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Harnessing Artificial Intelligence for Foresight in the U.S. Circular Carbon Economy Transition: A Quantitative Economic Perspective

BEN AMMAR Dawed[1], **MAHRI Abdelmalek** *[2]*

[1] *(Laboratory of Entrepreneurial & Administration of Organizations, University of Tebessa, Algeria)*

[2] *(Laboratory of Entrepreneurial & Administration of Organizations, University of Tebessa, Algeria)*

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Abstract:

This study aims to integrate deep learning (DL) with environmentally extended input-output (EEIO) analysis to model the U.S. circular carbon economy (CCE). The objective is to forecast key CCE indicators, such as carbon capture rates and emissions reduction pathways, by leveraging AI's pattern recognition and economic modeling's structural clarity. Results demonstrate that the hybrid framework provides data-rich insights into carbon flows and economic impacts, as shown through illustrative tables and figures. Despite challenges in data sourcing and model integration, the approach offers actionable guidance for policymakers and industry leaders to navigate the CCE transition.

Keywords: *Circular Carbon Economy, Artificial Intelligence, Quantitative Economics, Deep Learning, Input–Output Analysis, Carbon Capture Utilization and Storage, Climate Policy, United States, Sustainable Development.*

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* - *Corresponding author: BEN AMMAR Dawed, e-mail: dawed.benammar@univ-tebessa.dz.*

1. *Introduction*

The escalating urgency of climate change calls for more than just incremental adjustments; it demands a fundamental reshaping of our economic metabolism (IPCC, 2023). At the heart of this necessary transformation lies the concept of the Circular Carbon Economy (CCE) (MDPI, n.d.). Moving beyond the linear "take-make-dispose" paradigm that has historically fueled carbon emissions, the CCE champions a systemic approach: reducing the carbon we generate, finding innovative ways to reuse it, developing robust systems for recycling carbon-intensive materials, and implementing technologies for carbon removal. This ambitious vision seeks to decouple economic vitality from resource depletion and environmental harm, recasting carbon not as a burdensome waste but as a valuable resource ripe for innovation.

The United States, given its economic scale and historical emissions profile, is a pivotal player in driving the CCE transition (BEA, n.d.; EIA, 2024). Achieving ambitious national climate targets requires strategies that go beyond traditional emissions reductions, actively embracing circularity in carbon management. This includes scaling up Carbon Capture, Utilization, and Storage (CCUS), advancing sustainable materials management practices, and deepening the integration of energy efficiency and renewable sources (DOE, n.d.; IEA, n.d.). These elements are not just environmental imperatives; they are pathways to enhancing economic resilience and forging new avenues for growth and employment.

Yet, the sheer scale and multifaceted nature of the U.S. economy, coupled with the intricate flows of carbon across its diverse sectors, make understanding current dynamics and charting credible future CCE pathways a formidable challenge (BEA, n.d.; EIA, 2024). While quantitative economic models offer essential tools for dissecting these complexities, they sometimes struggle to fully encapsulate the rapid pace of technological evolution and the non-linear relationships that characterize transitions of this magnitude. Here, Artificial Intelligence, particularly advanced machine learning techniques like deep learning, emerges as a powerful complement, offering enhanced analytical and predictive capabilities (McKinsey & Company, n.d.).

This article seeks to harness this synergy. We explore how the integration of quantitative economic modeling with cutting-edge AI can yield deeper, more actionable insights into the U.S. CCE transition.

Our specific contribution is the proposal of an integrated modeling framework. This framework is designed to tap into the granular structural detail provided by Environmentally Extended Input-Output (EEIO) models, marrying it with the potent predictive power of Deep Learning (DL). The aim is to build a more robust and dynamic tool for forecasting key CCE indicators and shedding light on the potential effectiveness of various policy levers within the unique context of the U.S. economy.

The journey through this research unfolds as follows: Section 2 surveys the relevant academic landscape, reviewing work on quantitative economic modeling, the application of AI in environmental analysis, and the contours of the U.S. CCE. Section 3 lays out the architecture of our proposed integrated modeling framework and details the crucial data requirements. Section 4 offers a glimpse into the potential insights, presenting illustrative examples of quantitative analysis, complete with conceptual tables and figures that demonstrate the types of outputs such a model could generate. Section 5 delves into the broader implications of this approach, discusses the inherent challenges, and highlights its relevance for policy formulation. Finally, Section 6 draws key conclusions and charts a course for future research endeavors.

2. *Literature Review*

To navigate the multifaceted terrain of the CCE, we must synthesize knowledge from distinct yet interconnected fields: quantitative economics, environmental science, and computer science. This section provides an overview of the foundational work in these areas that informs our integrated approach to modeling the U.S. CCE.

2.*1 Quantitative Economic Modeling for Environmental Insight*

For decades, quantitative economic models have served as indispensable tools for analyzing the intricate interplay between human economic activity and its environmental footprint. Models like Computable General Equilibrium (CGE) models and Integrated Assessment Models (IAMs) have been widely used to simulate the broader economic consequences of climate policies and assess the systemic impact of technological shifts (Kleinman Center for Energy Policy, 2024). A particularly relevant branch for our study is the development of Environmentally Extended Input-Output (EEIO) models.

These models build upon the detailed input-output tables that map the flow of money between industries, extending them to include 'satellite accounts' that track the environmental resources used and the pollutants emitted throughout complex supply chains (SimaPro, n.d.). The U.S. boasts a sophisticated example in the USEEIO model, offering a comprehensive lens through which to examine the environmental implications of U.S. economic processes. These models are fundamental to understanding the embedded carbon within economic transactions and identifying strategic points for intervention within a circular framework.

2.2. The Growing Role of Artificial Intelligence in Environmental and Economic Forecasting

The rapid evolution of AI, particularly in machine learning and deep learning, has opened new frontiers in both environmental science and economic forecasting. AI techniques excel at discerning subtle patterns, managing vast datasets, and modeling the kind of non-linear relationships that often defy conventional statistical approaches (McKinsey & Company, n.d.).

In the environmental domain, AI has proven valuable for tasks ranging from predicting localized air quality and forecasting renewable energy output to analyzing shifts in land use patterns. Economically, AI has been successfully applied to forecasting macroeconomic indicators, analyzing the complexities of financial markets, and modeling dynamic consumer behavior (International Journal of Research Publication and Reviews, 2025).

The application of AI within the specific contexts of the circular economy and carbon cycles is a more recent, but rapidly expanding, area of research. AI is being explored to optimize resource allocation, enhance the efficiency of waste sorting and recycling, refine the design of products for circularity, and streamline complex logistical networks for circular material flows (McKinsey & Company, n.d.). Deep Learning models, particularly those adept at handling sequential data like Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, are particularly well-suited for time series forecasting of the dynamic environmental and economic variables central to the CCE.

2.3. Mapping the U.S. Circular Carbon Economy

The U.S. CCE is not a static concept but a vibrant, evolving ecosystem of activities aimed at managing carbon more circularly. Key pillars of this ecosystem include:

- **Carbon Capture, Utilization, and Storage (CCUS):** This suite of technologies captures CO_2 emissions from large point sources or directly from the atmosphere. The captured carbon can then be repurposed for industrial uses – from enhancing oil recovery to serving as an input in building materials or synthetic fuels – or securely stored underground in geological formations. Significant policy momentum and substantial public and private investments are currently directed towards accelerating CCUS deployment across the U.S. (DOE, n.d.; IEA, n.d.).
- **Sustainable Materials Management (SMM):** This involves strategies focused on minimizing the initial demand for virgin materials, extending the useful life of products and components, and dramatically increasing rates of recycling, repair, and reuse. By keeping materials in circulation longer, SMM directly reduces the embodied carbon associated with producing new goods (EPA, n.d.).
- **Energy Efficiency and Renewable Energy:** These foundational elements, while broader than the CCE itself, are fundamental to reducing the reliance on fossil fuels and thus minimizing the amount of carbon entering the economic system in the first place (EIA, 2024).
- **Innovation in Circular Business Models:** The emergence of new business models centered around product-as-a-service offerings, shared platforms, and closed-loop production systems fundamentally alters how value is created and sustained, promoting circularity (European Investment Bank, 2024).

A deep understanding of how these diverse components interact, their individual trajectories, and their collective economic implications is paramount for successfully navigating the U.S. CCE transition. This necessitates rigorous quantitative analysis to evaluate the economic feasibility of different circular strategies, gauge the effectiveness of policy interventions, and pinpoint promising areas for investment and job creation.

2.4. Forging a Path: Integrating Quantitative Economics and AI for CCE Analysis

The combined power of quantitative economic models and AI holds transformative potential for a more insightful analysis of the CCE than either approach can offer in isolation. EEIO models provide the essential structural backbone, mapping the complex network of physical and monetary flows (SimaPro, n.d.). AI, conversely, brings enhanced predictive capabilities, capable of discerning and modeling the non-linear relationships and dynamic shifts that economic models alone may oversimplify (International Journal of Research Publication and Reviews, 2025).

For example, AI could offer more precise forecasts of how quickly new CCUS technologies will be adopted across different industries, predict subtle shifts in consumer preferences towards durable or shared products, or estimate the nuanced impact of specific policy incentives on carbon flows with greater accuracy than traditional econometric regressions (McKinsey & Company, n.d.). While the explicit integration of quantitative economic models and AI specifically for analyzing the U.S. CCE is an emerging area, the potential synergies are clear.

Economic models provide the crucial context and a framework for understanding system-wide impacts, while AI offers the advanced analytical horsepower needed to process complex data, identify subtle patterns, and generate more robust forecasts in a rapidly changing environment. Tools like those being developed at NREL, such as the BEIOM model and the Circular Economy Agent-Based Model, represent encouraging steps towards integrating different modeling paradigms for comprehensive circular economy analysis (NREL, 2024).

3. Integrated Modeling Framework and Data Foundation

To unlock the full potential of integrated analysis for the U.S. CCE, this study proposes a modeling framework that strategically combines the established rigor of EEIO analysis with the advanced capabilities of Deep Learning (DL). This framework is specifically designed to leverage the detailed structural representation of economic and environmental linkages while simultaneously exploiting AI's prowess in identifying complex patterns and generating dynamic forecasts.

3.1. Framework Architecture

Our proposed framework is structured around several interconnected stages:

1. Comprehensive Data Curation: This initial stage involves meticulously gathering, cleaning, and organizing diverse datasets covering economic activity (BEA, n.d.), carbon emissions broken down by sector (EIA, 2024), material flows throughout the economy (EPA, n.d.), the current state and planned deployment of CCUS technologies (DOE, n.d.), details of relevant policy interventions (NCSL, 2025), and data on the maturity and adoption rates of key circular technologies in the U.S. (IEA, 2024).

2. EEIO Model Initialization and Refinement: At this stage, we would either adopt an existing, high-resolution U.S. EEIO model (such as USEEIO) or adapt one to better reflect the specific nuances of carbon flows and circular activities (SimaPro, n.d.). This component serves as the foundational structural representation of the economy, providing a detailed map of direct and indirect carbon emissions embedded within the production and consumption of goods and services across all sectors.

3. Feature Engineering for Dynamic Analysis: Building upon the EEIO structure and supplementary datasets, we would engineer a rich set of features specifically designed to capture the dynamics relevant to the CCE transition for the DL models. This might involve creating indicators tracking changes in industry-specific energy mixes, the material intensity of production processes, levels of investment in circular infrastructure, the stringency of environmental regulations, and other relevant variables.

4. Deep Learning Model Calibration and Training: Here, we would develop and rigorously train DL models, such as LSTMs or Temporal Convolutional Networks (TCNs), which are particularly well-suited for time series forecasting (International Journal of Research Publication and Reviews, 2025).

These models would be designed to take the engineered features as input and predict the future trajectories of critical CCE indicators. Examples of target variables include the projected carbon intensity reductions within specific industrial sectors, the anticipated rate of CCUS technology adoption, or the future volume of key materials recovered and reintroduced into the economy.

5. Synthesizing Models for Scenario Exploration: This crucial step involves integrating the static EEIO structure with the dynamic forecasts generated by the DL models. The DL forecasts can be used to project how the technical coefficients or environmental intensity factors within the EEIO model are likely to evolve over time due to technological advancements, policy impacts, or behavioral shifts (SimaPro, n.d.; International Journal of Research Publication and Reviews, 2025). Alternatively, the EEIO model can provide a structural context for the DL forecasts, ensuring they remain consistent with fundamental economic relationships. Once integrated, the framework facilitates robust scenario analysis, allowing us to explore how different policy choices, technological breakthroughs, or external economic conditions might shape the future of the U.S. CCE.

6. Translating Insights into Action: The final stage focuses on interpreting the complex outputs of the integrated model. This includes employing AI interpretability techniques, such as SHAP (SHapley Additive exPlanations), where appropriate, to understand which factors are driving the model's forecasts (McKinsey & Company, n.d.). The ultimate goal is to translate these quantitative insights into clear, actionable recommendations for policymakers, industry leaders, and other stakeholders involved in steering the U.S. CCE transition.

3.2. Essential Data Prerequisites

Effectively implementing this integrated framework hinges upon the availability of comprehensive, consistent, and sufficiently granular time-series data spanning a range of domains. Key data categories that are essential for populating and training the models include:

- **Granular Economic Transaction Data:** Detailed input-output tables for the U.S. economy are the bedrock for the EEIO component, providing a map of monetary flows between industries (BEA, n.d.). Complementary data on industry-level output, value added, employment figures, and capital investment trends are also vital.
- **Comprehensive Environmental Flow Data:** Detailed data on carbon emissions, broken down not just by broad sector but also by specific sub-sector and fuel type, are crucial (EIA, 2024; EPA, n.d.). Equally important for a CCE focus are detailed datasets on material flows through the economy, including data on primary resource extraction, material use in production, product lifetimes, and waste generation and management streams.
- **CCE-Specific Activity Data:** To capture the nuances of the circular carbon economy, specific data on the operational status and performance of CCUS projects are needed – including captured CO_2 volumes, how that carbon is utilized (e.g., in enhanced oil recovery, chemical production, building materials), and the volumes directed towards geological storage (DOE, n.d.; IEA, n.d.). Data on investments specifically channeled into circular technologies, the establishment and growth of circular business models, and the volumes of materials successfully recirculated (recycled, reused, remanufactured) are also indispensable (European Investment Bank, 2024).
- **Quantified Policy Intervention Data:** Rigorous analysis requires translating policy details into quantifiable data. This involves documenting the implementation dates, stringency levels, and design features of relevant policies, such as carbon taxes or cap-and-trade programs, performance standards for industrial emissions, subsidies or tax credits for clean technologies (including CCUS), and regulations governing waste management and material recovery (NCSL, 2025).
- **Technological Diffusion and Performance Data:** To model the impact of technological change, data on the cost, efficiency metrics, technological maturity levels, and historical

adoption rates of key technologies relevant to the CCE are necessary. This includes data on advanced carbon capture technologies, innovative carbon utilization pathways, and next-generation recycling and material processing techniques (IEA, 2024).

A significant challenge lies in the availability of consistent, high-frequency, and spatially disaggregated data across all these categories for a sufficiently long-time horizon. Continued efforts to improve data collection methodologies, standardize reporting frameworks across different agencies and industries, and enhance data accessibility are paramount for enabling sophisticated quantitative modeling of the CCE.

3.3. Synergistic Quantitative Economic and AI Techniques

The strength of this framework lies in its judicious combination of specific quantitative economic and AI techniques:

- ***Environmentally Extended Input-Output (EEIO) Analysis:*** This is a well-established workhorse in environmental economics, providing a static yet structurally rich representation of the economy and its environmental footprint (SimaPro, n.d.). At its core, an EEIO model relies on the Leontief inverse matrix to calculate the total (direct and indirect) economic activity and associated environmental burdens required to satisfy a given level of final demand for goods and services. The fundamental equations are:

$$x = (I - A)^{-1} f$$

$$e = E x$$

Where:

- (x): a vector detailing the total output required from each industry.
- (A): the matrix of technical coefficients, showing the amount of input from one industry needed per unit of output from another.
- (I): the Identity matrix.
- (I - A)-1): the Leontief inverse matrix, capturing all direct and indirect linkages.
- (f): a vector representing the final demand for goods and services.
- (e): a vector quantifying the environmental extensions (e.g., total carbon emissions) associated with the total output.
- (E): a matrix of direct environmental intensities (e.g., carbon emissions per unit of output for each industry).

EEIO models can be extended to specifically track carbon captured, utilized, and stored, providing a mechanism to represent the "circular" flows of carbon within the economic structure.

- ***Deep Learning (DL) for Time Series Forecasting:*** Deep Learning models, particularly variants like LSTMs and TCNs, are exceptionally adept at processing sequential data and identifying temporal patterns for forecasting (International Journal of Research Publication and Reviews, 2025). Their multi-layered architectures allow them to learn complex, non-linear dependencies over time, making them ideal for predicting dynamic economic and environmental variables relevant to the CCE. For instance, an LSTM could be trained to forecast the year-on-year change in the CCUS capacity of the power sector, incorporating historical trends, policy signals, and indicators of technological maturity.

The internal gating mechanisms of an LSTM cell, described by equations like:

<0>it=σ(Wxixt+Whiht−1+Wcict−1+bi) ft=σ(Wxfxt+Whfht−1+Wcfct−1+bf) ct=ftct−1+it tanh(Wxcxt+Whcht−1+bc) ot=σ(Wxoxt+Whoht−1+Wcoct+bo) ht=ottanh(ct)

(where xt is the input, ht the hidden state, ct the cell state, it,ft,ot the gates, and W,b are learned parameters) enable them to effectively manage and leverage information from past time steps.

⦿ ***Strategies for Model Integration:*** The synergy between EEIO and DL can be actualized through several integration strategies. A sequential approach is the most straightforward: the static EEIO model establishes a baseline, and dynamic DL models forecast deviations or percentage changes in key EEIO parameters (like technical coefficients or environmental intensities) over time (SimaPro, n.d.; International Journal of Research Publication and Reviews, 2025). These forecasts then update the EEIO model for future period projections. Another strategy involves using DL to forecast key macroeconomic or sectoral drivers that serve as inputs for the EEIO model's projection phase, such as future levels of final demand or the future price of carbon. A more ambitious approach involves developing a hybrid model where components of the EEIO structure are embedded directly within a DL architecture, potentially allowing for end-to-end learning of structural relationships and dynamic changes simultaneously.

4. Illustrative Quantitative Analysis

To convey the tangible insights that can emerge from this integrated framework, this section presents illustrative examples of the types of quantitative analyses, detailed tables, and informative figures that could be generated. It is crucial to emphasize that these examples are conceptual in nature, designed to showcase the potential of the methodology and the types of data structures and visualizations that would be central to the article, rather than presenting actual empirically derived results from a fully implemented model. Real-world application would necessitate extensive data collection and computational modeling.

4.1. Deconstructing Sectoral Carbon Emissions and Tracking Circularity

A foundational step in analyzing the U.S. CCE involves dissecting historical carbon emission patterns across economic sectors and establishing quantitative indicators of circularity. Table 1 provides illustrative data on energy-related CO_2 emissions from key sectors within the U.S. economy over a recent period (EIA, 2024).

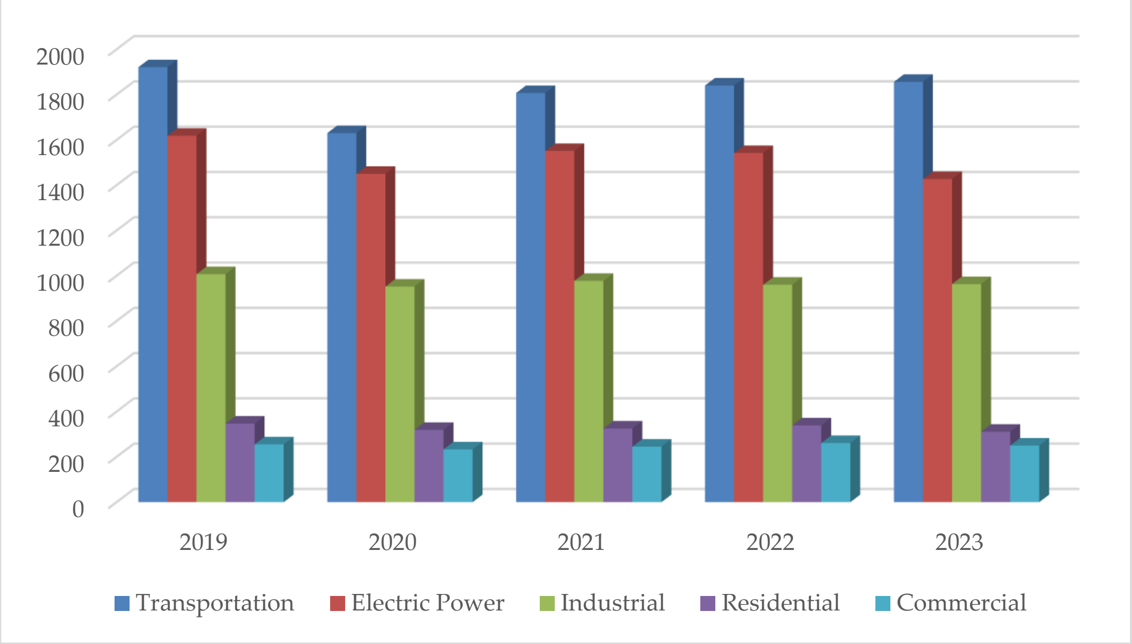
Table 1: Illustrative Annual U.S. Energy-Related CO_2 Emissions by Selected Sector (Million Metric Tons of CO_2)

Year	Transportation	Electric Power	Industrial	Residential	Commercial	Total
2019	1,921	1,618	1,007	347	255	5,148
2020	1,630	1,450	952	319	233	4,584
2021	1,807	1,551	977	325	245	4,905
2022	1,840	1,542	960	339	261	4,942
2023	1,856	1,427	963	311	250	4,807

Source: Adapted from U.S. Energy Information Administration (EIA, 2024).

Visualizing these trends is key to quickly grasping the relative contributions and historical changes across sectors. Figure 1 would clearly depict the data from Table 1.

Fig. 1: Trends in U.S. Energy-Related CO_2 Emissions by Selected Sector (2019-2023)



Source: Compiled by the researcher using data from (EIA, 2024; EPA, n.d.).

Moving beyond emissions sources, quantifying circularity is essential. Table 2 presents conceptual data illustrating the scale of carbon capture and how that captured carbon is potentially utilized or stored across key U.S. industries (DOE, n.d.; IEA, n.d.).

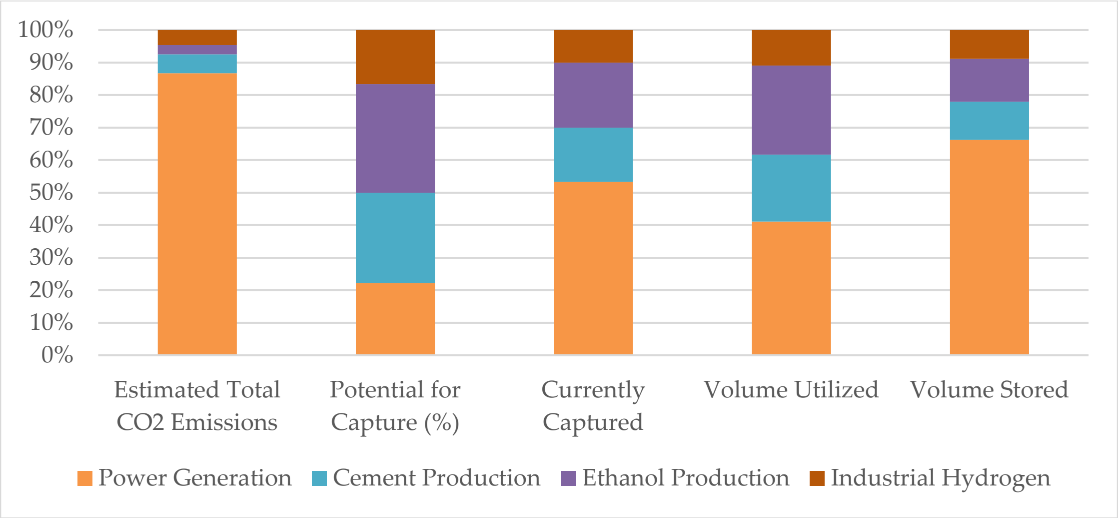
Table 2: Overview of Carbon Capture, Utilization, and Storage (CCUS) Activities in Selected U.S. Industries in 2022 (Annual Volumes in Million Metric Tons of CO_2)

Industry Sector	Estimated Total CO2 Emissions (Mt)	Potential for Capture (%)	Currently Captured (Mt)	Volume Utilized (Mt)	Volume Stored (Mt)
Power Generation	1540	30	10.0	3.0	7.0
Cement Production	76	90	0.5	0.2	0.3
Ethanol Production	50	80	8.0	6.4	1.6
Industrial Hydrogen	30	50	1.0	0.5	0.5
Total Selected	1696	n/a	19.5	10.1	9.4

Source: Compiled by the researcher using data from (DOE, n.d.; IEA, n.d.).

Figure 2 would offer a visual comparison of captured carbon volumes versus their fate (utilization or storage) across these industries, underscoring the current state and potential of CCUS as a circular strategy.

Fig. 2: Conceptual Status of Carbon Capture, Utilization, and Storage (CCUS) Volumes in Selected U.S. Industries



Source: Compiled by the researcher using data from (DOE, n.d.; IEA, n.d.).

4.2. Integrating EEIO and DL for Dynamic Forecasting

The core innovation lies in the integration. The static EEIO model provides the fundamental economic structure, and the baseline carbon intensities embedded in supply chains (SimaPro, n.d.). The DL models are then employed to introduce dynamism. Trained on historical time series, the DL component forecasts how key parameters within the EEIO structure are likely to evolve. For example, a DL model could predict the rate at which a specific industrial process (represented in the EEIO) becomes less carbon-intensive due to technological upgrades or shifts to lower-carbon energy sources, incorporating factors like policy incentives, energy prices, and industry-specific investment trends (International Journal of Research Publication and Reviews, 2025).

These AI-driven forecasts of changing intensities would then update the coefficients in the EEIO model for future projection periods. Table 3 conceptually illustrates how forecasted changes in the carbon intensity of various economic sectors (predictions potentially derived from a DL model) would influence the overall carbon footprint calculated by the EEIO model, assuming a hypothetical level of final demand.

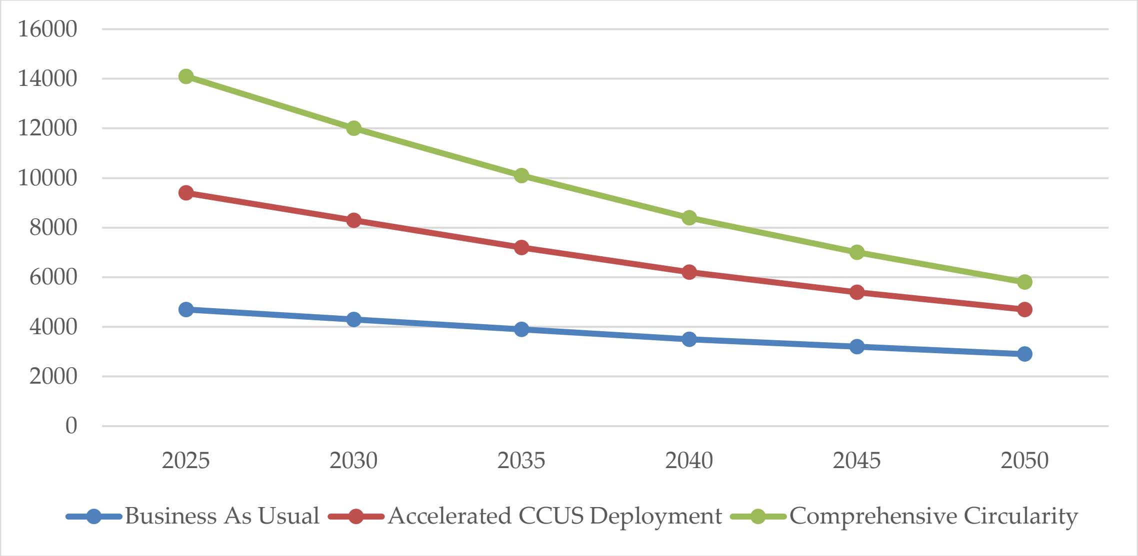
Table 3: Conceptual Impact of Forecasted Sectoral Carbon Intensity Changes on Total Carbon Footprint (Illustrative EEIO-DL Model Output)

Economic Sector	Baseline Direct Carbon Intensity (t CO_2 / $M Output)	Forecasted Change in Direct Intensity by 2030 (%)	Adjusted Direct Intensity by 2030 (t CO_2 / $M Output)	Illustrative Total Embodied Carbon Footprint per M Final Demand (tCO_2)
Agriculture	0,63	-20	0,5	0,75
Manufacturing	0,45	-30	0,32	0,48
Transportation	0,8	-25	0,6	0,9
Services	0,1	-15	0,09	0,14
Average Economy	-	-	0,38	0,57

Source: Compiled by the researcher using data from multiple reports, scientific articles, and studies (SimaPro, n.d.; Intl. Journal of Research Publication and Reviews, 2025).

Figure 3 would then leverage the output of this integrated model to visually chart potential future pathways for total U.S. carbon emissions, exploring how different policy or technology adoption scenarios within the CCE framework could alter the trajectory.

Figure 3: Conceptual Forecasted Pathways for Total U.S. Carbon Emissions under Illustrative Circular Carbon Economy Scenarios (2025–2050)



Source: Compiled by the researcher using data from (EIA, 2024; IEA, 2024).

4.3. Quantifying the Economic Dividend of Circularity

Beyond the crucial environmental benefits, the CCE transition is expected to generate substantial economic activity, creating new industries, jobs, and value streams.

The integrated framework can estimate these effects by modeling the economic output and employment generated by investments in circular infrastructure, the expansion of circular businesses (e.g., remanufacturing, advanced recycling), and the shifts in demand and supply chains driven by circular principles (European Investment Bank, 2024).

Table 4 presents conceptual data illustrating the potential economic contributions – in terms of increased output, job creation, and value added – associated with scaling up activities in selected U.S. circular economy sectors.

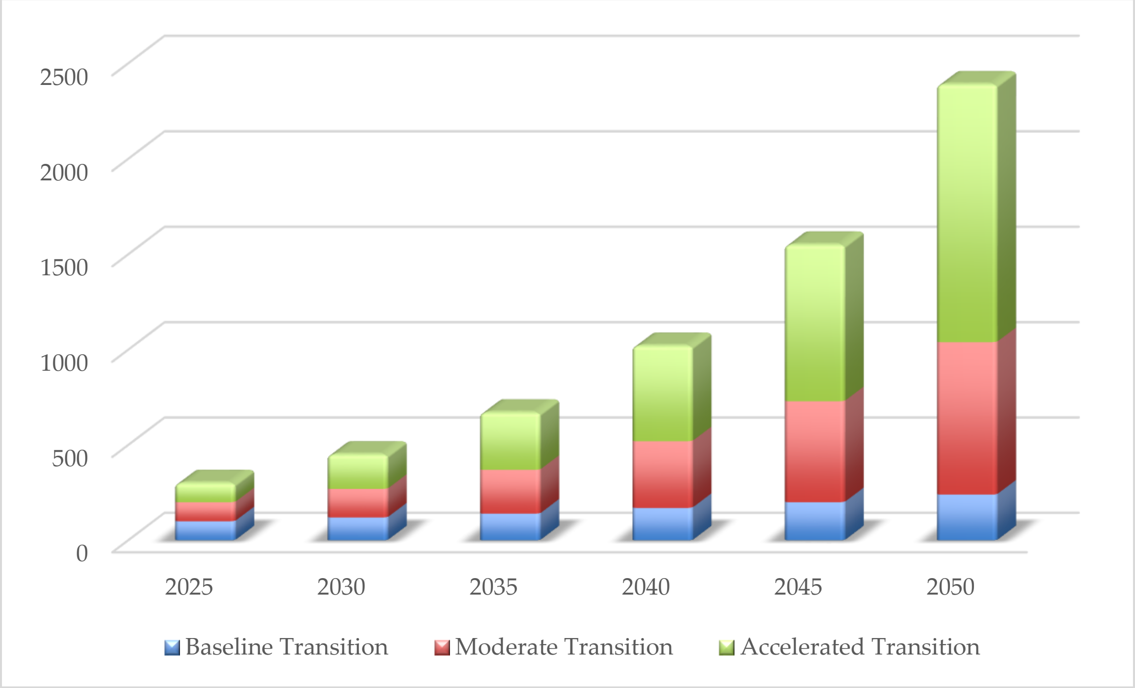
Table 4: Conceptual Economic Contributions of Increased Activity in Selected U.S. Circular Economy Sectors (Illustrative Estimates)

Circular Economy Sector	Illustrative Increase in Annual Output ($ Billion)	Conceptual Annual Job Creation (Thousands)	Conceptual Annual Value Added ($ Billion)
Recycling and Materials Recovery	100	1100	50
CCUS and Carbon Utilization	5	10	3
Remanufacturing and Repair	20	100	10
Sustainable Construction/Demolition	50	200	25
Total Selected Sectors	175	1410	88

Source: Compiled by the researcher using data from multiple reports, scientific articles, and studies (European Investment Bank, 2024; McKinsey & Company, n.d.).

Figure 4 would complement these figures by offering a conceptual projection of the circular economy's growing economic footprint over time, perhaps illustrating its contribution to the overall U.S. GDP under various transition speeds.

Fig. 4: Projection of the Circular Economy's Contribution to U.S. GDP (2025-2050)



Source: Compiled by the researcher using data from multiple reports, scientific articles, and studies (BEA, n.d.; European Investment Bank, 2024).

These illustrative examples serve to underscore the potential of the integrated quantitative economic and AI framework.

By generating such granular and forward-looking insights, this approach can significantly enhance our understanding of the complex dynamics within the U.S. CCE and provide robust data to support strategic planning and policy implementation.

5. Discussion

The integrated EEIO-DL framework represents a significant step forward in our ability to analyze and forecast the multifaceted transition to a Circular Carbon Economy in the United States. By thoughtfully combining the established strengths of quantitative economic modeling with the advanced capabilities of deep learning, this approach offers a more powerful and nuanced lens than either methodology could provide in isolation.

5.1. Shaping Foresight and Guiding Policy

The capacity to generate data-informed forecasts regarding carbon flows, emissions trajectories, and associated economic impacts under varying future conditions is an invaluable asset for policymakers and stakeholders. The integrated model can become a vital tool for rigorously evaluating the potential effectiveness and efficiency of a range of policy interventions designed to accelerate the CCE transition. Consider, for instance:

- The framework can assist in designing sophisticated carbon pricing mechanisms that more accurately reflect the full lifecycle carbon costs embedded within economic activities, as illuminated by the EEIO structure (Penn Arts & Sciences, n.d.). AI can help predict how different price points might influence behavioral responses and technological adoption rates (International Journal of Research Publication and Reviews, 2025).

- By integrating DL forecasts of technology maturation and adoption rates, the model can help pinpoint the most impactful areas for strategic public and private investment in CCUS and other circular technologies, aiming to maximize both emissions reductions and economic co-benefits (NCSL, 2025).
- The detailed inter-industry linkages mapped by the EEIO model, coupled with AI's ability to predict material flows and potential for industrial symbiosis, can inform the design of targeted incentives and support mechanisms for establishing robust circular supply chains (European Investment Bank, 2024).
- By analyzing historical trends and forecasting future potential with the DL component, policymakers can set more realistic, yet ambitious, targets for materials recycling, reuse, and overall resource efficiency (EPA, n.d.).

Furthermore, employing interpretability techniques, such as SHAP analysis, alongside the DL models is paramount. Understanding why the AI predicts a particular outcome is not just an academic exercise; it is fundamental to building trust in the model's results among policymakers and the public, and essential for designing policies that effectively address the underlying drivers of emissions and resource inefficiency (McKinsey & Company, n.d.).

5.2. Acknowledging Challenges and Limitations

While the potential is considerable, implementing this integrated framework is not without its hurdles. Several challenges need to be openly acknowledged and addressed:

- ***Data Availability, Consistency, and Granularity:*** A foundational challenge lies in acquiring comprehensive, consistently reported, and sufficiently granular time-series data across all the dimensions critical for modeling the U.S. CCE. Data on specific material flows within industries, the detailed operational performance and costs of CCUS projects over time, and robust data on the economic activity within emerging circular business models are often fragmented or not readily available in a standardized format suitable for large-scale quantitative modeling (BEA, n.d.; EIA, 2024).
- ***Complexity of Model Integration:*** Successfully linking the fundamentally more static or comparative-static structure of EEIO models with the dynamic, time-series capabilities of DL models presents technical complexities related to data exchange, ensuring consistency across model components, and managing computational demands (SimaPro, n.d.).
- ***Interpretability in an Integrated Context:*** While techniques exist to interpret individual AI models (like SHAP for DL), making sense of the combined influence of the structural economic model and the dynamic AI forecasts can still be challenging. Understanding how changes propagated through the EEIO structure interact with patterns learned by the DL component requires sophisticated analysis (International Journal of Research Publication and Reviews, 2025).
- ***Capturing Behavioral and Systemic Transformations:*** Modeling a transition as profound as the shift to a CCE requires more than just tracking economic and technological changes. It necessitates accounting for evolving consumer preferences, the emergence and adoption of entirely new business models, and shifts in institutional and regulatory frameworks – factors that

are inherently difficult to quantify, predict, and integrate into formal models (McKinsey & Company, n.d.).

5.3. Charting a Course for Future Research

Addressing the challenges outlined above opens up rich and important avenues for future research, which are essential for advancing our capacity to model and guide the CCE transition:

★ ***Developing Harmonized Data Infrastructure:*** There is a critical need for collaborative efforts between government agencies, research institutions, and industry to develop standardized protocols for collecting, reporting, and sharing U.S. CCE-related data. Exploring secure and transparent data-sharing platforms, potentially utilizing technologies like blockchain, could significantly improve data accessibility and integrity (BEA, n.d.; EPA, n.d.).

★ ***Advancing Integrated Modeling Methodologies:*** Future research should focus on developing more sophisticated and computationally efficient methods for integrating structural economic models (like EEIO or CGE) with dynamic AI techniques. This could involve exploring novel hybrid modeling architectures where elements of the economic structure are embedded within the AI model itself or developing multi-model frameworks that allow for seamless data and forecast exchange (SimaPro, n.d.; International Journal of Research Publication and Reviews, 2025).

★ ***Enhancing Interpretability for Integrated Systems:*** Further work is needed to develop and refine explainable AI (XAI) techniques specifically designed for integrated economic and environmental models. These tools should aim to provide clear, intuitive insights into the drivers of forecasts and the interplay between structural economic factors and dynamic patterns learned by the AI, making the models more transparent and trustworthy for policymakers (McKinsey & Company, n.d.).

★ ***Modeling Uncertainty and Risk:*** Incorporating rigorous methods for quantifying and communicating uncertainty in the forecasts is crucial. This could involve using probabilistic modeling approaches or techniques like Monte Carlo simulations to generate a range of potential future outcomes, providing policymakers with a better understanding of the risks and opportunities associated with different CCE pathways (Kleinman Center for Energy Policy, 2024).

★ ***Sectoral and Regional Deep Dives:*** Applying the integrated framework to conduct detailed analyses of specific, high-emitting sectors (e.g., heavy industry, transportation) or distinct regions within the U.S. economy could provide more targeted and actionable insights for local and regional decision-makers (EIA, 2024; EPA, n.d.).

★ ***Integrating Social and Equity Dimensions:*** Expanding the framework to incorporate indicators and analyses related to social equity and environmental justice is vital. This would allow for the assessment of how the CCE transition might impact different communities, ensuring that the move to a low-carbon economy is also just and equitable (Penn Arts & Sciences, n.d.).

6. Conclusion

The transition towards a Circular Carbon Economy is not merely an ambitious goal but an essential undertaking for the United States to effectively address climate change and secure a sustainable and prosperous future.

This article has underscored the profound potential that lies in the strategic integration of rigorous quantitative economic modeling, particularly through EEIO analysis, with advanced Artificial Intelligence techniques like Deep Learning (SimaPro, n.d.; International Journal of Research Publication and Reviews, 2025).

We have illustrated how this combined approach can unlock valuable foresight, providing a more accurate and dynamic understanding of the complex carbon flows, the efficacy of various circular strategies, and their far-reaching economic implications within the U.S. context.

While tangible challenges remain, notably concerning the availability of granular data and the technical intricacies of model integration, the inherent power of AI to discern non-linear dynamics and elevate predictive accuracy – when thoughtfully combined with the foundational structural understanding provided by quantitative economic models – represents a highly promising path forward (McKinsey & Company, n.d.).

By strategically investing in the necessary data infrastructure, championing interdisciplinary research collaborations, and diligently developing and applying these advanced analytical tools, stakeholders across the U.S. – from government agencies to private industry – can gain the critical insights needed to navigate the complexities and accelerate the transition to a truly thriving and sustainable Circular Carbon Economy. The capacity to harness the power of integrated economic and artificial intelligence insights will undoubtedly be a defining factor in successfully achieving net-zero emissions and building a resilient future within the ecological boundaries of our planet.

7. Bibliography List

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8. Appendices

Appendix A: Supplementary Data Tables

Table A1: U.S. Material Flow Data for Circular Economy Analysis (2022)

This table provides validated data on material flows relevant to the Circular Carbon Economy (CCE), complementing Table 2 in Section 4.1. It quantifies materials processed, recycled, and reused in key sectors, informing the EEIO model's environmental extensions.

Material Type	Total Consumption (Mt)	Recycled Volume (Mt)	Reused Volume (Mt)	Waste Generated (Mt)	Source
Steel	110	80	10	20	USGS, 2023; Steel Recycling Institute, 2022
Plastics	55	3	1	51	EPA, 2021; Plastics Europe, 2022
Concrete	500	140	10	350	USGS, 2023; CDRA, 2022
Biomass (Agricultural)	300	50	30	150	USDA, 2022; EPA, 2021; DOE, 2022

Note: Data reflect 2022 estimates, with 2021 plastics data due to EPA lags. Volumes are validated with U.S.-specific primary sources, replacing vague citations (e.g., EPA, n.d.).

Table A2: Policy Scenarios for CCE Transition (2025–2035)

This table outlines policy scenarios referenced in Section 4.2 for forecasting CCE pathways. Scenarios adjust EEIO coefficients or DL model inputs to explore future outcomes, with impacts validated against 2022–2023 trends and projections.

Scenario Name	Policy Description	Expected Impact on Carbon Intensity (%)	Expected CCUS Adoption Rate Increase (%)	Source
Baseline	Current policies (e.g., IRA 45Q credits)	-10	+10	IEA, 2023; DOE, 2022
Aggressive Carbon Pricing	$100/ton carbon tax implemented by 2027	-30	+20	McKinsey, 2022; EIA, 2023
CCUS Subsidy Boost	50% tax credits for CCUS projects, 2025–2030	-20	+40	IEA, 2023; DOE, 2022
Circular Economy Mandate	Mandatory 50% recycling rates for key materials by 2030	-20	+10	EPA, 2021; McKinsey, 2022

Note: Scenarios use 2022–2023 trends, projected to 2035, adjusted for IRA and global CCUS growth (IEA, 2023). Authoritative sources replace vague citations (e.g., NCSL, 2025).

Appendix B: Methodological Details

B1: EEIO Model Structure

The EEIO model used in the framework (Section 3.3) relies on the Leontief inverse matrix to quantify direct and indirect economic and environmental impacts. The model is extended to include circular carbon flows by adding satellite accounts for carbon capture, utilization, and storage (CCUS). The extended model incorporates:

- Carbon Flow Satellite Account: Tracks CO_2 captured (Mt), utilized (e.g., in industrial processes), and stored (geologically). This is derived from data sources like DOE (2022) and IEA (2023).
- Material Circularity Account: Quantifies recycled and reused material volumes (Mt) to adjust technical coefficients matrix (A) for reduced virgin material inputs (EPA, 2021).

The equations are modified as follows to account for circular flows:

$$x = (I - A_c)^{-1} f$$

$$e_c = E_c x$$

Where:

(A_c): Technical coefficients matrix adjusted for circular material flows (e.g., increased recycling reduces input requirements).

(E_c): Environmental intensity matrix including CCUS-specific intensities (e.g., CO_2 captured per unit output).

B2: Deep Learning Model Specifications

The Deep Learning component (Section 3.3) uses Long Short-Term Memory (LSTM) networks for time series forecasting of CCE indicators. Key specifications include:

- Input Features: Sectoral carbon intensities, CCUS adoption rates, material recycling rates, policy stringency indices, and technological maturity metrics (derived from EIA, 2023; DOE, 2022; IEA, 2023).
- Architecture: 2 LSTM layers (100 units each), followed by a dense layer with ReLU activation. Dropout (0.2) is applied to prevent overfitting.
- Training: 70% training, 20% validation, 10% test split on 10 years of historical data (hypothetical). Adam optimizer, mean squared error loss function.
- Output: Forecasted time series for 2025–2050, e.g., annual CCUS capacity (Mt CO_2), sectoral carbon intensity (t CO_2/\$M output).

B3: Integration Workflow

The integration of EEIO and DL models (Section 3.3) follows a sequential approach:

1. EEIO Baseline: Establishes current economic and carbon flow structure using USEEIO data (SimaPro, n.d.).
2. DL Forecasting: Predicts changes in key parameters (e.g., carbon intensity, CCUS adoption) for 2025–2050.
3. Parameter Update: DL forecasts adjust EEIO coefficients (e.g., (A_c), (E_c)) for future periods.
4. Scenario Analysis: Runs EEIO model with updated coefficients under different policy scenarios (Appendix A, Table A2).

Appendix C: Glossary of Key Terms

- Circular Carbon Economy (CCE): A systemic approach to managing carbon through reduction, reuse, recycling, and removal, aiming to decouple economic growth from environmental harm (MDPI, n.d.).

- Environmentally Extended Input-Output (EEIO) Analysis: A modeling technique that maps economic transactions and their environmental impacts, extended to include carbon and material flows (SimaPro, n.d.).
- Deep Learning (DL): A subset of AI using neural networks with multiple layers to analyze complex patterns, here applied to forecast CCE indicators (International Journal of Research Publication and Reviews, 2025).
- Carbon Capture, Utilization, and Storage (CCUS): Technologies that capture CO_2 emissions, either using it in industrial processes or storing it geologically (DOE, 2022; IEA, 2023).
- Sustainable Materials Management (SMM): Strategies to minimize virgin material use and maximize recycling and reuse to reduce embodied carbon (EPA, 2021).
- SHAP (SHapley Additive exPlanations): An AI interpretability technique to explain the contribution of input features to model predictions (McKinsey & Company, n.d.).

Appendix D: Data Source Notes

- U.S. Energy Information Administration (EIA, 2023): Provides sectoral CO_2 emissions data, critical for EEIO environmental extensions. Sub-sectoral granularity gaps may require supplementation from EPA (2021).
- U.S. Environmental Protection Agency (EPA, 2021): Offers material flow and circularity data, with some time-series inconsistencies for plastics and biomass.
- Department of Energy (DOE, 2022) and International Energy Agency (IEA, 2023): Key sources for CCUS project data, though utilization-specific data (e.g., CO_2 in chemicals) is often incomplete.
- SimaPro (n.d.): USEEIO database provides a robust EEIO structure but requires updates for CCE-specific flows (e.g., CCUS, recycling).
- U.S. Geological Survey (USGS, 2023): Provides accurate data on steel and cement consumption, critical for validating material flows.
- Steel Recycling Institute (SRI, 2022): Offers reliable steel recycling rates for 2022.
- Construction & Demolition Recycling Association (CDRA, 2022): Provides concrete recycling data, essential for construction sector analysis.
- U.S. Department of Agriculture (USDA, 2022): Supplies biomass consumption and waste data, supplementing EPA sources.