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Research article

Integrating deep learning and policy frameworks for green GDP accounting: A path to sustainable economic growth

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Abstract: This study introduces a novel method for integrating green technology innovation into green GDP accounting. It does this by adjusting for environmental pollution and incorporating policy frameworks that consider the effects of global geopolitical risks. Using data from the Anhui Province in 2019, a deep learning-based green GDP accounting model is proposed, which combines environmental costs and economic outputs. The methodology unfolds in two stages: the first stage develops a framework for pollution adjustment across solid, air, and water pollutants to highlight the environmental costs impacting various industries. The second stage applies the long short-term memory (LSTM) algorithm to predict green GDP, demonstrating superior accuracy over conventional methods. Additionally, the study explores the influence of geopolitical uncertainties and policy frameworks on green technology investments, emphasizing strategies for sustainable growth in emerging economies. The findings reveal that pollution-adjusted green GDP closely aligns with traditional green GDP metrics, with the pollution adjustment accounting for 1.96% of green GDP. These results underscore the critical role of green technology and policy in promoting sustainable economic growth amidst global uncertainties.

Keywords: deep learning; environmental pollution; green GDP; green technology innovation; policy frameworks; sustainable economic growth; emerging economies
Mathematics Subject Classification: 68T05, 91B64

1. Introduction

The relentless expansion of global economic activity has precipitated severe environmental degradation, compelling nations to prioritize green development as a fundamental objective [1,2]. Traditional gross domestic product (GDP)—the cornerstone of economic measurement—fails to internalize ecological costs, such as natural resource depletion, pollution damage, and ecosystem degradation, producing systematically inflated assessments of progress and masking unsustainable growth trajectories [3–6]. This omission not only obscures the long-term welfare losses associated with environmental harm but also perpetuates policy frameworks prioritizing short-term output over resilience and ecological health [7–11]. In response, green GDP has been advanced to adjust conventional GDP by deducting quantified environmental depletion and pollution costs, thereby yielding a net indicator of economic contributions to societal well-being [12]. Despite its conceptual promise, the practical implementation of green national accounts has stalled: no country has yet established a fully integrated, comprehensive system for environmental–economic accounting, underscoring an urgent need for robust methodologies that can be applied at scale [13,14].

The intellectual foundations of green GDP trace back to the late 1960s, when rising ecological crises prompted economists to critique the GDP's inability to capture socio-environmental trade-offs [15]. Seminal work by Repetto et al. introduced the term "net green GDP" and demonstrated adjustments for timber extraction, fossil-fuel consumption, and soil erosion in Indonesia, revealing significant overstatements of growth under conventional measures [16,17]. Building on these early insights, the United Nations published the System of Environmental-Economic Accounting (SEEA) in 2012, providing a standardized international framework for integrating environmental and economic data. In 2009, the European Commission's "Green GDP and Beyond" initiative leveraged SEEA to promote complementary social and environmental indicators, catalyzing pilot green-account experiments in Germany and the Netherlands [18–21]. China followed suit in 2004 by establishing provincial green GDP working groups tasked with monetizing losses from land degradation, energy over-consumption, and mineral extraction [22,23]. Collectively, these initiatives reflect a convergent trend toward redefining prosperity through indicators that balance economic output with ecological integrity and social welfare [24–27].

Initial implementations encountered significant methodological and institutional barriers, particularly in monetizing environmental externalities and ensuring consistency. Hoff et al. highlighted pronounced subjective bias in environmental cost valuation and institutional hurdles in adopting green GDP measures. Discontinuities in statistical yearbooks and remote-sensing break-point observations further impaired spatial and temporal continuity in green GDP time series [28,29].

Empirical analyses have employed diverse econometric and modeling techniques to explore the green growth–green GDP nexus. Hussain et al. used a cross-sectional ARDL model to show that while linear increases in green GDP foster green growth, non-linear dynamics may paradoxically inhibit it. Xia et al. tested the Environmental Kuznets Curve across 67 countries (1971–2018), uncovering a robust positive linkage between globalization and carbon emissions that challenges conventional growth paradigms [30].

China, as the world's largest energy consumer, has featured prominently in green transition research. Rehman et al. documented the asymmetric impacts of economic growth, forestry, and grain production on CO_2 emissions from 1970 to 2017, emphasizing the strategic importance of renewable energy for carbon neutrality [31]. Arslan et al. found that natural resource rents between 1970 and 2016 contributed to environmental sustainability but constrained economic growth, highlighting ecological blind spots in traditional accounting [32].

To address linearity and data-continuity limitations, scholars have integrated advanced predictive models. Gong et al. combined ARIMA with LSTM networks to forecast climate change's effects on green GDP, improving predictive performance over standalone econometric methods [33]. Li et al. applied emergy-based spatial econometrics to map China's agricultural green GDP distribution from 2003 to 2018, though conventional techniques still struggled with non-linear threshold effects and dynamic feedbacks [34].

Traditional econometric tools—such as panel regressions and GMM—have been critiqued for their inability to capture complex non-linearities and high-dimensional policy interactions [35,36]. Ensemble methods like random forests effectively capture high-order feature interactions and have demonstrated robust predictive performance across diverse problems, serving as a reliable benchmark for modern data mining tasks [37,38]. The long short-term memory (LSTM) architecture was originally proposed by Hochreiter & Schmidhuber to overcome vanishing-gradient issues in recurrent neural networks, enabling learning of long-range dependencies [39]. Building on this, deep LSTM models have been applied to electric-vehicle charging demand forecasting, achieving significantly lower error rates compared to classical time-series approaches [40]. In computer vision, spiking-network frameworks incorporating multi-box detection strategies—drawing inspiration from LSTM's gated design—have reduced false positives in low-light object detection scenarios [41]. Within control engineering, LSTM-driven co-design methods have facilitated H_∞ control of quantized Takagi–Sugeno fuzzy systems over lossy network channels, guaranteeing stability despite communication constraints [42]. Hybrid architectures that integrate LSTM layers with one-dimensional convolutional networks have further advanced human activity recognition, improving accuracy on benchmark datasets by over 5 percent [43]. Graves later refined LSTM for supervised sequence labeling, demonstrating state-of-the-art gains in speech and handwriting recognition tasks [44]. Reviews of the LSTM model catalog ongoing optimizations in gating mechanisms and regularization, underscoring its flexibility across applications [45]. More recently, LSTM variants extended to recursive structures have shown promise for modeling hierarchical data, enhancing performance in language modeling and parsing tasks [46]. Associative LSTM architectures further enable analysis of long-term policy transmission path dynamics [47]. Hybrid CNN-GRU-Attention models have demonstrated superior accuracy in forecasting sector-specific carbon emissions, notably in Jiangsu Province [48], and neural networks have been developed to analyze green finance–carbon emission relationships [49].

Artificial intelligence is reshaping green economic analysis. Iqbal et al. employed a panel-VAR framework to examine interactions among AI adoption, renewable energy deployment, green human capital, geopolitical risk, and carbon emissions, highlighting institutional quality's moderating role [50]. Alonso-Robisco et al. mapped machine learning applications in climate-finance research, identifying key domains and methodological gaps [51]. Fang et al. used a two-stage OLS model to show that R&D investment and industrial upgrading drive green economic rebounds in South Asia [52].

Building on these advances, this study proposes a comprehensive LSTM-based green GDP accounting model for Anhui Province. Our approach integrates three key innovations: (1) a holistic pollution valuation framework quantifying air, water, and solid-waste losses within industrial output metrics; (2) policy-responsive forecasting by encoding carbon tax rates, emission standards, and green-bond instruments as exogenous inputs into a grid-optimized three-layer LSTM [53–55]; and (3) long-term predictive robustness through LSTM memory-cell dynamics and rigorous cross-validation to stabilize multi-period forecasts and outperform conventional models.

By synthesizing ecological economics theory, SEEA standards econometric critique, and cutting-edge AI methodologies, our framework addresses three historical challenges in green GDP accounting: subjective valuation biases, data discontinuities, and linear policy effect limitations, thus providing a scalable, policy-relevant foundation for integrating environmental costs into national economic accounts.

The remainder of this paper is structured as follows. Section 2 reviews existing green GDP methodologies and predictive modeling literature. Section 3 details our pollution-adjusted accounting framework. Section 4 presents the design, training, and policy-integration methodology of the LSTM forecasting model. Section 5 validates the proposed approach against benchmark models and analyzes scenario-based policy simulations. Finally, Section 6 concludes with implications for sustainable development policy and directions for future research.

2. Related work

Since its formalization in the United Nations' System of Environmental-Economic Accounting (SEEA) in 2012, the concept of green GDP has evolved as a foundational indicator for integrating environmental costs into national accounts. Early scholars like Korten [56] and Hills & Glennerster [57] proposed the "net green GDP" framework to internalize costs such as deforestation and resource depletion, though subjective valuation assumptions often limited comparability across studies.

Initial implementations encountered significant methodological and institutional barriers, particularly in monetizing environmental externalities and ensuring result consistency. Hoff et al. highlighted these challenges, noting pronounced subjective bias in environmental cost valuation and institutional hurdles in adopting green GDP measures. Additionally, discontinuities in statistical yearbooks and remote-sensing break-point observations impaired spatial and temporal continuity in green GDP time series.

Empirical investigations into the green growth–green GDP nexus have employed a variety of econometric and modeling techniques. Hussain et al. analyzed high-GDP countries using a cross-sectional ARDL model, finding that while linear enhancements in green GDP foster green growth, non-linear dynamics may paradoxically inhibit it. Xia et al. tested the Environmental Kuznets Curve hypothesis across 67 countries (1971–2018), uncovering a robust positive linkage between globalization and carbon emissions, which challenges conventional green GDP growth paradigms. Research in Indonesia by Resosudarmo and Anderson & Kusters further demonstrated how green fiscal policies and resource dependencies shape sustainable growth trajectories.

China, as the world's largest energy consumer, has been a central case in green transition research. Rehman et al. documented the asymmetric impacts of economic growth, forestry, and grain production on CO_2 emissions from 1970 to 2017, emphasizing renewable energy's strategic importance for carbon neutrality. Arslan et al. found that while natural resource rents contributed to environmental sustainability between 1970 and 2016, they concurrently constrained economic growth—highlighting the ecological blind spots of traditional green GDP accounting.

To overcome linearity and data continuity limitations, scholars have integrated advanced predictive models. Gong et al. combined ARIMA with LSTM networks to forecast climate change's effects on green GDP, illustrating improved predictive performance over standalone econometric methods. Li et al. applied emergy-based spatial econometrics to map China's agricultural green GDP distribution from 2003 to 2018, yet conventional techniques still struggled with non-linear threshold effects and dynamic feedbacks.

Traditional econometric tools—such as panel regressions and the generalized method of moments (GMM)—have been critiqued for their inability to capture complex non-linearities and high-dimensional policy interactions. Consequently, machine learning approaches have gained prominence. Random Forests leverage ensemble learning to model multidimensional interactions, while LSTM networks, introduced by Hochreiter & Schmidhuber and elaborated by Graves, effectively address long-term dependencies in environmental-economic time series. Associative LSTM architectures further enable analysis of long-term policy transmission paths. Hybrid CNN-GRU-Attention models have demonstrated superior accuracy in forecasting transportation carbon emissions in Jiangsu Province, and improved neural networks have been developed to explore green finance–carbon emission relationships.

Artificial intelligence is reshaping green economic analysis beyond prediction. Iqbal et al. employed a panel-vector-autoregression framework to examine interactions among AI adoption, renewable energy deployment, green human capital, geopolitical risk, and carbon emissions, highlighting institutional quality's moderating role. Alonso-Robisco et al. provided a comprehensive mapping of machine learning applications in climate-finance research, identifying key domains and methodological gaps. Fang et al. used a two-stage OLS model to demonstrate that R&D investment and industrial upgrading significantly drive green economic rebounds in South Asia.

Building on these advances, the present study adopts a three-layer LSTM architecture (64–128–32 units) with empirically set dropout rates (0.2, 0.5, 0.25) for green GDP forecasting, acknowledging that the absence of systematic hyperparameter optimization (e.g., grid or random search) may risk overfitting or underfitting. Future research should integrate automated hyperparameter tuning—such as Bayesian optimization techniques demonstrated by Liang et al. [58], Kushwah & Agrawal [59], Zhu et al. [60], and Guo et al. [61]—to enhance model robustness and generalizability. Moreover, fusing multi-source heterogeneous data (satellite remote sensing, ground monitoring, socio-economic indicators) can address spatial-temporal data fragmentation, while incorporating policy levers (carbon taxes, emission caps, green subsidies) offers actionable insights for decision-makers. Explainability frameworks, such as those by Yao et al. [62] and Wang et al. [63], further support interpretation of deep learning outputs in environmental contexts.

By synthesizing ecological economics theory, econometric critique, and cutting-edge AI methodologies [64], this integrative framework effectively tackles three historical challenges in green GDP accounting: subjective valuation biases, data discontinuities, and linear policy effect limitations. It provides a cross-disciplinary foundation for establishing standardized, policy-relevant green national economic accounting systems.Li et al. introduced UrbanEV, a comprehensive urban charging–demand dataset that enables rigorous benchmarking of predictive models [65], while Orzechowski et al. developed a medium-term forecasting framework combining temporal clustering with data-driven model selection to capture seasonal demand patterns [66]. Rashid et al.'s survey then compared statistical and machine-learning techniques—highlighting that ensemble and deep-learning models often strike the best balance between accuracy and interpretability [67].

Zhu et al. showed that deep architectures, especially stacked LSTM and convolutional–LSTM hybrids, outperform classical baselines in both short- and medium-horizon load forecasting [68]. Han et al. further enhanced LSTM by adopting a Bayesian formulation, which yields tighter uncertainty estimates when assessing air-pollution control impacts [69]. Porter & van der Linde's foundational work framed environmental regulation as a driver of innovation, setting the stage for linking policy to model-based forecasting [70].

Lu & Tao demonstrated that local government environmental attention boosts urban green-land use efficiency via industrial restructuring mechanisms [71], and Zhao et al. provided empirical evidence that AI deployment accelerates green economic growth through optimized resource allocation [72]. Zhang et al. applied iterative learning control (ILC) to linear parabolic distributed-parameter systems with moving boundaries, illustrating LSTM-inspired feedback for improved process tracking [73].

Jasti et al. proposed a modular framework for green product development that embeds lifecycle assessment at each design phase [74], and Tong et al. reviewed the technical and economic hurdles facing large-scale compressed-air energy storage in China, pinpointing cost and regulatory barriers [75]. Ziegel's concise review of "The Elements of Statistical Learning" reaffirmed its status as a cornerstone reference for both statistical and machine-learning practitioners [76].

Jin applied neural networks to provincial carbon-emissions forecasting, achieving lower mean absolute errors than panel regressions [77]. Lam et al. identified institutional biases hindering interdisciplinary research publication, advocating reforms to broaden methodological inclusion [78]. Finally, Gogas & Papadimitriou surveyed machine-learning applications in economics and finance, underscoring their growing impact on risk modeling and policy analysis [79].

3. Green GDP accounting model

This study adopts the concept that the "green GDP accounting system" is an accounting method that subtracts the costs of environmental degradation control and natural resource consumption from traditional green GDP. This approach aims to represent the net positive effect of national economic growth, offering a more accurate reflection of a nation's green economy development and the living standards of its citizens. To account for the value of air, water, and solid waste pollutants and to understand the effects of economic development activities on the ecological environment, this study's green GDP accounting system is based on the adjustment of environmental pollution losses. The system evaluates the relationship between green GDP, natural resources, and the environment by creating a statistical database of environmental indicators and natural resources while maintaining the traditional green GDP accounting framework. It calculates green GDP by generating accounts for resource depletion and environmental degradation.

However, the current model primarily considers the environmental costs associated with water pollution, air pollution, and solid waste. It overlooks other critical externalities, such as soil heavy metal contamination, the valuation of ecosystem services, and greenhouse gas emissions—factors that significantly contribute to environmental degradation. Their exclusion could result in a substantial underestimation of the total environmental costs in the green GDP calculations. These additional environmental factors should be integrated into the model to develop a more comprehensive approach. For example, soil pollution from heavy metals, which impacts agricultural productivity and ecosystem health, along with assessing the impact of greenhouse gas emissions and the loss of ecosystem services, would provide a more accurate representation of the environmental costs linked to economic activities. Incorporating these factors would enhance the precision of the green GDP model and offer a more holistic view of the region's environmental sustainability, aligning the model with contemporary environmental economics frameworks.

3.1. Green GDP accounting based on environmental pollution loss adjustment

Environmental pollution loss accounting involves both physical quantity accounting and value quantity verification. This study selects three common pollutants for analysis—water pollution, solid waste pollution, and air pollution. These pollutants' physical and value quantities are calculated, and their total value is then adjusted to the green GDP to obtain the final environmental pollution-adjusted green GDP. However, the sources of key parameters used in the value calculation, such as the virtual treatment cost for industrial wastewater and the shadow price of SO_2, have not been specified. It is essential to explicitly identify whether these values are derived from the Anhui Province Environmental Statistics Yearbook, third-party studies, or other sources. The lack of transparency regarding the sources of these parameters could limit the method's reproducibility. Documenting the origin of these parameters will significantly enhance the robustness and reproducibility of the proposed green GDP accounting framework, making the approach more reliable for future applications.

Figure 1 below illustrates the technical route of this study. The technological framework for mitigating environmental pollution losses is a comprehensive structure designed to address how pollutants impact the environment. The process of accounting for different contaminants is outlined in the diagram. The first step involves the physical quantity accounting of pollutants, which is categorized into primary groups such as contaminants in solid waste, wastewater, and the air. To quantify the pollution, these primary accounts are further divided into secondary accounts, each associated with specific computational methods.

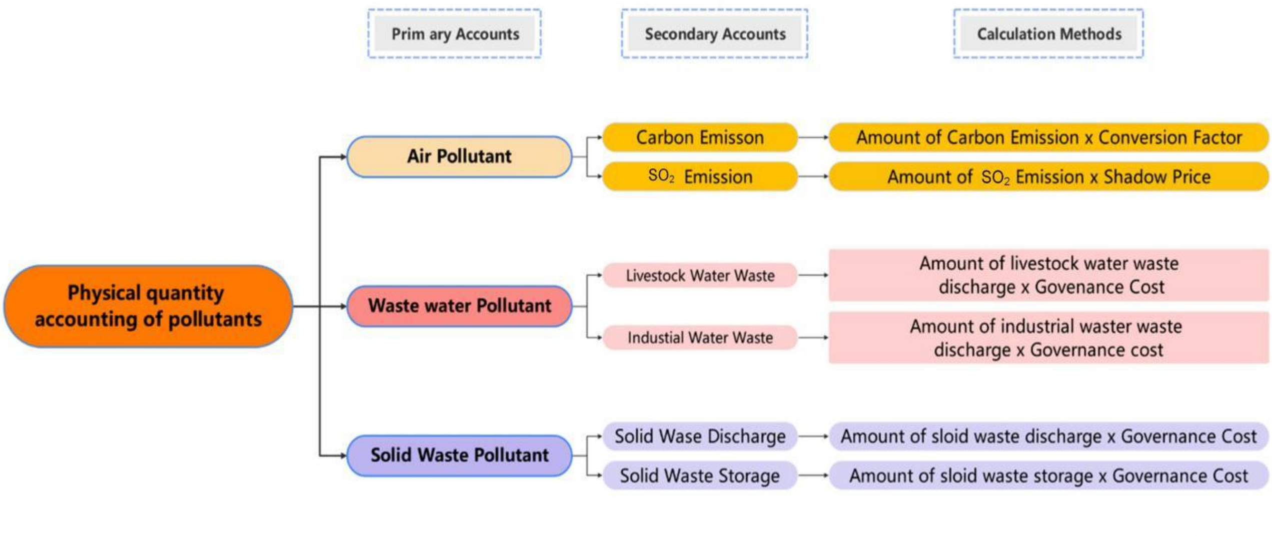

Figure 1. Environmental pollution losses and its measures.

3.2. Establish an accounting model for the value of environmental pollution

Environmental value accounting comprises three parts: water pollution value accounting, air pollution value accounting, and solid waste value accounting. The following value accounting models are established for the three types of pollutants.

3.2.1. Accounting for the value of water pollution

The accounting of water pollution value primarily includes wastewater from livestock and poultry breeding, industrial production, and urban domestic sources. The total water pollution value is obtained by estimating the economic value of these wastewater types and aggregating the results. In this section, the value of wastewater from livestock and poultry breeding is calculated first, and the following model is established to estimate its economic value:

$$\mathrm{OC_{sw}} = \sum_{i=1}^{5} \mathrm{OC_{sw(i)}} = \sum_{i=1}^{5} \mathrm{T_{sw(i)}} \cdot \mathrm{OC_{swwu(i)}}, \tag{1}$$

$$\mathrm{VOC_{sw}} = \sum_{i=1}^{5} \mathrm{VOC_{sw(i)}} = \sum_{i=1}^{5}\left(\sum_{n=1}^{2} \mathrm{D_{sww(i)(n)}} \cdot \mathrm{OC_{sww(i)(n)}}/10\right). \tag{2}$$

In the above formula, $\mathrm{OC_{sw}}$,and $\mathrm{OC_{sw(i)}}$ indicates the actual treatment cost of total livestock and poultry breeding and various livestock and poultry breeding wastewater,per 10,000 yuan; $\mathrm{T_{sw(i)}}$ indicates the amount of livestock and poultry wastewater treated, per 10,000 tons;and $\mathrm{VOC_{sw(i)}}$,and $\mathrm{VOC_{sw}}$ respectively represents the virtual treatment cost of wastewater for a variety of livestock and poultry breeding and total livestock and poultry breeding, per 10,000 yuan.

Secondly, establish a cost-accounting model for industrial wastewater treatment:

$$\mathrm{VOC_{iw(i)}} = \sum_{n=1}^{5} \mathrm{DW_{iwe(i)(e)}} \cdot \mathrm{OC_{iwu(i)(u)}}/10. \tag{3}$$

Above formula, $\mathrm{VOC_{iw(i)}}$ represents the virtual wastewater treatment cost of different industries, per 10,000 yuan; $\mathrm{OC_{iwu(i)(u)}}$ represents the virtual treatment cost of wastewater in different industries, in yuan/kg; n indicates the type of pollutant; and $\mathrm{DW_{iwe(i)(e)}}$ indicates the cost of pollutant treatment in wastewater in different industrial industries, in yuan/kg.

Finally, the cost accounting model of urban domestic wastewater treatment is established:

$$\mathrm{VOC_{mw}} = \sum_{n=1}^{2}\left(\mathrm{DW}_{\mathrm{mww(n)}} \cdot \mathrm{OC_{mwwu(n)}}/10\right). \tag{4}$$

$\mathrm{DW_{mww(n)}}$ indicates the amount of municipal domestic wastewater pollutant discharge, in tons; $\mathrm{VOC_{mw}}$ represents the cost of urban domestic wastewater treatment, per 10,000 yuan; $\mathrm{OC_{mwwu(n)}}$ represents the cost of pollution treatment per unit of urban domestic wastewater, in yuan/kg, n represents the type of pollutant.

3.2.2. Air pollutant value quantity accounting model

Air pollution value accounting consists of two parts: the virtual treatment cost of different types of pollutants, and the actual treatment cost. Using statistical data to calculate the actual treatment cost of industrial waste gas, the virtual cost should be calculated and analyzed according to the emission of different pollutants; the actual treatment cost and virtual treatment cost of several pollutants common in air pollution are modeled and calculated, which are soot, sulfur dioxide, nitrogen oxides, and dust. The following is a virtual model for the value and quantity of air pollutants:

$$SO_2\text{:}\ \ \mathrm{DSC_i} = (\mathrm{SDQ_i} + \mathrm{PDW}) \times \mathrm{vPS_i}. \tag{5}$$

DSC denotes the virtual treatment cost of CO_2 (per 10,000 yuan); PDW represents SO_2 emissions from various processes (10,000 tons); SDQ refers to SO_2 emissions from combustion in the industrial sector (10,000 tons); and vPSi indicates the unit cost of SO_2 treatment (yuan/ton).

$$\text{Smoke:}\ \ \mathrm{DSA_i} = \mathrm{AQ_i} \times \mathrm{vSA_i}. \tag{6}$$

Above formula, $\mathrm{AQ_i}$ represents industry soot emissions, per 10,000 tons; $\mathrm{DSA_i}$ represents the virtual treatment cost of industry soot, per 10,000 yuan; and $\mathrm{vSA_i}$ represents the cost of soot control per unit of the industry, yuan/ton.

$$\text{Dust:}\ \ \mathrm{DSPA_i} = \mathrm{PW_i} \times \mathrm{vPA_i}. \tag{7}$$

The above formula $\mathrm{PW_i}$ represents industry dust emissions, 10,000 tons; $\mathrm{DSPA_i}$ represents the virtual treatment cost of industry dust, million yuan; $\mathrm{vPA_i}$ represents the unit treatment cost of dust in the industry, in yuan/ton.

$$\text{Nitrogen oxide:}\ \ \mathrm{DSN_i} = \mathrm{NL_i} \times \mathrm{vSN_i}. \tag{8}$$

Above formula $\mathrm{NL_i}$ represents the industry's nitrogen oxide emissions, 10,000 tons; $\mathrm{DSN_i}$ represents the industry's nitrogen oxide virtual treatment cost, per 10,000 yuan; and $\mathrm{vSN_i}$ represents the unit treatment cost of nitrogen oxides in the industry, in yuan/ton.

$$\text{Industry air pollution virtual governance cost} = \mathrm{DSC} + \mathrm{DSA} + \mathrm{DSPA} + \mathrm{DSN}. \tag{9}$$

3.2.3. Solid waste value accounting model

The components of solid waste value accounting are domestic and industrial solid waste, and the pollution value of industrial solid waste is calculated according to different industries. Household waste is accounted for according to the region.

The virtual remediation cost of industrial solid waste is calculated, consisting of the virtual remediation cost spent during storage and discharge waste treatment. It is calculated by the following three formulas (10), (11), and (12):

$$\mathrm{VGDW} = \mathrm{SC}\ \times (\mathrm{DGC} - \mathrm{SGC}). \tag{10}$$

In Eq (10), VGDW means the virtual governance cost for disposing of stored waste, SC represents storage capacity, DGC represents the disposal unit governance cost, and SGC represents the storage unit governance cost.

$$\mathrm{VGIW} = \mathrm{VGDW} + \mathrm{VGDDW}. \tag{11}$$

In formula (11), VGIW stands for virtual governance cost of industrial solid waste, VGDW stands for virtual governance cost of disposing of stored waste, and VGDDW stands for virtual governance cost of disposing of discharged waste.

$$\mathrm{ATCDDW} = \mathrm{CD} \times \mathrm{DU}. \tag{12}$$

In Eq (12), ATCDDW represents the actual treatment cost of disposing of discharged waste, the CD represents the cost of discharging, and DU represents the disposal unit.

The cost of virtual treatment of domestic waste is calculated, which is calculated by the following formulas (13) and (14):

$$\mathrm{WDC} = \mathrm{ACT} - \mathrm{SLV} - \mathrm{IV} - \mathrm{CV}. \tag{13}$$

In Eq (13), WDC represents the waste dumping capacity, ACT represents the cleaning and transportation, SLV represents the sanitary landfill volume, IV represents the incineration volume, and CV represents the compost volume.

$$\mathrm{VTCSLT} = \mathrm{SV} \times \mathrm{SLUT}. \tag{14}$$

In Eq (14), VTCSLT stands for the virtual treatment cost of sanitary landfill treatment of piled waste, SV stands for stacking volume, and SLUT stands for sanitary landfill unit treatment.

3.3. Green GDP accounting based on environmental pollution loss adjustment

Gross domestic product (green GDP) is traditionally used to measure economic growth, but does not account for the environmental costs associated with expansion. In contrast, green GDP factors in the costs incurred by climate change and the monetization of biodiversity loss. Certain environmental specialists prefer using physical metrics to create indices, such as the "Sustainable Development Index", which includes measures like "trash per capita" or "carbon dioxide emissions per year" [80]. However, the current green GDP model primarily focuses on water pollution, air pollution, and solid waste pollution while omitting several critical externalities, such as soil heavy metal contamination, the valuation of ecosystem services, and greenhouse gas emissions. This omission leads to an underestimation of environmental costs. For example, soil contamination by heavy metals can degrade agricultural productivity and biodiversity. At the same time, the loss of ecosystem services, such as carbon sequestration and water filtration, plays a crucial role in environmental accounting. Additionally, greenhouse gas emissions, particularly CO_2 from industrial activities, must be integrated into the pollution accounting framework. Including these factors would provide a more comprehensive and accurate depiction of the environmental costs associated with economic activities, thereby improving the precision of green GDP calculations. Expanding the model to account for soil contamination, ecosystem service loss, and greenhouse gas emissions would align the green GDP model with contemporary environmental economics principles. Incorporating these missing externalities would significantly enhance the model's robustness and the credibility of its environmental cost estimates.

Modifying standard green GDP calculations to reflect losses due to environmental degradation is central to the concept of green GDP, which aims to quantify economic growth while accounting for its environmental costs. In the previous sections, we calculated the depletion value of natural resources, the cost of ecological degradation, and the cost of natural resource restoration. This process involves assigning financial values to environmental effects, often based on the current value of anticipated net returns from future resource use for commercial purposes. Such an approach helps understand the economic performance and long-term sustainability of a nation's development. The study, however, relies on data from a single year (2019) to calculate and predict green GDP for Anhui Province. While this provides a snapshot of the province's economic-environmental status, it limits the model's ability to capture long-term trends and seasonal variations. Using data from only one year misses important economic shifts, the effects of policy changes, and fluctuations caused by external events, such as geopolitical risks or energy price changes. It would be beneficial to incorporate multi-year data to improve the model's robustness and predictive accuracy, enabling a more comprehensive time series analysis. This would allow the model to capture long-term trends better, assess the impact of various policy changes, and offer more reliable forecasts for green GDP. Moreover, multi-year data would enhance the model's generalization ability, making it more resilient to short-term economic shocks and better suited for informing policy decisions related to sustainable growth.

$$\text{Green GDP} = \text{GDP} - \text{EVPCC}. \tag{15}$$

In Eq (15), the green GDP stands for the domestic product, and EVPCC stands for the environmental virtual pollution control cost.

$$\text{Green GDP Index} = \text{Green GDP}/\text{GDP} \times 100. \tag{16}$$

Algorithm 1. Summarizes the steps of followed for the green GDP accounting.

Algorithm 1: Green GDP Accounting
Step 1: Carry out the identification of the main pollutants in the following ways:
Let P be the set of pollutants,that is $P = \{p_1, p_2, p_3\}$,where p_1 represents the water pollutants, p_2 represents the solid waste pollutants,and p_3 represents the air pollutants.
Decompose P_i into two accounts, that is, primary p_i and secondary S_i.
Step 2: Account for the physical quantity by doing the following:

Let Q_{p_i} be the physical quantity of P_i. It may be in tons or kgs.

Calculate $Q_{p_i} = f(P_i, S_i)$ by following the corresponding counting techniques.

Step 3: Verify the value of each quantity as follows:
First,calculate the value (V) for each pollutant, and then integrate it with the corresponding physical quantity Q_{p_i} as VQ_{p_i}.

Compute $Q_{p_i} = g(Q_{p_i}, \text{cost parameters})$.

Step 4: Establish the accounting model for the value of each pollutant, such as water, air, and solid waste.
Step 5: Account for the green GDP by using the environmental pollution loss adjustment.

4. Green GDP accounting and prediction using LSTM

This study focuses on green GDP accounting and prediction using the LSTM deep learning model applied to Anhui Province, China. With its large population and rapid economic growth, China significantly influences global economic trends and is highly affected by climate change. Due to its vast territory and diverse climate, China provides a representative case for understanding the effects of climate change on economies. Figure 2 illustrates the overall architecture of our proposed green GDP prediction model, which consists of three modules: data collection and preprocessing, LSTM model training, and green GDP prediction.

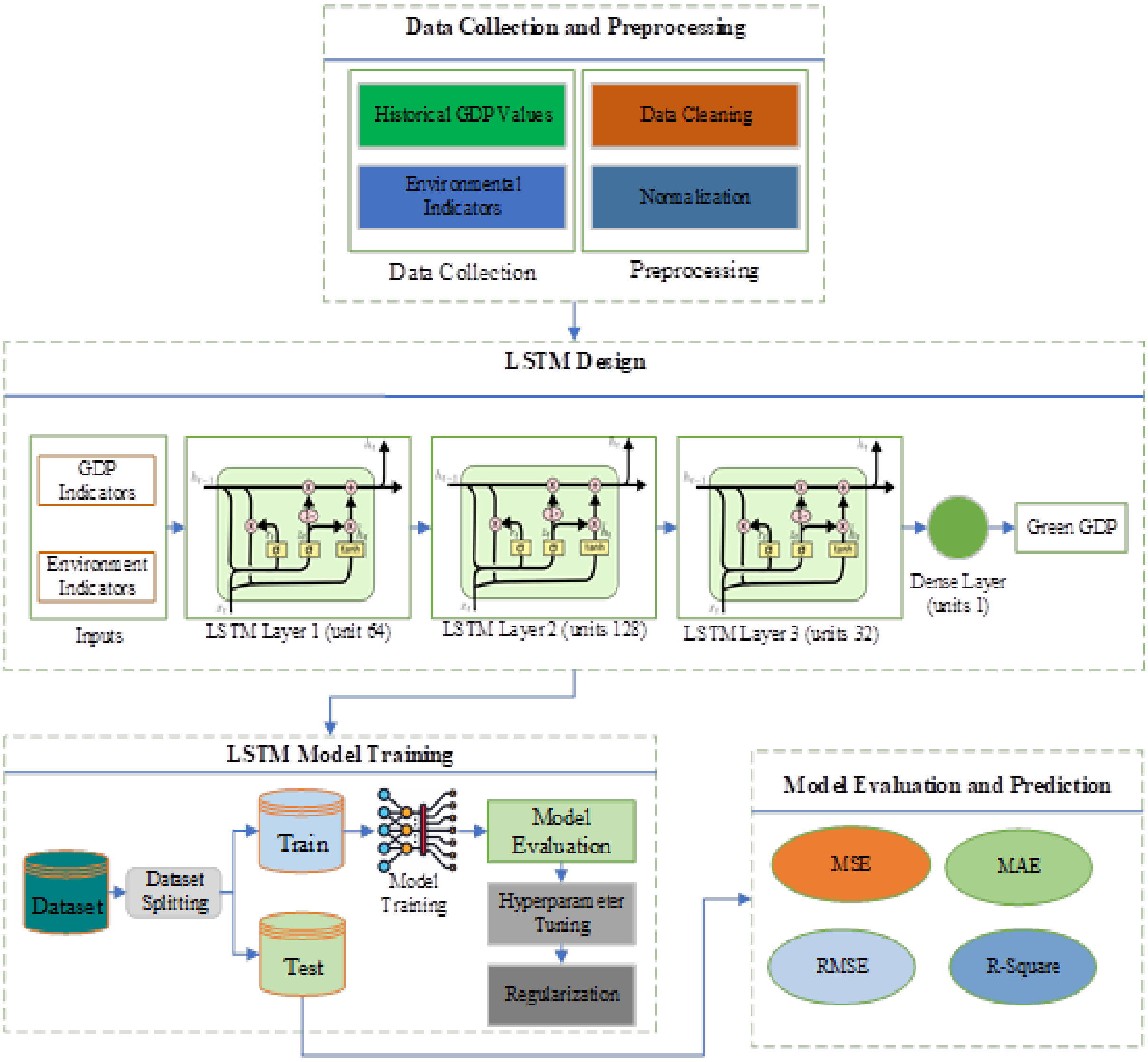

Figure 2. Green GDP and prediction with the help of LSTM model.

In the first phase, environmental and economic-related data are collected, including indicators such as air, water, solid waste data, and green GDP growth rates [81]. Following data collection, standard preprocessing steps, such as normalization and cleaning, are applied to ensure the data is suitable for use with the LSTM model. The LSTM model is designed, trained, and tested in the second phase on the processed data. Finally, in the last step, the performance of the developed deep learning-based model is evaluated during both the training and validation phases.

While the study examines the impacts of green technology investments and policy frameworks, it does not propose mediating or moderating hypotheses to explain how these interventions influence the relationship between pollution adjustments and green GDP changes. To enhance the understanding of these pathways, it is recommended to introduce hypotheses linking policy and green technology interventions to pollution adjustments, affecting green GDP. For instance, policies like carbon pricing or green technology incentives could be modeled as mediators, influencing environmental changes that subsequently impact green GDP. Moreover, to rigorously validate these relationships, structural equation modeling (SEM) could be employed to examine both the direct and indirect effects of policy interventions and technological changes on green GDP. This approach would provide a more nuanced understanding of how green policies and technologies affect both the environment and economic outcomes, offering actionable insights for policymakers.

4.1. The detailed step-by-step process is discussed in the following sections

4.1.1. Data collection and preprocessing

The Anhui Statistical Yearbook 2021 focuses on showcasing the accomplishments of statistical departments in supporting the development of a modern and beautiful Anhui in the new stage. It does this by thoroughly and methodically compiling the economic and social statistical data of the entire province and all cities and counties in 2020. It is a yearly reference magazine that fully captures the social and economic advancement of the province of Anhui. Internationally recognized measuring units are employed as the units of measurement in this text [82]. Environmental ecology and economic growth data collected from relevant sources such as the Environmental Statistics Yearbook of Anhui Province. The environmental indicators and pollution data include water, air, and solid waste data. On the other hand, the data related to economic growth includes green GDP growth. We also consider the specific data of the Anhui Province that helps us find and localize the growing economy's environmental impact on the region.

4.1.2. The design and training of the LSTM model

It has been demonstrated that a deep neural network's capacity to be made up of many non-linear functions is a critical component of a successful neural network. The network can intuitively learn characteristics at different levels of abstraction between the raw data and the prediction, thanks to many layers of non-linear functions. This, however, comes at the expense of explainability, as it remains a challenging open question to provide a human-intelligible interpretation of a complex composition of several nonlinear functions. Thus, although less accurate, still interpretable models like decision trees and linear regression may be used in safety-critical applications, such as criminal justice, credit allocation, and health diagnostics.

Despite the numerous available deep learning models, the LSTM model is primarily used for green GDP prediction and accounting. This is because the model performs well on sequential data, which is our primary concern in this study. The three-layer LSTM module is employed, and the specific parameters are listed in Table 1.

Table 1. Specific parameter settings for the LSTM model.

Layer	Parameters	Values
Input	green GDP Indicators	Environmental variables and green GDP variables
LSTM 1	Units	64
	Recurrent Activation	ReLU
	Dropout	0.2
	Recurrent Dropout	0.1
	Recurrent Kernel	Randomly initialized weights
LSTM 2	Units	128
	Activation Function	ReLU
	Dropout	0.5
LSTM 3	Units	32
	Activation Function	ReLU
	Dropout	0.25
Output	Dense Units	1
	Activation Function	Linear

4.1.3. Model evaluation and prediction

Several performance indicators are used to measure the model's performance and assess its effectiveness. When evaluating the model, we measured its performance on the validation set using measures such as mean absolute error (MAE), mean squared error (MSE), or R-squared (R^2). When making predictions, we applied the trained model to estimate green GDP values for data that had not yet been seen (test set or future periods).

5. Result analysis of the green GDP accounting model

The concept of the “green GDP accounting system”, which we adopted for this study, is the accounting system that subtracts the cost of natural resource consumption and environmental degradation control from the traditional green GDP. This represents the net positive effect of national economic growth, more accurately reflecting the state of development of a nation's green economy and the living standards of its citizens. This paper's implementation of the green GDP accounting system is based on a deep learning model that generates the accounting index for green GDP, incorporating environmental and natural resource considerations.

This section first covers the specific environmental statistics of Anhui Province and then performance evaluation of the overall developed system. We also compared our system with the already existing system.

5.1. Current situation of the research area

In recent years, Anhui Province has established several economic and technological development zones and industrial parks to promote the rapid development of the province's economy. However, the pollutants emitted by a large number of industrial parks have also increased, making environmental governance more challenging. Relevant data show that in 2019, 1.981 billion tons of wastewater in Anhui Province did not meet the standard of discharging "tertiary production" wastewater, accounting for 57.3% of the total wastewater discharge. The emission of air pollutants was 2.9423 million tons, accounting for 18.95% of the total air pollutants.The storage capacity of industrial waste was 4.7156 million tons, accounting for 8.12% of the total production; The amount of domestic waste was 2.734 million tons, accounting for 35.55% of the total domestic waste. Based on this data, Anhui Province has had to implement vigorous reforms of the national accounting system and establish a green national economic system.

5.2. The calculation results are based on the environmental pollution value accounting model

Here, according to the environmental pollution value accounting model established above, the 2019 green GDP data for Anhui Province are substituted into the calculation, and the accounting results for water pollution value, air pollution value, and solid waste value are obtained.

5.2.1. Accounting results of water pollution value quantity

This section highlights significant differences between virtual and actual values for several key pollutants across various businesses, as shown in Table 2. The following table presents an insightful comparison of total wastewater pollution, ammonia nitrogen (NH_3-N), and chemical oxygen demand (COD). The cattle and poultry breeding sector, in particular, is a notable example of significant differences in measured parameters, such as COD, NH_3-N, and wastewater pollution, with the real values showing remarkably higher values than the equivalent virtual counterparts.

Table 2. Accounting results of wastewater pollutant value in the livestock and poultry breeding industry (unit: per 10,000 yuan).

Industry	COD		NH_3-N		Wastewater	
	Actual value	Virtual value	Actual value	Virtual value	Actual value	Virtual value
Livestock and poultry breeding industry	1520.0	502.11	652.3	1510.43	2172.3	2012.54

Figure 3 shows the calculated value accounting results of wastewater pollutants in livestock and poultry farming, in which COD represents the unit treatment cost, NH_3-N is the ammonia nitrogen treatment cost, and the total actual wastewater treatment cost is calculated after accumulation is 21.723 million yuan. The virtual treatment cost is 20.1254 million yuan.

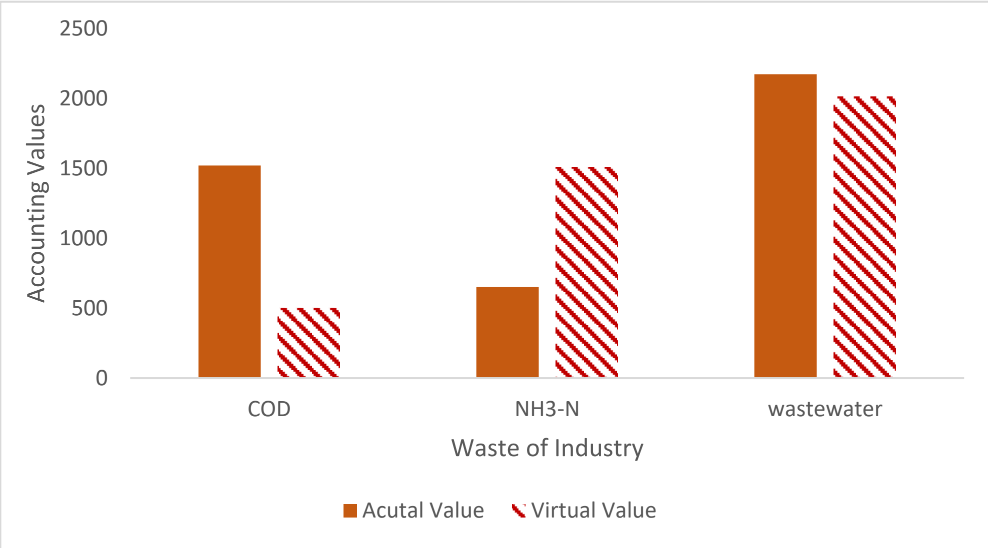

Figure 3. Waste of livestock and poultry breeding industry.

The accounting results for industrial water pollution — showing both "virtual" pollutant-by-pollutant costs and the actual total treatment cost—are summarized in Table 3. Using 2019 data from the Anhui Province Environmental Statistics Yearbook, we calculate a total actual treatment cost of 196 231 per 10,000 yuan and virtual costs of 259 312.79 (COD), 2.13 (cyanide), 0.61 (heavy metal), 169.66 (petroleum), and 2405.34 (NH_3-N), all in units of per 10,000 yuan.

Table 3. Accounting results of industrial water pollution value (unit: per 10,000 yuan).

COD	Cyanide	Heavy metal	Petroleum	NH_3-N	The total amount of wastewater	
259312.79	2.13	0.61	169.66	2405.34	19623.1	261890.23

Table 4 reports the analogous urban figures: the virtual treatment costs for COD and NH_3-N, the total virtual cost of urban domestic wastewater, and the actual treatment cost as recorded by local sewage-plant statistics. Based on the established urban domestic wastewater treatment cost accounting model, the COD virtual treatment cost is calculated to be 49.1631 million yuan, the NH3-N virtual treatment cost is 1.8712 million yuan, the total virtual treatment cost of urban domestic wastewater is 51.0343 million yuan, and the actual treatment cost is 48.2637 million yuan according to the relevant data of sewage treatment plants in environmental statistics.

Table 4. Accounting results of urban water pollution value (unit: per 10,000 yuan).

Industry	COD	NH_3-N	Urban domestic wastewater	
	4916.31	187.12	5103.43	4826.37

5.2.2. Air pollution value accounting results

According to the air pollution value accounting model established above, the calculation results of air pollutant value are calculated, which are detailed in the following Table 5.

Table 5. Accounting results of air pollution value (unit: per 10,000 yuan).

Industry	SO_2	Smoke	Nitrogen oxide	Dust	Actual cost of air pollution control
	Virtual value	Virtual value	Virtual value	Virtual value	
Power industry	16102.3	137.26		--	7316.4
Other industries	3592.12	2693.97	42002.12	711.23	10328.5
Cement				841.29	
Life and others	2084.76	969.36	2897.65	--	0
Total	21779.18	3800.59	44899.77	1552.52	17644.9

Table 5 above shows the amount of air pollution value obtained by the constructed air pollution value accounting model, of which the virtual treatment cost of sulfur dioxide is 217.7918 million yuan, the virtual treatment cost of smoke and dust is 38.0059 million yuan, the virtual treatment cost of nitrogen oxides is 44899.77 yuan, the virtual treatment cost of dust is 15.5252 million yuan, and the actual treatment cost of air pollution is 176.449 million yuan.

The outcomes of value accounting for air pollution in several businesses are displayed in Figure 4, which shows the recorded emissions of smoke, dust, nitrogen oxides, and sulfur dioxide (SO_2). The statistics illustrate how these pollutants affect the environment for each industry. The costs associated with controlling these pollutants are shown in the column labeled "Actual cost of air pollution control". For example, the power sector incurs significant expenses for pollution management and contributes substantially to sulfur dioxide emissions. There are also differences in pollution levels and associated control costs across other industries. The total figures in the table provide a broad overview of the amounts of pollution and the costs associated with reducing air pollution in different businesses, highlighting the economic and environmental implications of managing such emissions.

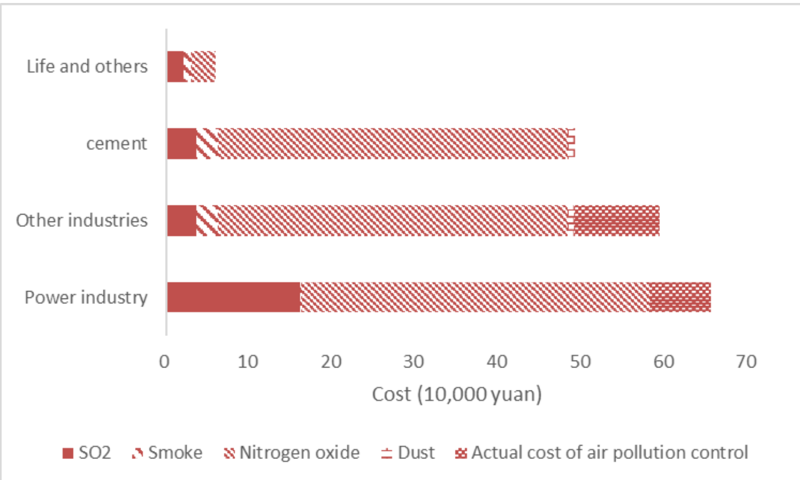

Figure 4. Accounting results of air pollution value.

5.2.3. Solid waste value accounting results

Based on the established industrial waste and domestic waste value accounting model, the solid waste value accounting results are calculated, and the specific data are listed in Table 6.

Table 6. Accounting results of solid waste value (unit: per 10,000 yuan).

Industrial solid waste			Domestic garbage	Virtual cost of solid waste	Actual treatment cost of solid waste
Virtual cost of storing general solid waste	Virtual cost of storing hazardous solid waste	Discharge general solid waste virtual cost			
851.23	15.02	3.5	4792.1	5661.85	2392.8

According to Table 6, the virtual treatment cost of industrial solid waste is 8.6975 million yuan, the virtual cost of domestic waste is 47.921 million yuan, and the total virtual cost of solid waste obtained by adding the two is 56.6185 million yuan, and the actual treatment cost is 23.928 million yuan.

5.3. Green GDP accounting results based on environmental pollution loss adjustment

Energy demand worldwide has been rising over time, particularly in developing market countries. This has the potential to have detrimental effects on the environment, particularly in the long term, affecting both nature and climate change. Goal 7 of the sustainable development targets agenda, which was approved by the UN General Assembly in 2015, acknowledges the critical role that energy plays in both social and economic development. It highlights three key facets of energy access: ensuring everyone has access to modern, affordable, and reliable energy services; significantly increasing the proportion of renewable energy; and doubling the rate at which energy efficiency is improving worldwide. Affordable and dependable energy is now essential for healthcare facilities during the SARS-CoV-2 health emergency, as the pandemic has brought attention to the importance of a steady and continuous electricity supply for medical facilities.

The results of using a green GDP accounting model that accounts for losses from environmental contamination are covered in this section. This approach would provide a more realistic picture of a country's economic development in terms of ecological sustainability by excluding the expenses related to natural resource use and environmental deterioration from the standard green GDP. The findings offer insights into the relationship between resource usage, economic development, and environmental health, highlighting the net positive effect of economic activity after accounting for ecological externalities. This methodology underscores the importance of incorporating ecological factors into economic evaluations to ensure that growth is consistent with sustainable practices.

5.3.1. Value quantity accounting results

The value accounting of environmental pollution comprises three parts: the value accounting of air pollution, water pollution, and solid waste. The results calculated above are summarized in Figure 5 below.

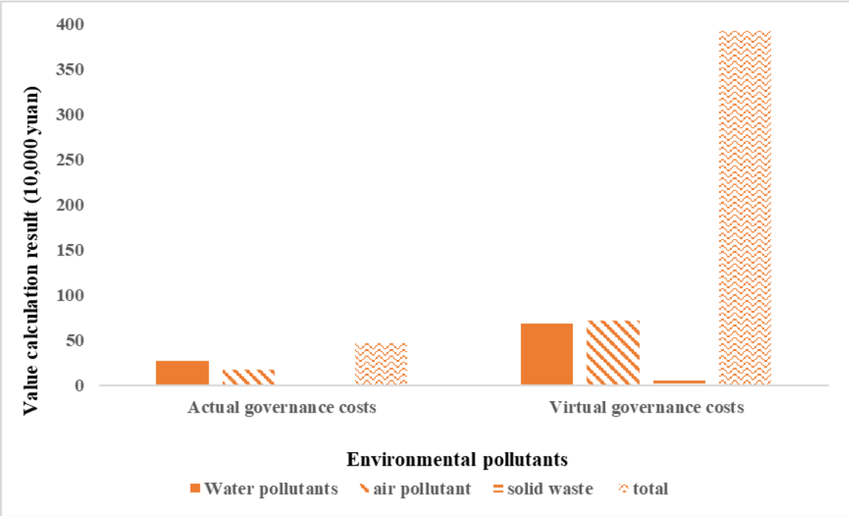

Figure 5. Histogram of environmental pollution value accounting results.

After summarizing and sorting, the data in the above Tables 1–5 were accumulated to calculate the accounting results of environmental pollution value. The virtual treatment cost was 345.7 billion yuan, the actual treatment cost was 466.5947 million yuan, and the total treatment cost was 392.359.58 billion yuan. Among them, the total treatment cost of water pollutants was 294627.97 million yuan, accounting for 75% of the total treatment costs, the treatment cost of air pollutants was 896.7696 million yuan, accounting for 22.9% of the total treatment costs, and the total treatment cost of solid waste was 80.5465 million yuan, accounting for 2.1% of the total treatment costs. It can be seen that the cost of air pollutants is relatively high, and reasonable measures need to be taken to reduce the emission of air pollutants.

5.3.2. Green GDP accounting results based on environmental pollution loss adjustment

Based on the green GDP accounting method of environmental pollution loss adjustment, this paper adjusts according to the income method. It substitutes the 2019 green GDP of Anhui Province into the formulas (15) and (16) to obtain the following accounting results of Anhui Province's environmental pollution loss adjusted green GDP, which are listed in Table 7. Figure 6 shows a histogram of green GDP based on ecological pollution loss adjustment.

According to the data in Figure 6, the analysis of the total green GDP accounting results, adjusted for the cost of virtual treatment of environmental pollution, reveals that Anhui Province’s green GDP in 2019 is 17,626,015 million yuan. After accounting for ecological degradation costs through virtual treatment, the adjusted green GDP is 17,280,314.89 million yuan, representing the green GDP after virtual cost adjustment. The green GDP index stands at 98.04%, indicating that environmental costs account for 1.96% of the total green GDP, as shown in Figure 7.

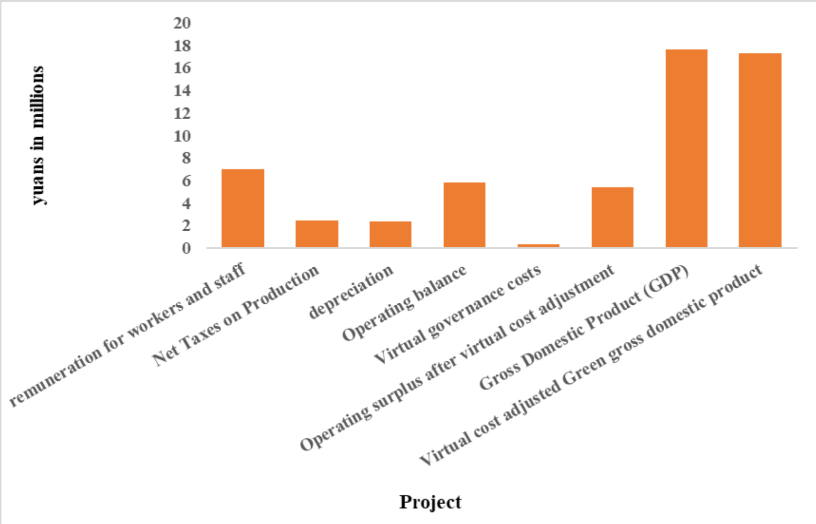

Figure 6. Histogram of green GDP based on environmental pollution loss adjustment.

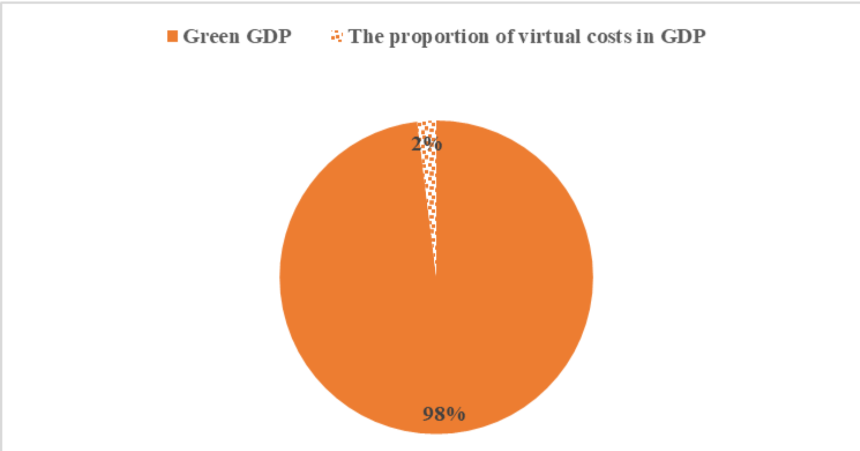

Figure 7. Green roofs and their effect on architectural design and urban ecology using deep learning approaches.

However, Table 7, which presents the green GDP results based on environmental pollution loss adjustments, does not specify the detailed composition of the “virtual governance cost”. Specifically, the contributions from water pollution, air pollution, and solid waste pollution are not outlined. This lack of transparency makes it challenging for readers to understand the relative importance of each pollutant in contributing to the overall environmental costs. To improve clarity and reproducibility, it is crucial to specify the proportional contributions of each type of pollutant. This could be based on data from the Anhui Province Environmental Statistics Yearbook, third-party studies, or other reliable sources. Providing this breakdown will not only enhance the reproducibility of the methodology but also give a clearer understanding of the sources of environmental costs within the green GDP model. Based on the LSTM model's predictions for green GDP, it would be insightful to compare these results with actual economic events, such as the environmental policy adjustments made in Anhui Province in 2019. Incorporating actual policy interventions, such as stricter emissions regulations or green technology incentives, as exogenous variables in the model could allow us to assess its sensitivity to policy shocks. For instance, by integrating policy changes like carbon tax rates or emission caps, we could analyze how these adjustments influence green GDP forecasts. This comparison would not only verify the model's predictive accuracy but also highlight its responsiveness to real-world economic and environmental policy changes. Such an approach could further enhance the practical applicability of the LSTM model for policymakers seeking to predict and evaluate the economic impacts of green policies.

Table 7. Total green GDP accounting table for virtual governance cost adjustment (unit: per 10,000 yuan).

Project	Serial number	Amount of money
Employee compensation	1	6983406
Net product tax	2	2456073
Depreciation of fixed assets	3	2403486
Operating balance	4	5783050
Virtual governance costs	5	345700.11
Operating surplus after virtual cost adjustment	6=4-5	5437349.89
Gross Domestic Product (GDP)	7=1+2+3+4	17626015
Virtual cost adjusted green gross domestic product	8=1+2+3+6	17280314.89
Green gross domestic product Index (%)	9=8/7	98.04%
The proportion of virtual costs in green GDP (%)	10=5/7	1.96%

5.4. Result analysis of green GDP using LSTM

This section presents the results of green GDP analysis based on an LSTM neural network. Given the temporal complexity and dependency of green GDP, the LSTM model is employed to forecast and capture its dynamic trends over time. The analysis includes evaluating the model’s performance and interpreting the results in the context of relevant economic and environmental factors.

Figure 8 displays the mean square error (MSE) performance of the LSTM for both training and validation over a 100-epoch. The Figure 8. shows that over the first 15 epochs, loss declines sharply from 0.5 to less than 0.1. After that, it remains constant with just minor fluctuations. Similarly, the validation loss from 0.1 to 0.002 over 100 epochs.

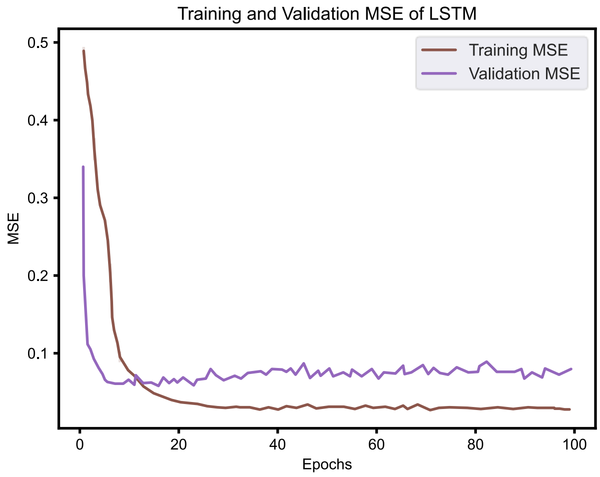

Figure 8. MSE of LSTM during training and validation.

Figure 9 shows the result of the proposed LSTM model in predicting green GDP. There are various performance measures for regression problems, but we chose MSE, and root mean squared error (RMSE) because we are dealing with regression tasks. We also compare the performance of our model with other similar models proposed by Gong et al., Zhao et al., and Sun for green GDP prediction. Our model outperforms these models in terms of performance measures, with an MSE value of 0.002, compared to 0.003, 0.004, and 0.005 for the other models. Here, lower MSE values indicate better performance. Similarly, in terms of RMSE, the model proposed in this study also outperforms the others, with an RMSE of 0.045, while the RMSE values for the other models are 0.067, 0.071, and 0.075.

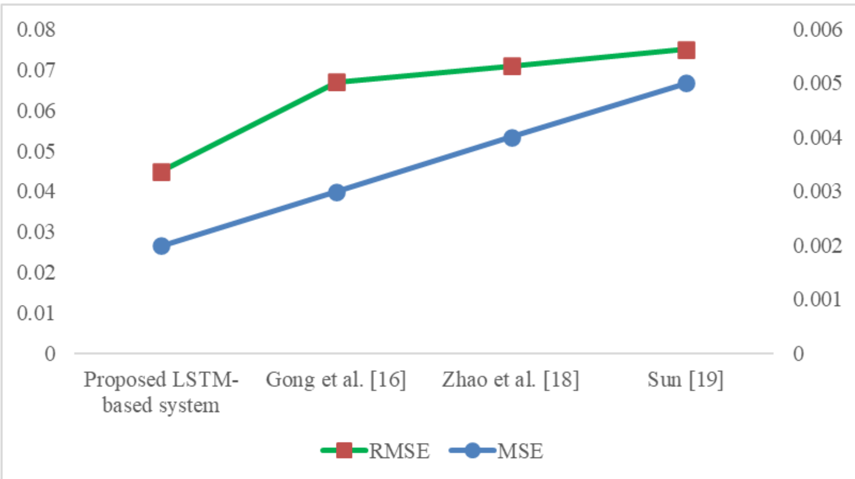

Figure 9. Green roofs and their effect on architectural design and urban ecology using deep learning approaches.

Figure 10 shows the performance of the LSTM in terms of MAE and R-squared value. These two performances metrics are essential for evaluating the performance of regression models. A lower value of MAE indicates better results, while a higher value indicates worse performance. The MAE recorded for the model proposed in this study is 0.032, which is lower than the values for other models proposed by Gong et al., Zhao et al., and Sun, whose MAE values are 0.045, 0.05, and 0.055, respectively. On the other hand, R-squared values indicate better performance when the value is high. The R-squared value for the model proposed in this study is 0.948, which is higher than those of the other models.

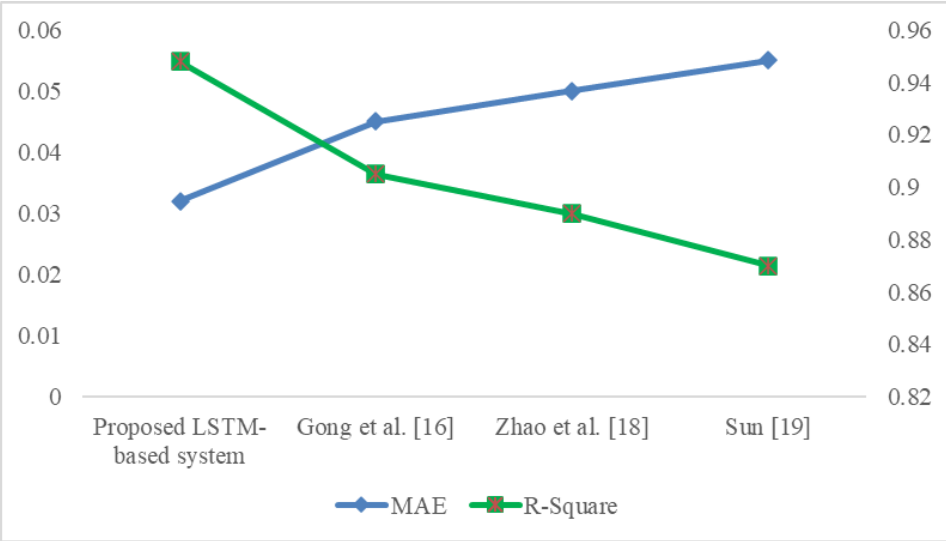

Figure 10. Green roofs and their effect on architectural design and urban ecology using deep learning approaches.

While the study proposes general measures such as “strengthening green technology investments”, it does not provide specific recommendations aligned with Anhui Province's unique industrial structure. Anhui, with its significant manufacturing sector, particularly in industries like steel and chemicals, faces unique environmental challenges. The steel and chemical industries are major contributors to pollution, and their environmental impact should be addressed more precisely. To optimize pollution accounting, tailored measures should be introduced that specifically consider the pollution profiles of these industries. For instance, adjusting the pollution valuation models to reflect the specific pollutants—such as sulfur dioxide, nitrogen oxides, and particulate matter—emitted by the steel and chemical sectors would improve the accuracy of the green GDP estimates. These adjustments would better capture the environmental costs associated with Anhui's industrial activities, ensuring that the green GDP accounting model more accurately reflects the region's economic and ecological realities.

The study highlights the importance of integrating policy frameworks and green technology investments to foster sustainable growth amid global geopolitical risks. However, the impact of these risks—specifically how geopolitical uncertainties affect Anhui's outward-oriented economy and energy imports—has not been fully explored in the discussion section. Given Anhui's significant reliance on external markets for its industrial output and energy needs, it is crucial to consider how these external dependencies could influence green GDP outcomes. For instance, fluctuations in energy prices or disruptions in international trade resulting from geopolitical tensions could significantly impact both the province's economy and its environmental performance.

Furthermore, the study does not detail how green GDP accounting could be used as a tool to mitigate such risks. green GDP accounting, by incorporating the costs associated with environmental degradation and resource depletion, could provide a more resilient economic metric that accounts for potential risks arising from energy price volatility or trade disruptions. By integrating such factors, the green GDP model could help policymakers identify vulnerabilities in Anhui's economic structure and formulate strategies that minimize the adverse impacts of external shocks on both economic growth and environmental sustainability.

6. Conclusions

This study employs the LSTM deep learning model to calculate and predict green GDP, incorporating adjustments for environmental pollution losses in Anhui Province. This approach presents a novel method for evaluating sustainable economic growth by incorporating the environmental costs associated with pollution. The research outlines a comprehensive technical framework for adjusting pollution losses. It develops an environmental pollution value accounting model that includes three key components: air pollution, water pollution, and solid waste. The model successfully calculates the respective pollution values for Anhui Province, demonstrating its ability to address the complexities inherent in environmental accounting.

A key contribution of this study lies in the application of LSTM modeling for forecasting green GDP, showcasing superior performance compared to traditional methods. By utilizing metrics such as MAE, MSE, R-squared, and root mean squared error (RMSE), the study highlights the accuracy, robustness, and predictive power of the proposed approach. These findings emphasize the critical importance of integrating environmental factors into economic growth assessments, offering a more realistic perspective on sustainable development.

The predictive capabilities of the model also carry significant policy implications. By accurately forecasting green GDP, the research provides policymakers with a practical tool to support sustainable economic growth, mitigate environmental degradation, and strike a balance between economic prosperity and ecological preservation. The study's results indicate that the green GDP of Anhui Province in 2019, adjusted for virtual governance costs, was 17.28 trillion yuan, corresponding to a green GDP index of 98.04%. This indicates that virtual governance costs accounted for only 1.96% of the green GDP, confirming the alignment between economic growth and environmental sustainability.

In conclusion, this study advances our understanding of the interaction between environmental factors and economic growth, laying a solid foundation for future research in green economic evaluation. The proposed framework offers policymakers and stakeholders valuable insights, providing a pathway to achieve sustainable development goals through data-driven and innovative approaches. Moreover, the integration of LSTM into green GDP forecasting opens new avenues for refining economic models to account for environmental costs in a more comprehensive and accurate manner.

Use of Generative-AI tools declaration

The author declares that he has not used Artificial Intelligence (AI) tools in the creation of this article.

Data availability

By requesting the data and materials, you may obtain all of the relevant information from the corresponding author.

Conflicts of interest

The author declares no conflicts of interest.

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