the model was trained on the current training window and used to generate a forecast for the next observation. The training window then expanded to include the newly observed point, preserving the chronological order of the data and ensuring that only past information was used for forecasting. This procedure was applied iteratively across the series, allowing robust assessment of one step ahead predictive performance while maximising the use of limited historical data and providing a basis for quantifying forecast uncertainty.

[4] https://scikit-learn.org/stable/index.html.

To assess model performance and compare predictive accuracy across different algorithms, two standard evaluation metrics were used: root mean squared error (RMSE) and mean absolute error (MAE). These metrics provide insight into the average magnitude of prediction errors. Lower values of MAE and RMSE indicate better model performance. It is important to consider RMSE penalises larger errors more than MAE, making it more sensitive to outliers. The formulas for these evaluation indices are provided below:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (1)$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (2)$$

In the formulas above, y_i represents the true value, $\hat{y}_i$ denotes the predicted value and n is the number of observations.

To quantify forecast uncertainty, we applied an iterative parametric bootstrap at each forecast step. For the initial one step ahead forecast, the residual standard deviation was estimated from the standard deviation of the training data residuals. This approach is consistent with the use of in-sample residuals in probabilistic forecasting when no prior out-of-sample residuals exist (Petropoulos et al., 2022) For subsequent forecasts, residuals from all previous out-of-sample predictions were used to update the estimate of prediction error variability. At each step, 1000 bootstrap replicates were generated by adding Gaussian noise with mean zero and standard deviation equal to that of the relevant residuals. From these replicates, we derived the mean forecast and 95% confidence intervals using the 2.5th and 97.5th percentiles. The interval width, defined as the difference between the 97.5th and 2.5th percentiles of the bootstrap distribution, provides a measure of forecast uncertainty at each time step. Residuals were updated after each forecast to incorporate the latest error, ensuring that uncertainty estimates reflect the most recent model performance and the expanding training set.

To enable comparison across indicators with different magnitudes and units, the interval widths were normalised relative to the mean value of the corresponding indicator. This yielded a relative interval width, facilitating the assessment of forecast stability independent of scale.

For indicator i at time t, the relative interval width is defined as

$$\mathrm{RIW}_{i,t} = \frac{U_{i,t} - L_{i,t}}{\bar{y}_i}, \quad (3)$$

where $U_{i,t}$ and $L_{i,t}$ are the upper and lower bounds of the prediction interval and $\bar{y}_i$ is the mean value of the indicator.

For each indicator and country, the average relative interval width across the test period was computed as

$$\overline{\mathrm{RIW}}_i = \frac{1}{T}\sum_{t=1}^{T}\mathrm{RIW}_{i,t}, \quad (4)$$

where T is the number of test observations. Smaller values of $\overline{\mathrm{RIW}}_i$ indicate more stable forecasts relative to the scale of the indicator.

Coverage was calculated to quantify how often the prediction intervals contain the true values. Coverage of the prediction intervals was evaluated as

$$\mathrm{Coverage}_i = \frac{1}{T}\sum_{t=1}^{T}\mathbf{1}\{L_{i,t} \le y_{i,t} \le U_{i,t}\}, \quad (5)$$

where $y_{i,t}$ is the observed value at time t and $\mathbf{1}\{\cdot\}$ is the indicator function equal to 1 if the observed value falls within the interval and 0 otherwise.

The relative interval widths and coverage values were averaged across all countries to produce a single summary metric per indicator.

Table 6
Number of significant lags by indicator and country.

Indicator	Country	Significant lags
Resource productivity	Hungary	1
	Luxembourg	1
	Slovakia	1
Material import dependency	Austria	1
	Bulgaria	1
	Cyprus	1
	Hungary	1
	Luxembourg	1
	Slovenia	1
Municipal waste generation	Ireland	2
	Lithuania	1
	Romania	1
	Spain	2
Recycling rate of municipal waste	Luxembourg	1
	Sweden	1

4. Results

This section presents and analyses the main empirical findings of the study. It begins by assessing temporal dependencies in the CE indicators using autocorrelation and partial autocorrelation functions, followed by an examination of optimal feature set size to determine the point of diminishing returns in model complexity. The subsequent subsection compares the predictive performance of the five chosen machine learning algorithms across 25 EU countries and 5 indicators. The results conclude with a discussion of their implications for policymakers and forecasters interested in the use of machine learning for CE monitoring and prediction.

4.1. Autocorrelation and partial autocorrelation functions

Table 6 summarises the autocorrelation results for country-indicator pairs exhibiting statistically significant lags. In this context, a lag refers to a previous time step in the same time series. A lag is considered statistically significant if the correlation between the latest value of the time series and its past value at a given lag exceeds the threshold expected by random chance at the 95% confidence level. In Fig. 2, the threshold is shown by the blue shaded region. Since no bar extends beyond this region, no significant lags are present.

Of 150 country-indicator pairs, 15 exhibit statistically significant autocorrelation at the tested lags, suggesting that for the majority of cases, past values do not strongly predict current values beyond short-term effects. Where significant lags exist, they tend to be limited to just one or two lags. This indicates that temporal dependencies, where present, are short-term rather than long-term. The limited and mostly short-term autocorrelation suggests that autoregressive models have limited effectiveness for predicting the indicators from this dataset.

4.2. Model selection and optimal feature set

The optimal feature set size was defined as the number of predictors included by each model before the marginal improvement in mean absolute error (MAE) fell below 2%. This 2% threshold was chosen to balance predictive accuracy with model simplicity: it represents a meaningful improvement in performance while avoiding overfitting, particularly given the limited size of the training datasets. Lasso regression was treated differently from other models: its L1 regularisation automatically shrinks uninformative coefficients to zero, effectively performing feature selection without requiring an explicit threshold. Across all five CE indicators, 465 out of 500 models (93%) reached the 2% MAE improvement threshold after only two features, indicating that additional predictors provided minimal additional benefit. This

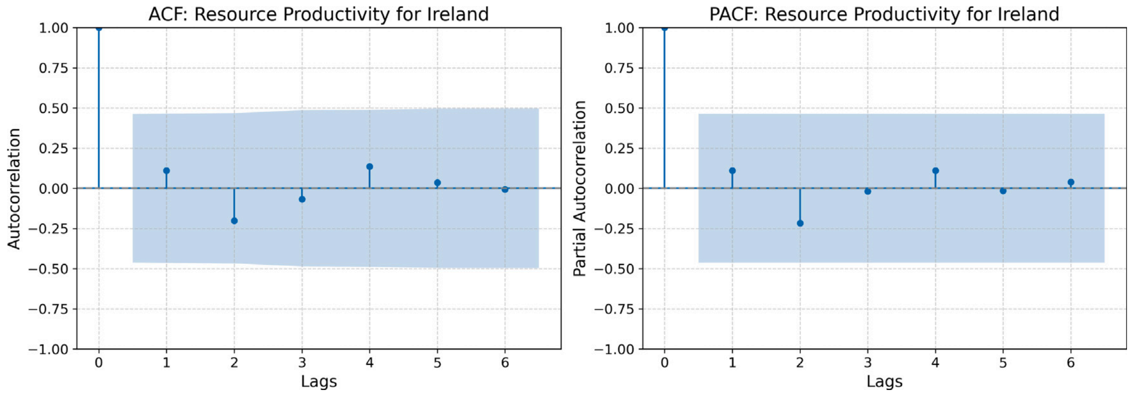

Fig. 2. ACF and PACF plots Resource Productivity (Ireland).

pattern reflects the limited size of the training datasets, which constrains the usefulness of higher-dimensional feature spaces. For Lasso, the model was allowed to retain or discard features autonomously. For all other models, feature selection was standardised for the remainder of the study by retaining the top two predictors ranked by mutual information. This ensures comparability across models while capturing the majority of predictive signal and avoiding unnecessary complexity.

4.3. Forecast accuracy across indicators

In this subsection, we present results for four representative EU countries: Ireland, France, Sweden and Romania. These countries were selected to capture diversity in geography, economic development and CE performance. Results for the remaining countries are included in the supplementary material.

The predictive performance of the models varies considerably across the five indicators, reflecting differences in both the magnitude of errors and the degree of overfitting. For *Resource Productivity* (Table 7), errors are generally low across all models and countries, with test MAE and RMSE values closely matching training values in most cases. Random Forest exhibits slightly higher test errors in France, while SVR and XGBoost maintain stable predictions. Romania demonstrates consistently low errors across all algorithms, suggesting a relatively predictable series. Sweden shows that Random Forest achieves the lowest test errors, indicating strong generalisation for this indicator.

For *Municipal Waste Generation* (Table 9), the performance patterns are more varied. In Romania, Random Forest and XGBoost achieve smaller test errors relative to training errors, whereas Ridge, Lasso and SVR show larger gaps in certain cases. In Ireland, Ridge exhibits particularly high errors, suggesting that it struggles to capture the series' variability, whereas Lasso and XGBoost maintain better balance between training and test performance. France and Sweden exhibit moderate differences between training and test errors, with no single model consistently outperforming others across both MAE and RMSE.

Material Import Dependency (Table 8) demonstrates overfitting for Random Forest in Ireland and Sweden, with test RMSE far exceeding training RMSE, while Ridge, Lasso, SVR and XGBoost generally maintain smaller train-test gaps. France shows moderate overfitting for Ridge and Lasso, while Romania presents low and closely aligned errors for all models, suggesting limited sensitivity to algorithm choice.

For *Private Investment in CE related sectors* (Table 10), Random Forest exhibits pronounced overfitting in Ireland, with test RMSE substantially higher than training, whereas SVR and XGBoost display more stable performance. France and Romania show moderate differences across models, while Sweden demonstrates consistent results across Ridge, Lasso and XGBoost, with Random Forest again showing slightly elevated test errors.

Finally, for *Recycling Rate of Municipal Waste* (Table 11), Random Forest consistently demonstrates overfitting in Ireland and Romania,

Table 7
Resource Productivity.

Country	Model	Train (MAE/RMSE)	Test (MAE/RMSE)
France	Ridge regression	0.080/0.070	0.130/0.100
	Lasso regression	0.276/0.241	0.384/0.374
	SVR	0.081/0.076	0.106/0.088
	Random Forest	0.057/0.042	0.336/0.289
	XGBoost	0.237/0.202	0.377/0.367
Ireland	Ridge regression	0.080/0.060	0.220/0.180
	Lasso regression	0.646/0.586	1.441/1.415
	SVR	0.291/0.175	0.663/0.556
	Random Forest	0.077/0.060	0.187/0.182
	XGBoost	0.075/0.055	0.191/0.169
Romania	Ridge regression	0.020/0.020	0.020/0.020
	Lasso regression	0.040/0.031	0.032/0.030
	SVR	0.051/0.041	0.062/0.061
	Random Forest	0.037/0.028	0.027/0.021
	XGBoost	0.047/0.032	0.033/0.028
Sweden	Ridge regression	0.050/0.040	0.090/0.070
	Lasso regression	0.064/0.047	0.118/0.091
	SVR	0.070/0.061	0.116/0.103
	Random Forest	0.086/0.067	0.047/0.036
	XGBoost	0.078/0.054	0.070/0.049

with test RMSE exceeding training by a wide margin. Ridge and Lasso produce smaller train-test differences but do not always achieve the lowest errors. SVR performance varies across countries, with France and Sweden exhibiting relatively stable predictions, while XGBoost generally balances accuracy and stability across most countries, despite higher absolute test errors in some cases.

Overall, the results indicate that no single model uniformly dominates across all indicators. Random Forest frequently exhibits overfitting, Ridge and Lasso generate more conservative predictions and XGBoost and SVR generally provide a balance between predictive accuracy and stability. Evaluating both the magnitude of errors and the train-test gap is essential for understanding each model's capacity to generalise.

4.4. Forecast uncertainty and bootstrap intervals

Table 12 reports the average relative bootstrap interval width across indicators and models, providing a comparative measure of forecast uncertainty that is independent of the absolute scale of the variables. *Private investment in CE related sectors* exhibits the widest relative intervals across all models, indicating the highest degree of forecast uncertainty. This is followed by *Municipal Waste Generation* and *Recycling Rate of Municipal Waste*, both of which display comparatively large interval widths, particularly for non-linear models. In contrast, *Material Import Dependency* and *Resource Productivity* are associated

Table 8
Material Import Dependency.

Country	Model	Train (MAE/RMSE)	Test (MAE/RMSE)
France	Ridge regression	0.9763/1.2910	1.6994/1.9637
	Lasso regression	1.8113/2.0454	0.9066/1.0304
	SVR	0.5704/0.6745	1.5671/2.3003
	Random Forest	0.6636/0.9099	1.4994/1.7070
	XGBoost	1.4246/1.6975	0.8509/0.9291
Ireland	Ridge regression	1.4184/1.6095	1.4537/1.6521
	Lasso regression	1.8616/2.1759	2.5127/2.5999
	SVR	0.5273/0.6654	3.3239/3.6478
	Random Forest	0.6757/0.9708	1.4860/1.7778
	XGBoost	1.1535/1.6188	1.3569/1.6542
Romania	Ridge regression	0.7743/0.9266	0.6465/0.8448
	Lasso regression	0.9723/1.0944	1.0286/1.2377
	SVR	0.7568/0.8554	1.1887/1.3416
	Random Forest	0.5667/0.7569	0.6710/0.9470
	XGBoost	0.4629/0.5519	0.7164/0.9036
Sweden	Ridge regression	0.5644/0.6830	0.9239/1.0479
	Lasso regression	0.9029/1.1261	2.1868/2.2521
	SVR	0.4878/0.6235	1.2147/1.3281
	Random Forest	0.5055/0.6087	0.9150/1.0040
	XGBoost	0.3625/0.4147	0.8581/0.8828

Table 9
Municipal Waste Generation.

Country	Model	Train (MAE/RMSE)	Test (MAE/RMSE)
France	Ridge regression	10.200/12.020	13.350/15.260
	Lasso regression	8.556/10.459	12.620/15.349
	SVR	11.320/14.301	15.287/17.269
	Random Forest	7.743/10.395	16.927/22.480
	XGBoost	9.689/12.546	13.250/18.110
Ireland	Ridge regression	62.070/69.440	76.930/89.190
	Lasso regression	12.396/16.282	16.901/19.159
	SVR	32.167/46.722	32.693/39.603
	Random Forest	26.969/34.276	30.846/35.840
	XGBoost	42.448/50.046	25.574/31.338
Romania	Ridge regression	33.610/39.330	42.820/43.310
	Lasso regression	21.337/25.599	15.462/20.435
	SVR	38.187/45.755	15.987/19.758
	Random Forest	13.551/17.409	3.949/4.875
	XGBoost	10.025/11.961	4.046/4.396
Sweden	Ridge regression	9.060/11.060	11.340/11.920
	Lasso regression	10.719/12.761	12.250/15.407
	SVR	11.344/14.122	8.096/9.900
	Random Forest	5.702/7.892	16.727/18.489
	XGBoost	8.738/11.692	17.764/18.174

Table 10
Private Investment in CE related sectors.

Country	Model	Train (MAE/RMSE)	Test (MAE/RMSE)
France	Ridge regression	851.304/1052.064	1259.809/1333.630
	Lasso regression	773.986/958.160	3581.176/4848.670
	SVR	1467.42/1716.55	2774.08/2887.56
	Random Forest	728.35/968.57	1649.45/1832.23
	XGBoost	968.935/1389.285	1131.962/1294.126
Ireland	Ridge regression	161.724/250.056	158.042/165.617
	Lasso regression	154.192/235.503	239.484/312.440
	SVR	148.87/299.28	214.59/254.78
	Random Forest	84.69/142.32	508.67/644.02
	XGBoost	41.364/71.326	321.475/554.122
Romania	Ridge regression	133.100/171.158	158.116/183.385
	Lasso regression	112.123/154.670	189.084/246.579
	SVR	127.92/176.17	292.28/429.26
	Random Forest	146.79/194.13	280.15/357.13
	XGBoost	212.525/292.880	210.253/244.033
Sweden	Ridge regression	143.512/171.217	74.305/97.987
	Lasso regression	135.639/165.078	101.771/142.779
	SVR	282.72/359.14	552.95/578.10
	Random Forest	124.71/155.83	229.45/383.90
	XGBoost	216.892/280.374	151.411/224.044

Table 11
Recycling Rate of Municipal Waste.

Country	Model	Train (MAE/RMSE)	Test (MAE/RMSE)
France	Ridge regression	0.8015/0.9723	0.8330/1.1739
	Lasso regression	1.2447/1.4391	1.2830/1.4617
	SVR	0.6707/0.8807	0.7325/0.9092
	Random Forest	0.2863/0.3668	1.2128/1.7951
	XGBoost	0.4254/0.5931	1.1753/1.7155
Ireland	Ridge regression	1.6740/2.3306	3.0701/3.3862
	Lasso regression	1.5699/2.3343	1.9100/2.5129
	SVR	3.8127/6.9464	2.1237/2.5626
	Random Forest	1.0220/1.4938	1.9731/2.6174
	XGBoost	1.5842/2.0619	2.3419/2.5598
Romania	Ridge regression	1.7029/2.1621	2.0063/2.2010
	Lasso regression	2.6256/3.1741	2.3996/2.4460
	SVR	2.7751/3.4486	2.0078/2.4987
	Random Forest	3.9483/4.3391	5.3848/5.6563
	XGBoost	4.1716/4.2914	3.3208/3.7317
Sweden	Ridge regression	1.0435/1.3857	2.8302/3.8542
	Lasso regression	1.5920/1.9148	2.9468/4.3223
	SVR	1.0239/1.4372	3.0799/4.3640
	Random Forest	0.6192/0.7168	1.8662/3.4137
	XGBoost	1.3476/1.5769	2.1749/3.9465

with narrower relative intervals, suggesting more stable and predictable dynamics across countries.

Systematic differences are observed across model classes. Ensemble-based methods (Random Forest and XGBoost), consistently produce the widest relative intervals across all indicators. This indicates greater sensitivity of these models to resampling variation and underlying data heterogeneity. By comparison, the regularised linear models (Ridge and Lasso) yield substantially narrower intervals, reflecting more stable forecasts with lower dispersion across bootstrap samples. Support Vector Regression occupies an intermediate position, with slightly wider intervals than linear models but narrower intervals than ensemble methods.

These results highlight that lower uncertainty does not necessarily imply superior predictive performance, but rather reflects differences in model flexibility and robustness. Linear models prioritise stability through regularisation, whereas ensemble models capture complex patterns at the cost of higher forecast uncertainty.

Table 13 shows the proportion of true values falling within the 95% confidence intervals of each model's predictions, averaged across 25 countries. This metric reflects the reliability of model uncertainty estimates for each indicator.

Among the five indicators, *Private Investment in CE related sectors* exhibits the highest coverage overall, particularly for XGBoost and Ridge/Lasso regression, indicating that the confidence intervals for these models consistently capture the observed values. In contrast, *Municipal Waste Generation* and *Resource Productivity* display lower coverage for some models, with SVR showing particularly low coverage for *Municipal Waste Generation* and Ridge/Lasso showing lower coverage for *Resource Productivity*. These differences suggest greater predictive uncertainty for these indicators.

Across models, Random Forest and XGBoost tend to produce wider confidence intervals, leading to higher coverage in most cases, whereas Ridge and Lasso regressions have narrower intervals, resulting in slightly lower coverage for some indicators. SVR shows intermediate coverage across all indicators.

5. Discussion

5.1. Differences in forecast accuracy across indicators

Differences in forecasting performance across CE indicators can be explained by a combination of structural, institutional and data-related

Table 12
Average relative bootstrap interval width by indicator and model.

Indicator	Ridge regression	Lasso regression	SVR	Random Forest	XGBoost
Resource Productivity	0.158	0.157	0.170	6.165	6.592
Material Import Dependency	0.102	0.101	0.134	2.839	3.099
Municipal Waste Generation	0.115	0.115	0.113	6.698	6.571
Private Investment in CE related sectors	0.499	0.500	0.578	11.657	11.035
Recycling Rate of Municipal Waste	0.181	0.179	0.194	6.880	7.781

Table 13
Proportion of true values within 95% CI (Coverage) across countries.

Indicator	Ridge regression	Lasso regression	SVR	Random Forest	XGBoost
Resource Productivity	0.659	0.628	0.641	0.656	0.578
Material Import Dependency	0.721	0.706	0.632	0.588	0.676
Municipal Waste Generation	0.625	0.614	0.548	0.749	0.706
Private Investment in CE related sectors	0.771	0.791	0.555	0.736	0.833
Recycling Rate of Municipal Waste	0.708	0.703	0.677	0.656	0.750

factors. Indicators that exhibit higher predictability (*Resource Productivity* and *Material Import Dependency*) are closely tied to macroeconomic structures and long-term policy frameworks. These indicators evolve gradually, reflecting persistent drivers such as industrial composition, energy intensity and technological change. As a result, their trajectories display relatively smooth dynamics and limited short-term volatility, making them more amenable to predictive modelling.

By contrast, indicators related to waste generation and recycling rates are influenced by a broader set of short-term and context-specific factors. These include behavioural responses, regulatory changes, local infrastructure constraints and reporting practices, all of which can introduce abrupt shifts and non-linear dynamics. Such indicators are therefore less stable over time, reducing forecast accuracy even when advanced machine learning techniques are applied. Data quality and measurement consistency further amplify these differences. Predictable indicators tend to be derived from well-established national accounts or trade statistics, which benefit from harmonised methodologies and lower revision frequency. In contrast, waste-related indicators often rely on administrative data collected by multiple agencies, with varying definitions, coverage gaps and retrospective revisions. These features introduce additional uncertainty that limits the capacity of models to learn reliable patterns.

Finally, predictability is affected by the extent to which indicators are policy-driven versus structurally embedded. Indicators anchored in structural economic processes respond slowly to policy interventions and thus follow more regular trajectories. Conversely, indicators that are directly targeted by policy measures such as recycling rates, may exhibit discontinuities when new regulations, incentives or reporting standards are introduced. While these shifts are desirable from a policy perspective, they reduce temporal regularity and complicate forecasting.

Overall, the findings suggest that CE indicators are not uniformly predictable and that ability to forecast is highest where indicators are structurally determined, statistically robust and weakly affected by short-term institutional or behavioural shocks. This has important implications for both model selection and the interpretation of forecast outputs in CE monitoring frameworks.

5.2. Implications for CE policy and early intervention

The analysis of forecast uncertainty across CE indicators provides important insights for policy design and early intervention strategies. *Private Investment in CE related sectors* exhibits the widest relative forecast uncertainty, particularly under Random Forest and XGBoost models. This high level of uncertainty indicates that investment patterns are less predictable, potentially reflecting the influence of external shocks, market sentiment, or policy changes. For policymakers, this suggests that relying on predictive models for annual investment trends should be approached with caution and robust monitoring mechanisms are essential to detect deviations from expected trajectories.

In contrast, *Material Import Dependency* and *Resource Productivity* indicators show narrower relative forecast widths and consistently higher coverage rates under linear models (ridge and lasso), with true values captured within confidence intervals in 70%–72% of cases. This indicates more stable, structurally determined dynamics, making these indicators suitable for anticipatory interventions. For example, predictable trends in resource productivity allow policymakers to implement efficiency improvements or material substitution strategies with greater confidence in their likely outcomes. Likewise, stable import dependency patterns can inform proactive trade and supply chain policies to mitigate potential vulnerabilities.

The indicators of *Municipal Waste Generation* and *Recycling Rate of Municipal Waste* demonstrate moderate uncertainty and coverage rates, reflecting both structural and behavioural influences. For instance, *Municipal Waste Generation* may vary with socio-economic conditions or local policy responses, suggesting that adaptive measures such as iterative waste reduction programs or localised recycling incentives are more effective than rigid long-term targets.

Overall, the heterogeneous predictability and coverage across CE indicators underscore the importance of tailoring early intervention strategies. Indicators with high coverage and narrow relative width support proactive policy planning, while those with low coverage and wide uncertainty demand continuous monitoring, scenario analysis and adaptive governance to mitigate risks and enhance resilience.

5.3. Regime shifts and structural change

Major policy interventions, regulatory reforms or shifts in reporting standards can cause abrupt changes in indicator trajectories. Such events alter the underlying data-generating process, limiting the ability of models trained on historical patterns to extrapolate future outcomes accurately.

Regime shifts are particularly evident in indicators that are directly targeted by policy, such as recycling rates and waste management outcomes. When new regulations, economic incentives or compliance mechanisms are introduced, they can induce step changes rather than incremental trends. While these shifts often reflect successful policy action, they reduce temporal continuity and weaken the stability assumptions underpinning most forecasting methods.

From a policy perspective, the presence of regime shifts implies that forecasts should be interpreted conditionally on institutional and economic context. Rather than viewing forecast errors solely as model failures, deviations from predicted paths may signal genuine structural change triggered by policy or external shocks. Incorporating mechanisms to detect or account for such shifts such as rolling estimation windows or structural break diagnostics could enhance the usefulness of forecasting tools for CE monitoring.

6. Conclusions

6.1. Methodological contributions

This study addresses a key gap in CE monitoring research, where prior approaches have been largely descriptive and aggregate, with limited forecasting at the national level. By developing and evaluating a suite of machine learning models across five CE indicators for 25 EU Member States, we demonstrate the feasibility and limitations of predictive approaches. Analysis of ACF and PACF confirms that traditional autoregressive methods are unsuitable due to weak temporal autocorrelation and a replicable, scalable modelling pipeline has been established, enabling future research to extend the approach to additional indicators or contexts. Results also identify an optimal feature set size for generalisation and reveal structural limits in forecasting capacity when working with small CE datasets.

6.2. Empirical findings

Forecasting performance varies substantially across indicators and countries. *Resource Productivity* and *Material Import Dependency* are comparatively more predictable, reflecting stronger structural drivers and higher data quality. By contrast, indicators related to waste generation and recycling rates exhibit greater volatility and weaker predictive accuracy, largely due to data scarcity and lower precision of available statistics. Predictive benchmarks across the five indicators highlight where forecasts are reliable and where uncertainty remains high, emphasising the need for improved data collection to support CE monitoring.

6.3. Policy and public implications

The framework developed in this study produces forecasts accompanied by measures of uncertainty, such as relative interval widths and coverage. These metrics allow assessment of the stability and reliability of predictions across different indicators and countries, highlighting where forecasts are relatively more precise and where uncertainty remains high. Such information can support policymakers in identifying areas where forecasts provide stronger guidance and where caution is warranted, informing early-warning monitoring, priority-setting and the design of interventions.

6.4. Limitations and future research

While the machine learning models developed in this study provide useful predictive insights, their overall performance is constrained more by the characteristics of the data than by model choice. The primary limitation to more accurate CE forecasting is the availability and quality of data. The framework developed in this study provides a systematic approach to monitor CE indicators across Europe, but its predictive potential is constrained until datasets become more complete, consistent and granular. Efforts to improve data continuity, coverage and harmonisation are likely to yield greater gains in forecast reliability than further refinement of modelling techniques (Mohammed et al., 2025). With such improvements, this approach can enable more frequent, rigorous and evidence-based assessments of national CE performance. From a policy perspective, these results reinforce the role of machine learning as a decision-support and early-warning tool, rather than a definitive predictor. Forecasts are most reliable within the range of previously observed conditions, but deviations from model expectations can serve as a diagnostic signal. Systematic departures from predicted trends may indicate structural changes in the system such as technological innovation, policy intervention or behavioural shifts that warrant closer examination (Maffei et al., 2020). Monitoring the magnitude and direction of such deviations can therefore support timely policy evaluation and adaptive management.

The study also highlights several avenues for future research. First, expanding the EU CEMF and incorporating higher frequency or more granular data could improve forecast accuracy and enable more targeted policy applications. Second, integrating regime shift detection into the modelling framework would help account for structural breaks in the system, increasing the robustness of forecasts under evolving conditions. Third, combining predictive modelling with causal inference methods could provide a stronger basis for understanding the drivers of CE transitions, enhancing the relevance of forecasts for policy design.

As European data systems continue to expand and harmonise, the predictive framework developed here is expected to become increasingly reliable and actionable. Improved data quality and coverage will not only enhance the accuracy of forecasts, but also support adaptive, evidence-based policymaking, enabling EU and national authorities to anticipate trends, evaluate interventions and guide the transition towards a sustainable circular economy (European Commission, 2024).

CRediT authorship contribution statement

Niamh McMahon: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Colin Fitzpatrick:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition. **Cornelis P. Baldé:** Writing – review & editing, Methodology, Investigation. **Sara Bottausci:** Writing – review & editing, Methodology. **Eoin M. Grua:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Colin Fitzpatrick, Eoin M.Grua, Sara Bottausci, Niamh McMahon reports financial support was provided by Environmental Protection Agency Ireland. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jclepro.2026.147982.

Data availability

The data collected for this research consists of publicly accessible datasets from the Eurostat database. They are appropriately referenced in the paper.

The complete modelling framework and associated code supporting this study are publicly available at the following repository: https://github.com/niamhcmcmahon/CEIndicatorForecasting.

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