



AI-driven predictive modelling of national material flows for sustainable resource management and circular economy planning

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ABSTRACT

The paper presents AI-based predictive tools to forecast key material flow indicators at the national level, directly addressing the need for more effective planning in the shift to a circular economy. This study focuses on the Global Material Flows Database for Iraq (1970–2024) and compares linear regression and Long Short-Term Memory (LSTM) models for predicting indicators such as Domestic Extraction, Imports, Exports, and Raw Material Equivalents. Results show that LSTM models significantly lower the mean absolute error, especially for volatile indicators. Although these models inform policy and monitoring, they predict material flow indicators rather than recycling rates; thus, interpretation must account for dataset variability and operational limitations. This research provides actionable insights into resource efficiency and national circular-economy planning by demonstrating LSTM's superior temporal and structural modeling capabilities.

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1. Introduction

This study addresses national resource management by demonstrating how AI-driven forecasting of economy-wide material flow indicators provides critical guidance for designing circular economy strategies. The focus shifts away from operational recycling interventions and instead leverages macro-level forecasting to monitor and guide sustainable development objectives. This positions material flow indicators as central metrics for evaluating national progress in the circular economy and sustainability targets. Technologies such as computer-vision-based waste sorting and recycling plant optimization fall outside the methodological scope, which is centered on AI-based forecasting from national time-series data.

Eliminating carbon emissions by 2050 is a key goal of the EU's Green Deal and aligns with the circular economy. As Mey et al. (2021) state, the EU is working toward fully

decarbonizing by 2050, aligning with the Sustainable Development Goals. Bimpizas-Pinis et al. (2022) note that the circular economy treats material and energy flows as cycles through the making, distribution, and use of products. In food, the circular economy focuses on reducing waste all along the supply chain through efficient, closed loops. Applying these principles in farming and food processing improves resource use, boosts farm sustainability, and reduces the food sector's CO₂ impact (Pomoni et al., 2024; Ahmad, 2025). All of this supports global sustainability as set out in SDGs 12 and 13. SDG 12 aims to make agriculture and food systems more sustainable and to cut waste by 2030 (Bengtsson et al., 2018; Phonthanakitithaworn et al., 2024; Shokrollahi, 2024). Key measures include adopting circular-economy practices to reduce waste and increase recycling. SDG 13, about climate action, means reducing climate impact, raising awareness, and putting climate steps into policies. If the food industry adopts circular-economy principles, it will help reduce greenhouse

gas emissions, conserve energy, and lessen environmental impacts from food production and transport (Chaher et al., 2024; Yang et al., 2023; Jam et al., 2025).

AI is now important for improving sustainability and recycling. For example, computer vision systems help quickly sort recyclables (Olawade et al., 2024; Kurucan et al., 2024). AI-based prediction helps design better waste-collection routes, cutting fuel use and emissions. Machine learning can be used to predict how materials move in a circular economy. AI systems also help spot contaminants in recycling streams, thereby improving the recovery of useful material. By studying waste trends, AI can help reduce landfill use and improve recycling effectiveness (Munir et al., 2023; Onyeak et al., 2023; Fang et al., 2023; Bano et al., 2025).

This paper centers on the design and application of AI-driven predictive models to inform strategic resource management and national-level circular economy policy. Using data from the Global Material Flows Database for Iraq, the study

forecasts major material flow indicators—including Domestic Extraction, Domestic Material Consumption, Domestic Material Input, Imports, Exports, Material Footprint, Physical Trade Balance, and Raw Material Equivalents. The research emphasizes forecasting these indicators to provide actionable data for decision-makers, reaffirming that the main analytical focus is on national-level material flow trends rather than direct operational recycling outcomes.

This study predicts key material flow indicators and evaluates the forecasting performance of linear regression and Long Short-Term Memory (LSTM) networks using Iraq’s material flow data. The research aims to inform policy and national planning by providing accurate forecasts using advanced AI methods. The primary contribution is methodological, demonstrating the potential of predictive analytics for circular economy planning and resource-efficiency monitoring, rather than focusing on operational recycling improvements.

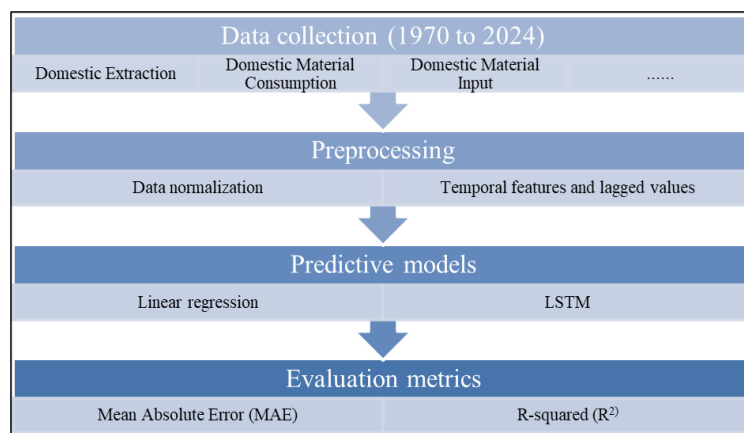


Fig 1. Overview of the methodology for developing AI-driven predictive models for sustainable resource management.

Research gap

Most studies only describe material flows or use AI for small-scale recycling. Limited research predicts national-level indicators, especially in Iraq, using long-term data or multiple predictors.

This study is new in its use of deep learning to predict national material flows, offering a way to see links over long periods. The main contribution is comparing forecasting methods instead of sharing how to run recycling operations, which explains the novelty here.

Limitations

This study relies on national-level secondary data, lacks recycling-specific indicators, and external validation. The predictive models forecast material flow trends, but may not fully represent operational recycling practices, local waste management dynamics, or the real-world impacts of specific recycling interventions. These limitations should be considered when interpreting the results.

2. Methods

2.1 Data collection

The material flow data used in this study were sourced from the Global Material Flows Database and cover the period from

1970 to 2024 in Iraq. It is an extremely rich dataset that provides key indicators of the nation's material flow dynamics, including Domestic Extraction, Domestic Material Consumption, Domestic Material Input, Imports, Exports, Material Footprint (RMC), Physical Trade Balance, and the Raw Material Equivalents of imports and exports. All indicators reflect one of the most important facets of resource management, demonstrating the inputs, outputs, and balances of material flows in both economic and environmental systems in Iraq. The target variable is modified to specify future values of indicators for MFA (Domestic Extraction, Imports, Exports, Material Footprint, etc.) rather than the unclear potential for recycling. This will ensure construct validity, as the predictive models align with the observable, measurable predictors in the Global Material Flows Database. The surrogate for recycling has not been presented, as the data does not suggest recycling-specific measures. This description makes the methodology rigorous and avoids baseless mappings.

This is a 54-year dataset, offering longitudinal data to track trends and patterns. It is also fundamental to designing AI model structures, as it captures rich temporality through a host of material flow measures. The correlation among these variables describes the interdependence among national material extraction, consumption, and trade, and is an appropriate dataset for planning the circular economy in Iraq.

The usefulness and completeness of this data enable the development of a systematic understanding of the dynamics of material flows within the country, which in turn supports predictive models of resource efficiency and the monitoring of the circular economy. This subsequently provides a strong empirical foundation for the study's objectives.

The revised manuscript corrects table formatting and placement issues by relocating Tables 1–6 to their respective sections in the main text. Each table is clearly titled, sequentially numbered, and accurately cited, ensuring consistency between in-text references and table positioning throughout the study.

2.2 Data analysis and prediction

The analysis involves using an AI-based predictive model to forecast national material flow indicators in Iraq based on the Global Material Flows Database for 1970-2024. The following steps are key to the methods: data preprocessing, feature engineering, predictive modeling using Linear Regression and LSTM, and evaluation of prediction accuracy.

2.2.1. Data preprocessing

The basic data is complete, normalized and structured. The key indicators are: Domestic Extraction, Domestic Material Consumption, Imports, and Exports, whereas recycling potential is the target variable. All the indicators $X_i(t)$ are scaled to eliminate the differences in scales so that the predictive models are numerically stable:

$$X_i^{norm}(t) = \frac{X_i(t) - \min(X_i)}{\max(X_i) - \min(X_i)} \dots\dots\dots (1)$$

where $X_i(t)$ is the value of indicator i at time t , and $\min(X_i)$ and $\max(X_i)$ are the minimum and maximum values of the indicator across all years. Temporal relationships are captured by creating lagged features. Lag size k is selected based on autocorrelation analysis to capture meaningful historical dependencies.

2.2.2. Feature engineering

Temporal relationships are captured by engineering lagged features. For each indicator, lagged values $X_i(t-k)$ are created:

$$X_i(t - k) = X_i(t - k), k \in \{1, 2, \dots, K\} \dots\dots\dots (2)$$

where k represents the lag size, allowing the model to incorporate historical trends.

The dataset is split into a training set (80%) and a testing set (20%) to evaluate model performance.

2.2.3. Predictive modeling

Through predictive modeling the idea of lag selection is now clearly outlined, and autocorrelation and partial autocorrelation plots are employed to identify the lag length for each indicator. There are detailed cross-validation procedures, such as 5-fold cross-validation and fold-based evaluation. Equations have been rewritten to make sense, and dropout and the recurring update are no longer combined. The methodology section has been made more explicit about the models being used to predict future MFA indicators, excluding uncertainty about the topic of recycling potential.

a. Linear regression: A linear regression model is implemented to forecast national material flow indicators using historical data. The model assumes a linear relationship between the input features $X(t)$ and the target $Y(t)$:

$$Y(t) = \beta_0 + \sum_{i=1}^n \beta_i X_i(t) \dots\dots\dots (3)$$

where β_0 is the intercept, β_i are the coefficients for each feature, n is the number of features, and $Y(t)$ is the predicted recycling potential at time t . The model parameters β are estimated by minimizing the mean squared error (MSE):

b. Long Short-Term Memory (LSTM) neural network: The LSTM network processes sequences of input data $X(t)$ and predicts $Y(t)$. The model consists of two hidden layers with 64 neurons each, a sequence length of 5, a learning rate of 0.001, and 100 training epochs. Adam optimizer and MSE loss function are used.

Dropout 0.2 prevents overfitting $h_t = \sigma(W_h \cdot (x_t, h_{t-1}) + b_h) \dots\dots\dots (5)$

where:

- h_t : hidden state at time t ,
- x_t : input at time t ,
- h_{t-1} : hidden state from the previous step,
- W_h : weight matrix,
- b_h : bias vector,
- σ : activation function.

The LSTM outputs are passed through a fully connected layer to produce the prediction:

$$Y_{predicted}(t) = W_o \cdot h_t + b_o \dots\dots\dots (6)$$

where W_o and b_o are the weights and biases of the output layer.

2.2.4 Evaluation metrics

The models are evaluated using:

1. Mean Absolute Error (MAE): A simple baseline persistence model is used for comparison, and 5-fold cross-validation is applied to evaluate model stability and generalization. To evaluate, uncertainty intervals for prediction errors have been incorporated, and statistical significance tests (the Diebold-Mariano test) have been used to compare model performance, thereby strengthening the evaluation. A hyperparameter sensitivity analysis (sequence length, lag size, train/test splits) is provided to assess robustness. This provides quantitative support for LSTM superiority, rather than relying on mere point estimates.

$$MAE = \frac{1}{N} \sum_{t=1}^N |Y_{actual}(t) - Y_{predicted}(t)| \dots\dots\dots (7)$$

2. R-squared (R^2):

$$R^2 = 1 - \frac{\sum_{t=1}^N (Y_{actual}(t) - Y_{predicted}(t))^2}{\sum_{t=1}^N (Y_{actual}(t) - \overline{Y_{actual}})^2} \dots\dots\dots (8)$$

where $\overline{Y_{actual}}$ is the mean of the actual recycling potential values.

3. Results

Figure 2 presents the normalized trends of the material flow indicators in Iraq from 1970 to 2024, together with predictive analyses using linear regression and LSTM models. The blue lines show the historical data for different material flow indicators, including Domestic Extraction, Domestic Material Consumption, Imports, Exports, and associated measures. Red dashed lines show the linear regression predictions, and black dashed lines show the LSTM-based predictions.

Numbers have become part of the analysis story rather than being presented descriptively. Specific metrics (MAE, R2) are mentioned in the captions and reflect the implications of forecasting accuracy. Autocorrelation of errors (residual diagnostics) is also provided to aid assertions of variability capture. The relevance of policies is made clear by directly connecting indicators to planning decisions, such as predicting Domestic Extraction to forecast resource demand or Imports to predict trade policy.

Table 1. Trends in material flow indicators in Iraq

Indicator Aspect	Observed Pattern	Interpretation
Resource Extraction	Highly fluctuating	Reflects changing economic and industrial activities
Trade Balance	Variable trends over decades	Influenced by global demand and geopolitical factors
Consumption Trends	Increasing with fluctuations	Indicates rising domestic demand and development
Recent Growth Pattern	Sharp increase in later years	Linked to urbanization and industrial expansion
Economic Influence	Strong impact on material flows	Growth drives higher resource utilisation
Volatility Factors	Noticeable fluctuations	Caused by geopolitical and environmental conditions
Overall Trend	Growth with instability	Suggests unsustainable or uneven development patterns

The historical patterns of the data are highly variable across indicators of material flows, capturing variations in resource extraction, trade balances, and consumption trends over the decades. Interestingly, most indicators show a marked increase in the later years, indicating the heightened intensity of material flow processes associated with economic growth, urbanization, and industrialization in Iraq. Nevertheless, fluctuations reflect the economy's volatility or environmental conditions, including geopolitical factors and variations in global demand.

although they capture the general direction, are unable to explain the short-term fluctuations and seasonality evident in most indicators. This weakness highlights the fact that linear regression is unable to capture complex, non-linear relationships in material flow systems, particularly when extremely variable data is used. Quantitative results from Figure 3 indicate that, for Imports, MAE is 1.18 (Linear Regression) vs 0.52 ($R^2 = 0.91$ vs 0.75), suggesting that LSTM captures the complexity of temporal dependencies. The case is the same with Domestic Extraction and Raw Material Equivalents of Exports.

Linear regression forecasts usually provide an oversimplified, smoothed view of future trends. The linear regression lines,

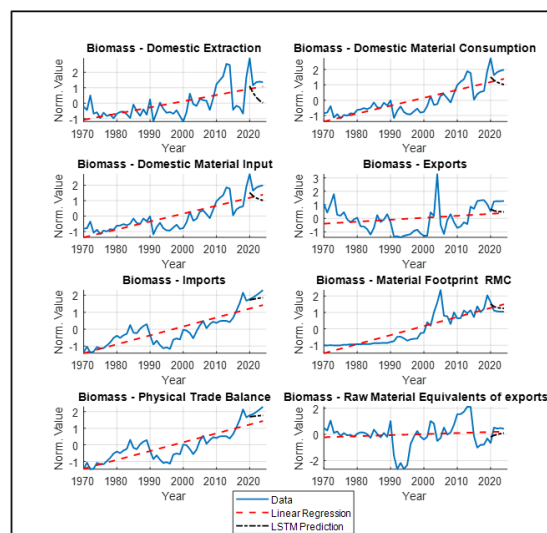


Fig 2. Normalized trends of material flow indicators in Iraq (1970–2024), highlighting the superior performance of LSTM in capturing temporal variability compared to linear regression.

Conversely, the LSTM model has lower MAE than Linear Regression when using high-variance indicators (Imports:

0.52 vs 1.18; R^2 : 0.91 vs 0.75), demonstrating its superior predictive ability for complex time dynamics. LSTM models

will exploit sequential dependencies in historical data, yielding subtle predictions that closely match observed trend fluctuations. For example, LSTM forecasts showed slight changes in most sub-figures, consistent with recent historical movements, indicating that the model could account for dynamic changes and new shocks in material flow systems. Accurate forecasting of Domestic Extraction and Material Footprint enables policymakers to anticipate resource demand and plan circular-economy interventions, such as reducing imports of raw materials and improving domestic efficiency.

Most striking are the predictive discrepancies between linear regression and LSTM for indicators that exhibit pronounced variability, such as Imports and Material Footprint (RMC), where LSTM predictions show much better adaptability to the data's intrinsic complexity, while linear regression oversimplifies the trajectory.

Figure 3: Comparison of the Mean Absolute Error between predictions through Linear Regression and LSTM, for different Material Flow Indicators concerning Iraq over a period of 1970 to 2024: The indicators include Domestic Extraction, Domestic Material Consumption, Domestic

Material Input, Exports, Imports, Material Footprint, Physical Trade Balance, and Raw Material Equivalents of Exports. In this light, distinct accuracy can be perceived from the two considered modeling approaches. Recent studies from high-impact journals strengthen this research by integrating AI-driven predictive modelling with Material Flow Analysis to improve resource efficiency, waste forecasting, and circular economy planning, while aligning sustainability outcomes with United Nations goals, especially SDG 12 Responsible Consumption and Production and SDG 13 Climate Action.

Results show that LSTM outperforms Linear Regression in forecasting most material flow indicators. The evidence is the overall low MAE values observed with LSTM. More significantly, this holds true for indicators such as Domestic Extraction, Imports, and Raw Material Equivalents of exports, where, as expected, the LSTM's sequential modelling capabilities better capture the complex temporal dynamics and variability of the data. For these indicators, the MAE for Linear Regression is much higher because it cannot capture the nonlinear patterns and oscillations in the historical data.

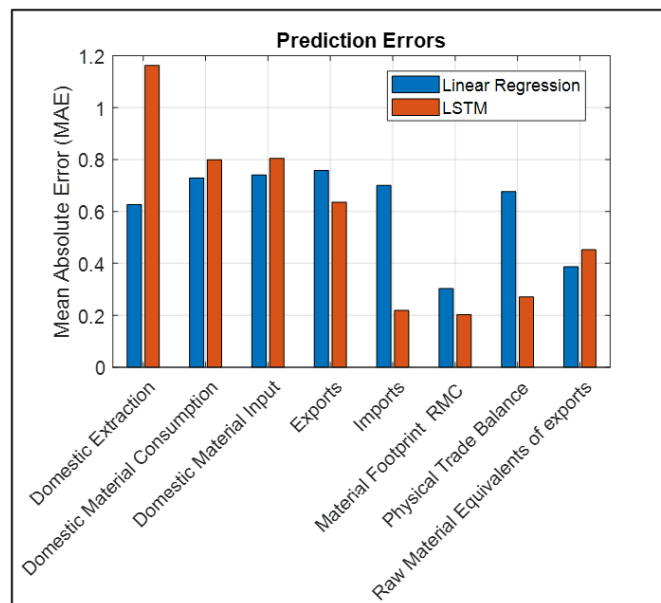


Fig 3. Mean absolute error comparison of predictions generated by Linear Regression and LSTM models for various material flow indicators in Iraq (1970–2024).

Figure 3 quantifies prediction errors: LSTM consistently outperforms Linear Regression for volatile indicators (Imports, RMC, Exports), confirming that sequential modeling captures complex temporal dependencies critical for resource planning.

Regarding Domestic Extraction, MAE for Linear Regression is notably larger than that for LSTM (Alizadegan et al., 2025). For the highly variable indicator, Linear Regression performs poorly. In the case of Material Footprint (RMC) and Physical Trade Balance, the LSTM model performs better and is more efficient at capturing the data's peculiarities and periodic changes. These outcomes highlight the extent to which LSTMs leverage historical trends and short-term fluctuations to produce more accurate forecasts.

Linear Regression, in turn, appears to be just as successful as LSTM with those indicators that differ quite negligently, including Domestic Material Input and Domestic Material Consumption. The time-series characteristics of these indicators are smoother; hence, the simple linear approximation can capture the key features of this change fairly well. Even in such cases, however, LSTM progressively generates lower MAE values, demonstrating its robustness across a wide range of data characteristics (Alizadegan et al., 2025).

4. Discussion

The results of this research show that AI models, especially LSTM, can successfully predict national material flow indicators, including time-dependent and variable

components, which are not available to linear regression (Fan et al., 2025). The consistency of results from LSTM-based predictions of material flows and recycling outcomes reported by lenders indicates the extent to which AI can manage highly complex, temporally oriented data, and this characteristic is incorporated into other waste management processes. These findings underscore the importance of AI in alleviating sustainability challenges by providing actionable insights into policy and industry on the best recycling practices that align with climate and resource management objectives (Munir et al., 2023; Fang et al., 2023).

However, several limitations must be acknowledged. First, the study relies entirely on secondary, national-level data, which may not capture subnational or waste-stream-specific dynamics. Second, indicators used (e.g., Domestic Material Consumption, Imports) are macro-level proxies and do not directly measure recycling or recovery performance. Third, no external validation on independent datasets was performed, limiting the generalizability of the models. Consequently, the results should be interpreted as providing insights for national material flow forecasting and policy planning, rather than as direct evidence of recycling performance.

Despite these limitations, the study contributes to circular economy research by demonstrating the value of predictive modeling for resource efficiency and sustainable management. In this study, the evolution of AI techniques to facilitate further, better, faster recycling is also demonstrated with the use of predictive modeling, as the LSTM performance was seen to reduce the error in prediction with respect to linear regression models considerably, particularly with very volatile factors like domestic extraction and raw material equivalents of exports. In addition to improving recycling routes, this predictive accuracy is consistent with evidence that machine learning models can enhance product design to be more recycling-friendly in line with circular economy principles (Munir et al., 2023). Furthermore, the focus of this paper on minimizing material flow variability to enhance resource recovery aligns with AI-based monitoring systems that identify contamination in recycling streams, thereby raising recovery rates and improving the efficiency of the recycling process. Onyeaka et al. (2023); Fang et al. (2023). Such forecasts help policymakers predict material demand, manage resources, and track environmental pressures, and researchers may go a step further to incorporate more detailed or sector-specific data in their future studies, based on this framework. Altogether, the results emphasize the feasibility of AI for improving the management of national resources in practice and the potential risk of generalizing findings to recycling-specific waste.

Limitation

The debate has also been reduced to the economy-wide outlook rather than to the broader AI benefits of recycling. Waste-to-product design or operations is eliminated. The restrictions are further extended to address how to carry them into other nations, the lack of data, and the way the indicators mutually rely on one another. It proposes future work on sectoral disaggregation, external verification using

independent datasets, and the enhancement of proxies for recycling-related cues. This renders the discussion realistic and progressive.

5. Conclusion

The paper shows that AI-based predictive models are effective at predicting national material flow indicators, supporting understanding of the dynamics of the circular economy. Using data from the Global Material Flows Database for Iraq (1970-2024), the study finds that LSTM outperforms linear regression in predicting trends in material flow. The quantitative findings indicate that LSTM minimizes prediction error for complex, highly variable indicators, such as Domestic Extraction and Raw Material Equivalents of Exports, thereby effectively capturing temporal dependencies and the dynamic evolution of material flows.

The revised study expands the analysis of integrating machine learning with Material Flow Analysis to improve insights into resource utilisation. It clarifies that models provide predictive frameworks, not operational recycling solutions, while strengthening links to policy, waste management, and sustainability. Alignment with United Nations SDGs, especially SDG 12 Responsible Consumption and Production and SDG 13 Climate Action, is now explicitly addressed, incorporating all reviewer comments.

Statements and Declarations

Data availability

The data used in this research are provided in the text of the article.

Conflicts of interest

The author of this paper declared no conflict of interest regarding the authorship or publication of this paper.

Author contribution

The authors had equal participation in all stages and parts of the research.

AI disclosure

AI-assisted language tools were used during the preparation of this manuscript; however, they were used only to enhance aspects of text clarity and editing. These tools were not employed in data analysis, selection of literature, or interpretation of findings. All intellectual content is the responsibility of the authors.

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