*sustainability*

MDPI

*Article*

# Modeling the Efficiency of Resource Consumption Management in Construction Under Sustainability Policy: Enriching the DSEM-ARIMA Model

**Pruethsan Sutthichaimethee [1], Grzegorz Mentel [2,3], Volodymyr Voloshyn [4], Halyna Mishchuk [5,6,*] and Yuriy Bilan [7,8,*]**

1 Faculty of Public Administration, Phitsanulok University, Amphoe Mueang Phitsanulok, Phitsanulok 65000, Thailand; pruethsan.s@plu.ac.th
2 Department of Quantitative Methods, Rzeszow University of Technology, 35959 Rzeszów, Poland; gmentel@prz.edu.pl
3 INTI International University, Persiaran Perdana BBN Putra Nilai, Nilai 71800, Malaysia
4 Department of Computer Technology and Economic Cybernetics, National University of Water and Environmental Engineering, Soborna St., 11, 33028 Rivne, Ukraine; v.s.voloshin@nuwm.edu.ua
5 Faculty of Economics, Széchenyi Istvàn University, Egyetem tér 1, 9026 Győr, Hungary
6 Department of Human Resources and Entrepreneurship, National University of Water and Environmental Engineering, Soborna St., 11, 33028 Rivne, Ukraine
7 Faculty of Economics and Business, University of Debrecen, Böszörményi út 138, 4032 Debrecen, Hungary
8 Academic and Research Institute of Business, Economics, and Management, Sumy State University, 2, Rymskogo-Korsakova St., 40007 Sumy, Ukraine
* Correspondence: mishchuk.halyna@sze.hu (H.M.); yuriy_bilan@yahoo.co.uk (Y.B.)

**Abstract:** The aim of this research is to study the influence of factors affecting the efficiency of resource consumption under the sustainability policy based on using the DSEM-ARIMA (Dyadic Structural Equation Modeling based on the Autoregressive Integrated Moving Average) model. The study is performed using the Thailand experience. The research findings indicate that continuous economic growth aligns with the country's objectives, directly contributing to continuous social growth. This aligns with the country's efficient planning. It demonstrates that the management aligns with the goal of achieving Thailand 5.0. Furthermore, considering the environmental aspect, it is found that economic and social growth directly impacts the ecological aspect due to the significant influence of resource consumption in the construction. The resource consumption in construction shows a growth rate increase of 264.59% (2043/2024), reaching 401.05 ktoe (2043), which exceeds the carrying capacity limit set at 250.25 ktoe, resulting in significant long-term environmental degradation. Additionally, considering the political aspect, it is found to have the greatest influence on the environment, exacerbating environmental damage beyond current levels. Therefore, the DSEM-ARIMA model establishes a new scenario policy, indicating that resource consumption in construction leads to environmental degradation reduced to 215.45 ktoe (2043), which does not exceed the carrying capacity. Thus, if this model is utilized, it can serve as a vital tool in formulating policies to steer the country's growth toward Thailand 5.0 effectively.

**Keywords:** resource consumption; sustainability policy; construction; efficiency; Thailand 5.0

check for updates

**Citation:** Sutthichaimethee, P.; Mentel, G.; Voloshyn, V.; Mishchuk, H.; Bilan, Y. Modeling the Efficiency of Resource Consumption Management in Construction Under Sustainability Policy: Enriching the DSEM-ARIMA Model. *Sustainability* **2024**, *16*, 10945. https://doi.org/10.3390/su162410945

Academic Editor: Antonio Caggiano

Received: 5 July 2024
Revised: 9 December 2024
Accepted: 10 December 2024
Published: 13 December 2024



## 1. Introduction

The new industrial revolution, named "Industry 5.0", is famous for the development of advanced technologies. This concept has evolved from Industry 4.0, which focused on revolutionizing industries through the integration of advanced technologies such as the Internet of Things (IoTs), Artificial Intelligence (AI), and Cyber-Physical Systems (CPS) into processes related to environmental sustainability [1–3]. These technologies, being the core of economic development worldwide, require the examination of the national strategies focused on defining the best approaches to sustainable technological development. In this regard, our research is based on Thailand's experience, where industrial development became the national priority. Thailand's development agenda currently emphasizes adapting to industrialization by utilizing advanced technology in operations, manufacturing, construction, and service delivery. This is evident through various supportive policies such as Thailand 4.0, the National 20-Year Strategy, the 12th and 13th National Economic and Social Development Plans, as well as the development concept of targeting 12 S-Curve Industries [4,5]. The core activities are focused on the development of the next-generation automotive industry, smart electronics, high-income tourism, health and wellness tourism, agriculture and biotechnology, and comprehensive medical and wellness services [6,7]. These industries have a high potential for significant income increase [8]. However, sometimes, the implications of these ideas on communities, society, and the environment may be overlooked. Therefore, in Europe, especially in Germany, a global leader in manufacturing industries, the concept of Industry 5.0 has been initiated, viewing Industry 4.0 as insufficient in steering industries towards sustainability [9–11].

The concept of Industry 5.0 focuses on developing technology and innovation with humans at the center. It emphasizes the importance of collaboration between humans and cutting-edge technology to enhance work efficiency and reduce errors in operations [12–14], being aligned with global trends [15,16]. This approach prioritizes safety, convenience, and human-friendly working environments while also aiming to minimize the negative impacts of work processes and production on communities, society, and the environment [17–19]. While Thailand may not have directly addressed Industry 5.0 in its policies, there have been significant efforts toward industrial development. The Board of Investment (BOI) has issued various support criteria for investors under the 5-Year Investment Promotion Strategy from 2023 to 2027. This strategy considers factors affecting investment directions to promote and develop Thailand's competitiveness [20]. Within this strategy, there is a focus on upgrading existing industries with distinct advantages and creating new industrial bases capable of generating value and responding to global trends. These policies are aimed at preparing Thailand for Industry 5.0, focusing on two main aspects: Smart and Sustainable Industry [20].

The term "Smart Industry" emphasizes integrating modern technology into work processes, production, and service delivery to enhance efficiency. Meanwhile, "Sustainable Industry" supports using renewable energy and waste reduction in production processes [21–23]. While many policies primarily support the transition to Industry 4.0, a closer examination reveals that Thailand's industrial development policies have strategically paved the way for Industry 5.0 [20]. Additionally, the focus on green industries, such as Green Factories or Eco-Towns, reflects the core principles of Industry 5.0 in minimizing the social and environmental impacts of operations and production processes.

Currently, Thailand implements sustainability policies effectively from an economic aspect. Particularly, foreign countries have continuously shown interest in investing in Thailand, leading to a continuous increase in investment rates, especially from China, Europe, and America [5,20]. This has brought a large amount of money into Thailand, allowing it to achieve the goals of Thailand 4.0 and move towards the full achievement of Thailand 5.0.

However, when considering the results of government policies regarding the environment, it is found that from 1990 to 2023, the rate of resource consumption has continuously increased, with a tendency to increase exponentially. This has increased greenhouse gas emissions by up to 95.21 percent (2023), particularly in construction, where resource consumption is highest and has seen exponential growth rates [4,5]. Additionally, total energy consumption has continuously increased. For these reasons, it is evident that the country's management under sustainability from 1990 to 2023 has been ineffective and has had significant adverse effects on the environment. High resource consumption in construction, especially with a long-term trend of increasing beyond the carrying capacity, is particularly concerning.

Therefore, this research identifies a gap in past research, revealing that despite Thailand's efforts to achieve Thailand 4.0 and, subsequently, Thailand 5.0, there has been a lack of suitable models as crucial tools for implementation. Instead, outdated models have been utilized, resulting in high inaccuracies in estimations and an inability to accurately and appropriately measure performance. This has led to significant errors in management and a failure in efficiency. Hence, this research has developed an approach to modeling resource consumption based on the DSEM-ARIMA model. It can serve as an effective tool in various sectors to analyze the patterns of resource consumption considering the sustainability policy requirements. The research is organized as follows. Section 2 provides the theoretical framework for the research, useful for formalizing the research process. Section 3 contains a description of the materials and methods. The empirical part of the research is available in Section 4. Finally, we conclude and discuss the findings in Section 5.

## 2. Literature Reviews

The construction stands at the forefront of global efforts to address energy consumption challenges, driven by the imperative to enhance sustainability, resilience, and efficiency. In this literature review, we examine various seminal studies spanning various facets of energy consumption in construction, ranging from integrating renewable energy technologies to predictive modeling of electricity demand and the environmental implications of innovative energy solutions. These studies collectively illuminate the multifaceted landscape of energy consumption in construction, offering insights into emerging technologies, policy implications, and strategic approaches to mitigate environmental impact while meeting the growing demand for energy services.

The integration of renewable energy technologies, such as piezoelectric energy harvesting systems (PE-EHSs) and solar stills (ST), presents promising avenues for reducing energy consumption and enhancing sustainability in the construction asserted by Pracucci et al. [24]; Bahrami et al. [25]. Concurrently, advancements in transportation systems, such as regenerative braking in medium-low-speed (MLS) maglev trains, require innovative approaches to manage power consumption and voltage fluctuations claimed by Huang [26]. Solar-powered cold rooms offer economic and environmental benefits in the food industry, particularly in fish storage, emphasizing the potential of renewable energy integration studied by Rami and Allouhi [27]. Understanding electricity consumption patterns in specific contexts, such as schools in Fiji, enables the development of predictive models to optimize energy usage and inform policy decisions posited by Prasad [28]. Meanwhile, peer-to-peer (P2P) energy trading systems, considering bounded rationality, strive to maximize benefits for prosumers and energy service providers, asserted by Hao et al. [29]. Additionally, the circular economy approach, utilizing second-life battery-based energy storage systems (SL-BESS), showcases environmental benefits and contributes to sustainable industrial practices, as performed by Silvestri et al. [30]. Decentralized energy systems, integrating renewable sources and district-level planning, demonstrate potential cost savings and resilience improvements, as claimed by Schnidrig [31]. Waste-to-energy initiatives, such as cogeneration from food waste, offer economic viability and environmental benefits, contributing to circular economy principles studied by de Oliveira et al. [32], Gedvilaite and Ginevicius [33]. Finally, strategies combining mechanical ventilation with indoor air quality and energy performance assessments underscore the importance of adaptive ventilation approaches for sustainable building practices, as investigated by Vasile et al. [34].

Moreover, Anušauskas et al. [35] investigated the energy and environmental impacts of bacteria-inoculated mineral fertilizers in spring barley cultivation, highlighting the potential for bioaugmented fertilizers to optimize agricultural sustainability. Altun and Kutlar [36] focused on optimizing energy management systems in hybrid electric vehicles, emphasizing the importance of reducing greenhouse gas emissions and fuel consumption in the automotive industry. Dragonetti et al. [37] presented a case study on the environmental and economic assessment of energy renovation in construction, using life cycle assessment and costing methodologies to evaluate renovation projects. Peta et al. [38]

analyzed the energy consumption of robotic welding stations, emphasizing the significance of energy-saving technological equipment and optimization of robot program codes. Jamshidi et al. [39] proposed a smart energy management approach for optimizing energy consumption in agricultural greenhouses, demonstrating significant reductions in grid energy consumption while maximizing the battery state of charge. Yang et al. [40] explored the impact of urbanization and technological innovation on urban land green use efficiency, highlighting the positive effects of green, digital, and transportation technological innovations in curbing energy consumption and pollution. Liang [41] investigated the effects of science and technology finance networks on carbon emissions, emphasizing the role of financial networks in low-carbon development. Vallati et al. [42] proposed the application of small-scale gas–liquid energy storage technology in residential buildings to mitigate renewable energy source production variability. Ping et al. [43] examined sandstone specimens' dynamic and energy consumption characteristics under dry and wet cycling, providing insights into energy dissipation and mechanical characteristics. Bao et al. [44] reviewed technological advancements in powertrains for Mining Haulage Trucks (MHT) and compared configurations based on system-level considerations to assess their future potential. Lastly, Richter et al. [45] developed a methodology for generating synthetic electricity load time series at the district scale, enabling the simulation of diverse scenarios for smart grid energy systems.

On the other hand, the literature on energy consumption forecasting in construction encompasses various methodologies and applications aimed at optimizing energy efficiency and sustainability. Postawa et al. [46] presented a method utilizing cascade-forward artificial neural networks (ANN) to predict the energy efficiency of photovoltaic modules, particularly in temperate climates. Osawa [47] investigated the configurations of residential energy systems in Japan, considering technologies like photovoltaic power generation (PV) and battery electric vehicles (BEVs). Senyapar and Aksoz [48] focused on accurately forecasting electricity consumption, employing advanced models like Exponential Smoothing and SARIMA. Zhao et al. [49] addressed the importance of accurately predicting energy consumption peaks in commercial buildings, proposing an Energy Peaks and Timestamping Prediction (EPTP) framework. Mystakidis et al. [50] reviewed various techniques and technologies for energy forecasting, highlighting their significance for applications like Demand Response Management and grid stability. Koukaras et al. [51] compared machine learning models for short-term load forecasting in construction, emphasizing the importance of data resolution and preparation in achieving accurate predictions. Bhuiyan et al. [52] analyzed fuel consumption trends in U.S. electricity generation, employing advanced statistical methods to forecast fuel consumption patterns. Parizad et al. [53] proposed a hybrid machine learning model for forecasting home energy demand and electricity prices, demonstrating improvements in prediction accuracy compared to conventional methods. Raudys and Gaidukevicius [54] developed forecasting models for solar energy generation and household electricity consumption, highlighting the importance of effectively utilizing renewable energy sources. Tian, Chen, and Zhao [55] proposed a combined prediction model for sizeable public buildings' energy consumption, integrating signal decomposition, feature screening, and deep learning techniques to improve prediction accuracy. El-Gohary, El-Abed, and Omar [56] utilized digital twin technology and artificial neural networks to forecast energy consumption in existing residential buildings in Lebanon, aiming to optimize energy efficiency and promote sustainability in building design and operation.

In addition, Al-Jamimi et al. [57] introduced a deep learning model for load forecasting, outperforming traditional methods. Alharbi and Csala [58] proposed a SARIMAX model for long-term performance forecasting in the electricity sector. Durand, Aguilar, and Moreno [59] explored energy consumption prediction in smart buildings using LSTM networks. Albatayneh [60] demonstrated significant energy savings through adaptive thermal models in different climates. Ding et al. [61] investigated integrating clustering with regression for short-term forecasting, enhancing prediction accuracy. Poczeta and Papageorgiou [62] introduced a nested fuzzy cognitive map approach for energy use forecasting, surpassing classic methods. Zawodnik et al. [63] tackled uncertainty in forecasting energy consumption for electric arc furnaces, highlighting the benefits of the energy transition. Chaganti et al. [64] proposed an ensemble machine learning model for heating and cooling load prediction, achieving superior accuracy. Chreng, Lee, and Tuy [65] developed a hybrid model incorporating climate variables, enhancing electricity demand forecasting. Huang, Algahtani, and Kaewunruen [66] compared machine learning models for energy forecasting in construction, emphasizing model selection's importance. Pu, Yao, and Zheng [67] utilized a BP neural network to forecast carbon emissions in China's construction, aiding policy formulation. Soyler and Izgi [68] focused on electricity demand forecasting for hospital buildings in Istanbul, emphasizing the complexity of demand prediction. Finally, Henzel et al. [69] proposed a novel approach using a digital twin model for energy consumption forecasting, highlighting the effectiveness of the Prophet method with conditional attributes for accurate predictions. These studies collectively advance the accuracy and efficiency of energy consumption forecasting. Together, these studies contribute to advancing energy forecasting methodologies and technologies, emphasizing the importance of accurate predictions for optimizing energy consumption and promoting sustainability, creating an appropriate theoretical framework for industries with essential resource use. One of these industries is construction. Its ecological footprint and essential resource needs require the development of a model of resource use under sustainability and alignment with sustainability policy. These reasons lead to choosing the construction as a case for analysis.

After reviewing the domestic and international literature, it was found that no research has yet developed the DSEM-ARIMA model. Most existing models are outdated and have been continuously applied and modified without thorough analysis for adaptation. This lack of in-depth analysis may lead to inaccuracies and undermine the reliability of their application. Moreover, using such models as critical policy-making tools could result in short-term, medium-term, and long-term damages, making formulating accurate future strategies challenging. Additionally, if scenarios are established, the likelihood of analytical errors increases significantly.

## 3. The Material and Methods

### *3.1. Dyadic Structural Equation Modeling Based on Autoregressive Integrated Moving Average (DSEM-ARIMA Model)*

The DSEM-ARIMA model is derived from the concept of structural equation modeling, which is used with interrelated paired data. Studying variables with such characteristics necessitates examining the relationships from pairs (dyads) data. The analysis mainly involves ANOVA and multiple regression analysis. Both analyses are known for their independence, meaning that after controlling for the variance caused by independent variables, the data remains independent from other data. This is divided into three concepts: non-independence, distinguishability, and the nature of the independent variable [17,70,71].

1. The concept of non-independence is the state of mutual non-independence between both dyads, which cannot be separated. The consequences of this close relationship occur in the form of partner effect, mutual influence, and common fate;
2. The concept of paired data in the form of distinguishability refers to dyads being separated by different variables. Dyads are considered distinct if there are factors that can differentiate between both dyads;
3. The concept of analyzing data based on the nature of the independent variable can be divided into three characteristics to help assess the suitability of the analysis.
    - The between-dyad variable refers to differences between pairs, but there will be no differences within pairs. However, within pairs, there will be similarities;
    - The within-dyad variable denotes differences between dyads within a pair, but when averaged across both dyads, each dyad will have the same average value;
    - The mixed variable is a characteristic of diversity both within pairs and between pairs.

The use of the DSEM-ARIMA model for this research is based on data from 1990 to 2023 in construction in Thailand [5]. The research employed the Linear Structural Relations (LISREL) software [70] and Econometric Views (EVIEWS) [71,72] for analysis. The research process is outlined as follows (Figure 1):

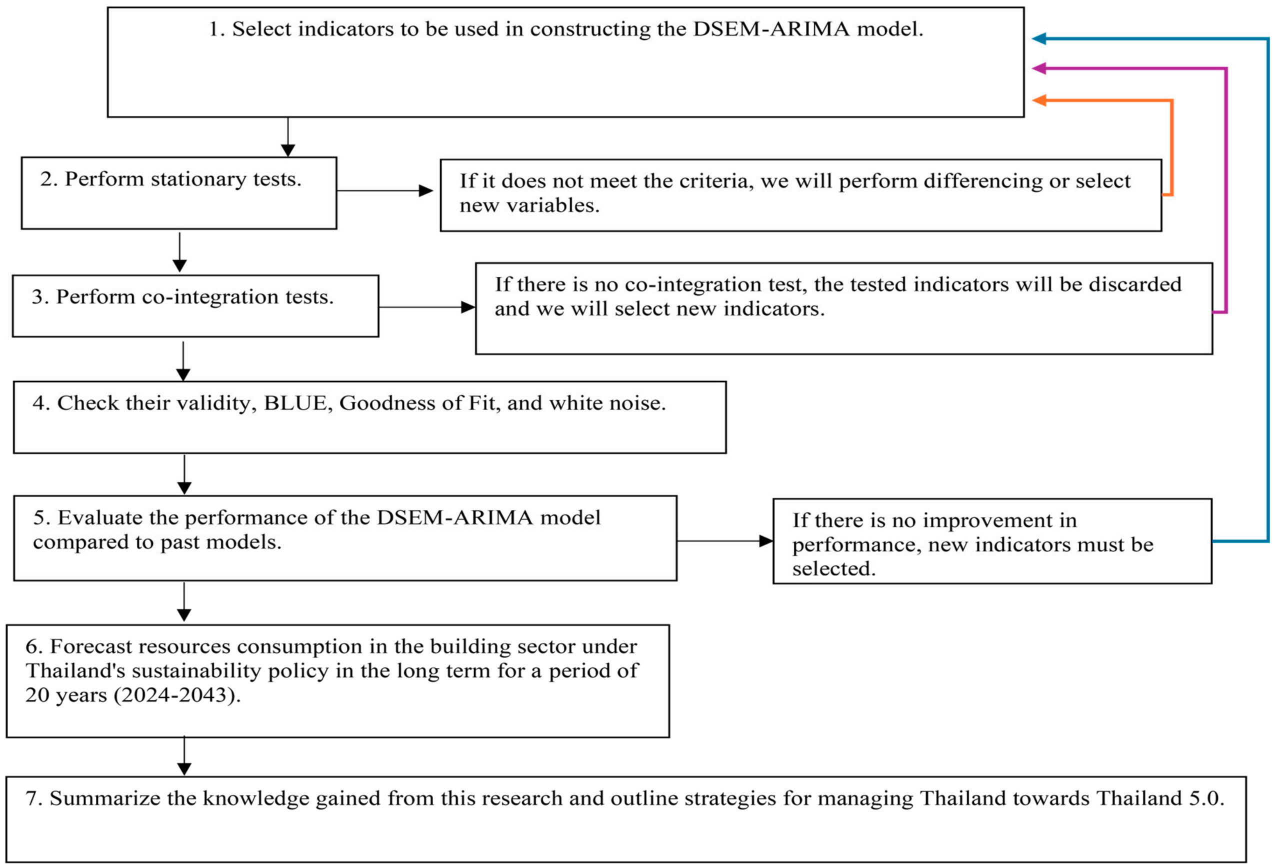


**Figure 1.** Research Process. Note: the color of the lines means the sequence of the analysis and the need to return to the initial stage in case of the negative test results on stages 2, 3, and 5, respectively.

Figure 1 illustrates the research steps of the DSEM-ARIMA model to study the influence of causal factors affecting the efficiency of resource consumption in the construction under sustainability policy in Thailand. The research procedure can be summarized as follows:

1. Define indicators aligned with the sustainability policy for generating the DSEM-ARIMA model. Based on available statistics and previously theoretical framework [5,6,8,17,22,69], the dataset includes income $(incom)$, urbanization rate $(urnba)$, industrial structure rate $(indus)$, total exports $(\exp om)$, indirect foreign $(ifroe)$, tourists rate $(touri)$, government expenditure $(go\exp)$, employment rate $(\exp e)$, health and illness $(heil)$, social security rate $(sose)$, education rate $(edur)$, consumer protection $(conp)$, resource consumption $(resc)$, carbon dioxide emissions $(CO_2)$, and energy intensity $(e\text{int})$;
2. Check the stationarity of all indicators using the Augmented Dickey–Fuller (ADF) concept [73];
3. Examine long-term relationships using the Johansen and Juselius concept [74–76].
4. Validate the DSEM-ARIMA model and check for the Best Linear Unbiased Estimators (BLUE), Goodness of Fit, and white noise [70];
5. Evaluate the performance of the DSEM-ARIMA model using Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) statistics [70,71] and

compare it with previous models such as MLR, BP, Grey, ANN, ANFIS, ARIMA, and ARIMAX models;

6. Apply the DSEM-ARIMA model to forecast resource consumption in the construction under Thailand's sustainability policy for the next 20 years (2024–2043) and define new scenario policies;
7. Summarize the knowledge gained from this research and outline strategies for efficiently managing Thailand towards Thailand 5.0.

### *3.2. Characteristics of the Dyadic Structural Equation Modeling Based on Autoregressive Integrated Moving Average (DSEM-ARIMA Model)*

The DSEM-ARIMA model is a model characterized by three relationship models. In the research, it is possible to select the relationship characteristics according to the appropriateness of the research problem and the research framework. The details are as follows [17,20,70,71]:

1. Standard Dyadic Design Model: Each dyad is a member of a pair, with only one pair being considered, constituting a 1:1 pairing. Each dyad is measured using the same variables, referred to as the actor–partner interdependence model (APIM). This method controls type I and type II errors;
2. Social Relations Model (SRM): This model is used to study behaviors that have relational group characteristics to analyze the structure of diverse data. The key principle of SRM is to reduce the variance of scores from pairs to other levels;
3. One-with-Many Design Model: This is the final model used to describe data with relational group characteristics. This model involves pairing multiple pairs together.

In this research, a relationship model described above as the third type of DSEM-ARIMA model is developed with the relationship of characteristics, as shown in Figure 2.

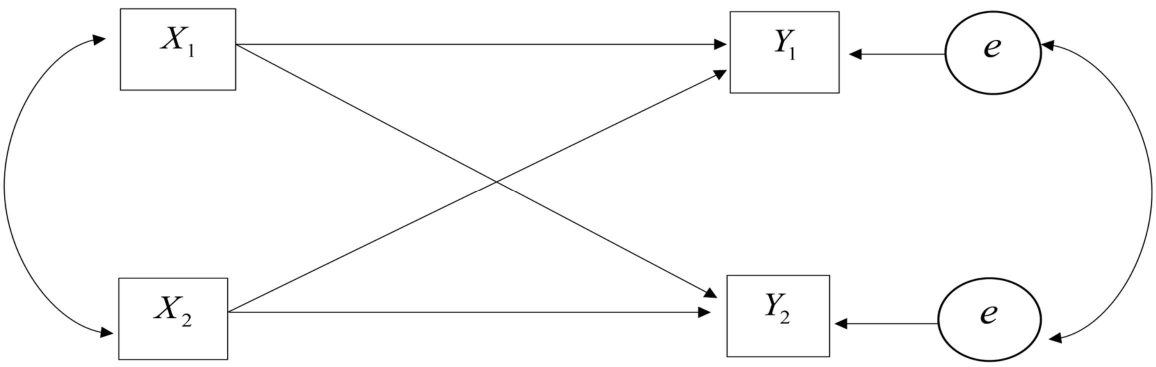


**Figure 2.** Characteristics of the DSEM-ARIMA model relationship.

From Figure 2, the characteristics of the relationship of the model are illustrated. Where $X_1, X_2$ are external latent variables, $Y_1, Y_2$ are internal latent variables, and $e$ is the error term. It is found that each factor influences one another, both directly and indirectly. The authors have specified the estimation guidelines of this model using the Autoregressive Moving Average method, with the details as follows [20,70].

### *3.3. Estimating DSEM-ARIMA Model Using Autoregressive Moving Average Method*

The time series used for analysis by the Autoregressive Moving Average method must exhibit stationary characteristics, which do not change over time. That is, the joint probability distribution of observed time series m with values of $z_{t1}, z_{t2}, \ldots, z_{tm}$, occurring at time $t_1, t_2, \ldots, t_m$, remains the same as the joint probability distribution of observed time series m with values of $z_{t1+k}, z_{t2+k}, \ldots, z_{tm+k}$ at times $t_{1+k}, t_{2+k}, \ldots, t_{m+k}$. In practice, it is difficult to know the joint probability distribution function of observed values of a time series. Therefore, in time series analysis, the property of weak stationarity is used, which includes the following characteristics for a time series $z_t, t = 1, 2, 3, \ldots, n$:

1. The mean of the stationary time series is constant, $E(z_1) = E(z_2) = \ldots = E(z_n)$;
2. The variance of the stationary time series is constant, $v(z_1) = v(z_2) = \ldots = v(z_n)$;
3. The autocovariance between $z_t$ and $z_{t+k}$ remains constant over time but depends on the lag k (lag k), that is $\text{cov}(z_1, z_{1+k}) = \text{cov}(z_2, z_{2+k}) = \ldots = \text{cov}(z_{n-k}, z_n) = \gamma_k$.

The time series that does not conform to the aforementioned properties, such as having a non-constant mean, a non-constant variance, or both, is called a non-stationary time series. A time series with similar characteristics but differing mean levels is referred to as Homogenous Non-stationary. This type of time series can be made stationary by taking differences. A non-constant variance time series can be made constant by using techniques like log transformation of the time series $\ln(z_t)$ instead of $z_t$ or by using Power Transformation [21,22,71].

For this model, it requires a time series that is sequentially ordered and has self-relation. It can be represented in the form of a linear combination of independent sequences, denoted as follows [71]:

$$z_t = \mu + a_t + \psi_1 a_{t-1} + \psi_2 a_{t-2} + \ldots = \mu \sum_{j=0}^{\infty} \psi_j a_{t-j} \tag{1}$$

From Equation (1), it is found that $a_t$ is a random variable with a fixed distribution, having a mean of 0 and constant variance. Denote the sequence $a_t, a_{t-1}, \ldots$ as the process White Noise, $\psi_j$. Let $\sum\limits_{j=0}^{\infty} \psi_j < \infty$, where in the term of $\psi_j$, there may be a finite number.

From Equation (1), in the case referred to as the Moving Average or MA, this model has an average value of $E(z_t) = \mu$, variance $v(z_t) = \gamma_0 = \sigma^2 \sum\limits_{j=0}^{\infty} \psi_j$, the covariance between $z_t$ and $z_{t+k}$ is equal to $\gamma_k = \sigma^2 \sum\limits_{j=0}^{\infty} \psi_j \psi_{j+k}$, and the correlation is as follows [17,70,71]:

$$\rho_k = \frac{\sum_{j=0}^{\infty} \psi_j \psi_{j+k}}{\sqrt{\sum_{j=0}^{\infty} \psi^2 \sum_{j=0}^{\infty} \psi^2{}_{j+k}}} \tag{2}$$

From Equation (2), it is found that $\sum\limits_{j=0}^{\infty} \psi_j < \infty$, which is a condition for the stationary state. Additionally, it is also found that ARIMA can be represented in another form as follows:

$$z_t = \delta + \pi_1 z_{t-1} + \pi_2 z_{t-2} + \ldots + a_t \tag{3}$$

From Equation (3), $a_t$ is a random variable with a fixed distribution, having a mean = 0 and constant variance $a_t, a_{t-1}, \ldots$, assumed to be a white noise process, $\pi_j$, is the weight, where $\sum\limits_{j=0}^{\infty} \pi_j^2 < \infty$, and Equation (2) is referred to as autoregressive (AR) [22,70,71].

## 4. Empirical Analysis

For this research study, the authors analyzed to investigate the influence of causal factors affecting the efficiency of resource consumption in construction under Thailand's sustainability policy. The quantitative research approach involved a DSEM-ARIMA model to study the causal relationships and predict the future over the next 20 years (2024–2043). The results of the analysis are detailed as follows:

### *4.1. Screening of Influencing Factors for Model Input*

This research study utilized the DSEM-ARIMA model to investigate the influence of causal factors affecting the efficiency of resource consumption in construction under Thailand's sustainability policy. The latent variables and observed variables are defined, including economic $(economic)$, social $(social)$, and environmental $(environmental)$ factors. Within each latent variable, observed variables were specified, consisting of income

$(incom)$, urbanization rate $(urnba)$, industrial structure rate $(indus)$, total exports $(\exp om)$, indirect foreign $(ifroe)$, tourists rate $(touri)$, government expenditure $(go\exp)$, employment rate $(\exp e)$, health and illness $(heil)$, social security rate $(sose)$, education rate $(edur)$, consumer protection $(conp)$, resources consumption in construction $(resc)$, carbon dioxide emissions $(CO_2)$, and energy intensity $(e\text{int})$. Furthermore, the authors designated the aspect of government policy utilization as political $(political)$. The results of the analysis of the stationarity of indicators using the Augmented Dickey–Fuller theory (ADF-test) are presented in Table 1.

**Table 1.** Stationary test.

| Tau Test | | | | MacKinnon Critical Value | | |
|---|---|---|---|---|---|---|
| **Variables** | **Level I(0) Value** | **Variables** | **First Difference I(1) Value** | **1%** | **5%** | **10%** |
| $\ln(incom)$ | −3.20 | $\Delta\ln(incom)$ | −5.00 *** | −4.20 | −3.55 | −2.75 |
| $\ln(urnba)$ | −2.75 | $\Delta\ln(urnba)$ | −5.15 *** | −4.20 | −3.55 | −2.75 |
| $\ln(indus)$ | −3.20 | $\Delta\ln(indus)$ | −5.02 *** | −4.20 | −3.55 | −2.75 |
| $\ln(\exp om)$ | −2.45 | $\Delta\ln(\exp om)$ | −5.15 *** | −4.20 | −3.55 | −2.75 |
| $\ln(ifroe)$ | −3.07 | $\Delta\ln(ifroe)$ | −5.05 *** | −4.20 | −3.55 | −2.75 |
| $\ln(touri)$ | −3.55 | $\Delta\ln(touri)$ | −5.19 *** | −4.20 | −3.55 | −2.75 |
| $\ln(go\exp)$ | −3.29 | $\Delta\ln(go\exp)$ | −4.75 *** | −4.20 | −3.55 | −2.75 |
| $\ln(\exp e)$ | −3.45 | $\Delta\ln(\exp e)$ | −4.55 *** | −4.20 | −3.55 | −2.75 |
| $\ln(heil)$ | −3.25 | $\Delta\ln(heil)$ | −4.51 *** | −4.20 | −3.55 | −2.75 |
| $\ln(sose)$ | −3.54 | $\Delta\ln(sose)$ | −4.45 *** | −4.20 | −3.55 | −2.75 |
| $\ln(edur)$ | −3.20 | $\Delta\ln(edur)$ | −4.78 *** | −4.20 | −3.55 | −2.75 |
| $\ln(conp)$ | −3.25 | $\Delta\ln(conp)$ | −4.70 *** | −4.20 | −3.55 | −2.75 |
| $\ln(resc)$ | −4.10 | $\Delta\ln(resc)$ | −5.75 *** | −4.20 | −3.55 | −2.75 |
| $\ln(CO_2)$ | −4.05 | $\Delta\ln(CO_2)$ | −5.72 *** | −4.20 | −3.55 | −2.75 |
| $\ln(e\text{int})$ | −3.70 | $\Delta\ln(e\text{int})$ | −5.11 *** | −4.20 | −3.55 | −2.75 |

Note: $incom$ is the income, $urnba$ is the urbanization rate, $indus$ is the industrial structure rate, $\exp om$ is the total exports, $ifroe$ is the indirect foreign, $touri$ is the tourists' rate, $go\exp$ is the government expenditure, $\exp e$ is the employment rate, $heil$ is the health and illness, $sose$ is the social security rate, $edur$ is the education rate, $conp$ is the consumer protection. $resc$ is the resource consumption in construction, $CO_2$ is the carbon dioxide emissions, and $e\text{int}$ is the energy intensity, *** denotes a significance, α = 0.01, Δ is the first difference, and ln is the natural logarithm.

Table 1 shows that all observed variables are non-stationary at level l(0), indicating that they are unsuitable for model building. Therefore, the model should be adjusted by taking the first difference to test. If all observed variables are still non-stationary after the first difference, it proceeds with a secondary difference. The analysis revealed that all observed variables exhibit stationarity after the first difference, with Tau-test values exceeding the MacKinnon critical value for all variables at a significance level of 0.01 (α = 0.01). Consequently, all 15 observed variables as indicators for the DSEM-ARIMA model are selected. Analyzing the influence of the DSEM-ARIMA model involves examining causal factors that can demonstrate the magnitude and direction of the relationship. The process proceeds as follows:

### *4.2. Analysis of Co-Integration*

For testing the relationship among indicators using co-integration analysis based on Johansen and Juselius, the results are presented in Table 2.

Table 2 shows that all indicators exhibit co-integration at $\alpha$ = 0.01 level. This is evident from the trace statistic test values of 225.01 and 125.55, which are higher than the MacKinnon critical values. Therefore, it is possible to use these indicators to construct the DSEM-ARIMA model, demonstrating the magnitude and direction of the relationships.

**Table 2.** Test results for the relationship of indicator variables.

| Variables | Co-Integration Test | | MacKinnon Critical Value | |
|---|---|---|---|---|
| | Trace statistic test | Max-Eigen statistic test | 1% | 5% |
| $\Delta\ln(incom)$, $\Delta\ln(urnba)$, $\Delta\ln(indus)$, $\Delta\ln(\exp om)$, $\Delta\ln(ifroe)$, $\Delta\ln(touri)$, $\Delta\ln(go\exp)$, $\Delta\ln(\exp e)$, $\Delta\ln(heil)$, $\Delta\ln(sose)$, $\Delta\ln(edur)$, $\Delta\ln(conp)$, $\Delta\ln(resc)$, $\Delta\ln(CO_2)$, $\Delta\ln(e\mathrm{int})$ | 225.01 *** | 125.55 *** | 15.11 | 12.20 |

*** denotes significance α = 0.01.

From Figure 3, it is observed that the DSEM-ARIMA model is a model with validity, Best Linear Unbiased Estimate (BLUE), and comprehensive goodness of fit, where $\chi^2/\mathrm{df}$ is 1.20, RMSEA is 0.01, RMR is 0.001, GFI is 0.97, AGFI is 0.95, R-squared is 0.97, F-statistic is 250.05 (probability is 0.00), ARCH test is 22.00 (probability is 0.1), and LM test is 1.20 (probability is 0.10). Additionally, it exhibits white noise, indicating no issues with autocorrelation, multicollinearity, or heteroskedasticity. Therefore, the DSEM-ARIMA model can effectively analyze the magnitude and direction of the relationships, as shown in Table 3.

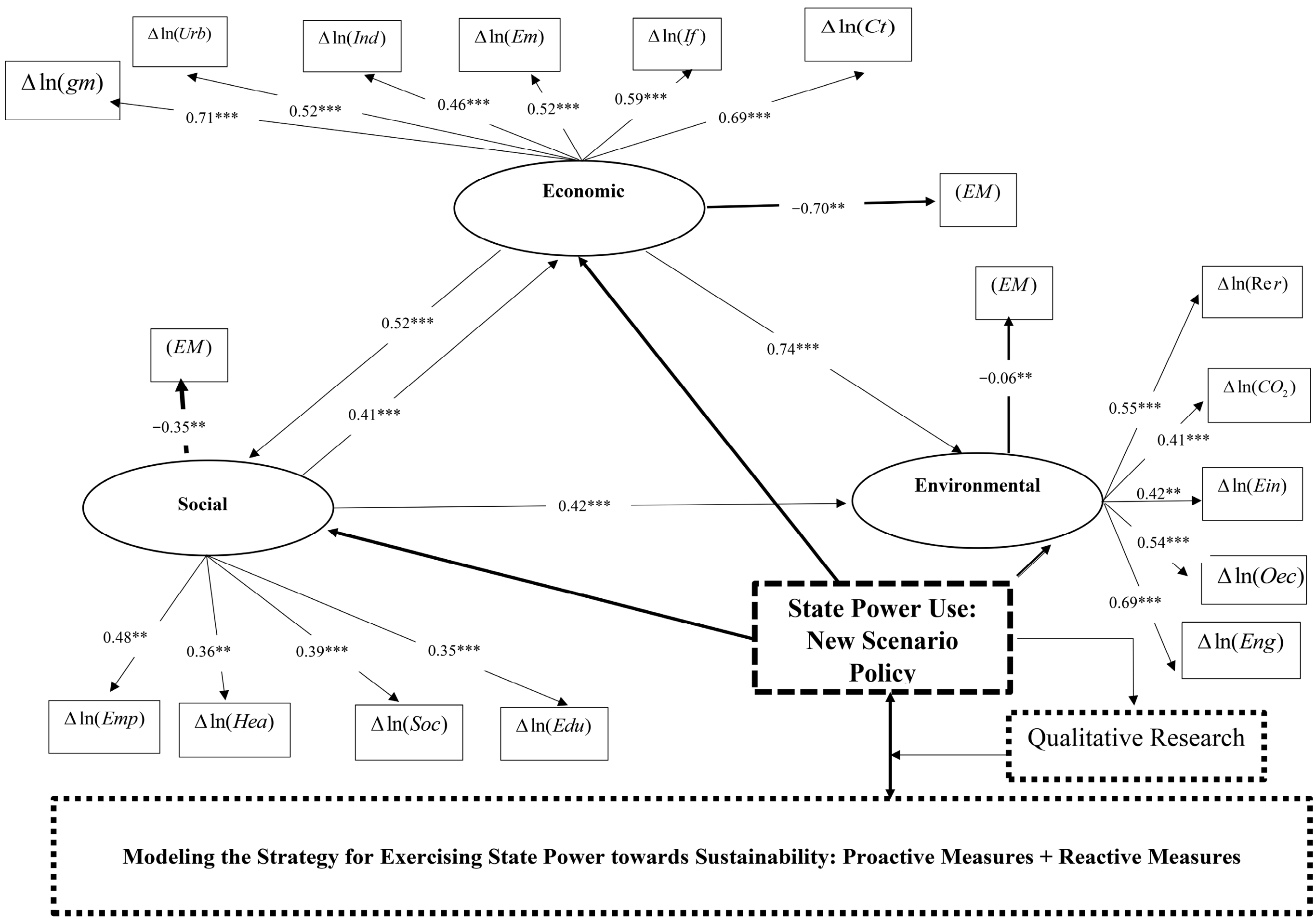


**Figure 3.** The relationship analysis results of the DSEM-ARIMA model. *** denotes significance α = 0.01, ** denotes significance α = 0.05.

**Table 3.** The magnitude of the relationship and the relationship direction of the DSEM-ARIMA model.

| Dependent Variables | Type of Effect | Independent Variables | | | | |
|---|---|---|---|---|---|---|
| | | Economic | Social | Environmental | Political | Error Correction Mechanism |
| Economic | DE | - | - | - | 0.50 *** | −0.81 *** |
| | IE | - | - | - | - | - |
| Social | DE | 0.31 *** | - | - | 0.35 *** | −0.35 *** |
| | IE | | - | - | - | - |
| Environmental | DE | (−0.65) *** | (−0.45) *** | - | 0.61 *** | −0.09 *** |
| | IE | (−0.11) *** | - | - | - | - |

Note: In the above, *** denotes significance α = 0.01, DE is the direct effect, and IE is the indirect effect.

From Figure 3 and Table 3, it is found that the DSEM-ARIMA model reveals the magnitude and direction of the relationships as follows:

1. The analysis using the DSEM-ARIMA model allows for examining the magnitude of the relationships. It is observed that economic factors have the highest direct effect on the environmental sector, at 65%, with a significant level of 1%. This indicates that a 1% change in economic factors leads to a 65% change in the environmental sector in the opposite direction. Additionally, there is an indirect effect through the social sector, which amounts to 11% in the opposite direction. Following this, social factors have a direct effect on the environmental sector, accounting for 47% of the total, with a significant level of 1%. This signifies that a 1% change in social factors leads to a 47% change in the environmental sector in the opposite direction. Furthermore, it is found that economic factors directly affect social factors, amounting to 31% with a significant level of 1%. This indicates that a 1% change in economic factors leads to a 31% change in social factors in the opposite direction;
2. This analysis shows that government policy has the most direct influence on the environmental sector, at 61%, with a significant level of 1%. This indicates that a 1% change in political impact leads to a 61% change in the environmental sector in the same direction. Following this, government policy also has a direct influence on the economic sector, accounting for 50% of the total, with a significant level of 1%. This signifies that a 1% change in policy leads to a 50% change in the economic sector in the same direction. Additionally, government policy directly influences the social sector, amounting to 35% with a significant level of 1%. This indicates that a 1% change in policy leads to a 35% change in the social sector in the same direction;
3. From this analysis, the DSEM-ARIMA model revealed that the environmental sector has the slowest ability to adjust to equilibrium, with an error correction mechanism $(ECM)$ of only 9%. This suggests that it takes the longest time to readjust when the ecological system is disrupted. Conversely, the economic sector can adjust to equilibrium fastest, with an error correction mechanism $(ECM)$ of 81%. Meanwhile, the social sector has the ability to adjust to equilibrium relatively quickly, with an error correction mechanism $(ECM)$ of 35%, second only to the economic sector;
4. The analysis and findings from this research enable the creation of new scenario policies. This is because the DSEM-ARIMA model demonstrates that resource consumption in construction has the most significant influence on environmental changes, at 67%. This means that a 1% change in resource consumption results in a 67% change in the environment in the same direction. Additionally, when the government utilizes state power to set policies, it has the highest influence on environmental changes. Therefore, the government must establish new scenario policies to ensure continuous economic and social growth in line with Thailand's goals. These policies should promote environmental growth efficiently in the future by introducing clean technology

to replace resource consumption in construction. The forecast details for the next 20 years (2024–2043) are as follows.

### *4.3. Forecasting Resources Consumption in Construction with New Scenario Policy*

For this research, a new scenario policy was established in the DSEM-ARIMA model. The forecasting results of resource consumption in construction for the next 20 years, from 2024 to 2043, are illustrated in Figure 4.

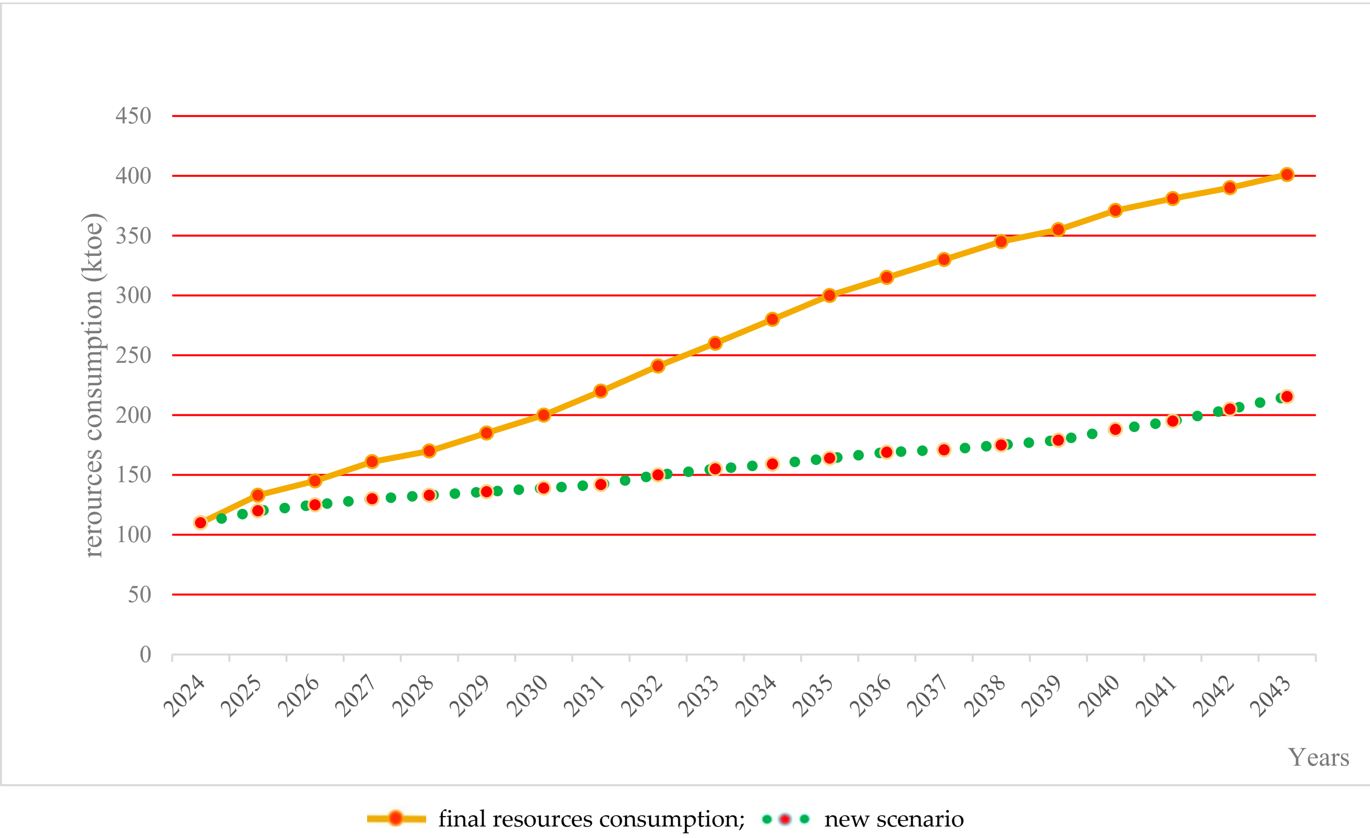


**Figure 4.** The future growth of resource consumption in construction (2024–2043).

From Figure 4, it is evident that Thailand's resource consumption in construction continuously increases from 2024 to 2043. This continuous increase leads to a corresponding rise in greenhouse gas emissions. The growth rate of resource consumption reaches 264.59% (2043/2024), with an increase of 401.05 ktoe (2043). This growth rate exceeds the carrying capacity limit of 250.25 ktoe, resulting in significant long-term environmental degradation. Considering the political aspect, it is found that government policy has the most influence on the environment. Therefore, the DSEM-ARIMA model has established a new scenario policy. As a result, resource consumption decreases, leading to a reduction in environmental degradation to 215.45 ktoe (2043), which is below the carrying capacity. Hence, the DSEM-ARIMA model is deemed the most suitable for guiding long-term national management strategies in the future.

## 5. Conclusions and Discussion

The research has developed a DSEM-ARIMA model, which is of the highest quality compared to other models in the past. This model exhibits validity, meets the criteria for Best Linear Unbiased Estimation (BLUE), demonstrates comprehensive goodness of fit, and indicates the absence of white noise issues such as autocorrelation, multicollinearity, and heteroskedasticity. Therefore, it is suitable for formulating policies and plans for Thailand's future. The analysis using the DSEM-ARIMA model reveals that economic factors have the most significant direct effect on the environmental sector in the opposite direction, with an indirect effect passing through the social sector in the opposite direction. Additionally, social factors have a direct impact on the environmental sector in the opposite direction. In addition, economic factors have a direct impact on the social factors in the opposite direction. Moreover, the analysis indicates that government policy has the most direct influence on the environment. Consequently, this research has led to the emergence of new insights, allowing the utilization of this knowledge to develop new scenario policies. The DSEM-ARIMA model highlights that resource consumption in construction has the most significant impact on environmental changes. When government power is utilized to formulate policies, it greatly influences environmental changes. Therefore, to ensure continuous growth in the economic and social sectors in line with Thailand's goals, the government must establish new scenario policies. These policies should promote adopting clean technology to replace resource consumption, thereby reducing environmental degradation. The forecast results for the next 20 years (2024–2043) show that resource consumption in construction will continue to rise, exceeding the carrying capacity. However, by implementing the new scenario policy developed using the DSEM-ARIMA model, it is projected that resource consumption in construction will lead to sustainable environmental growth, staying within the carrying capacity. Consequently, the DSEM-ARIMA model is the appropriate tool for guiding long-term national management strategies under sustainability policies, aligning with the goals of Thailand 5.0.

Regarding the recommendations from this research, it is found that the findings align with the assumptions set in all aspects. Therefore, Thailand should devise strategies for sustainable national management by promoting eco-tourism alongside new scenario policies, such as clean technology, and continuously reducing energy consumption. This is to achieve balance and simultaneous growth. Additionally, it is advisable to promote the tourism entrepreneurship sector in other areas alongside eco-tourism to ensure continuous growth and positive impacts on the economic, social, and environmental sectors. This is instead of solely focusing on economic growth as done in the past.

The study findings indicate that Thailand is ready for the forthcoming changes, but there are still gaps in development that adequately prevent achieving objectives. Therefore, five appropriate guidelines to propel Thailand into the "Industry 5.0" era can be proposed:

1. Industrial development should stem from the foundation of Industry 4.0, focusing on enhancing technology and innovation that prioritize collaborative work with humans to increase work efficiency and reduce errors in processes, considering safety, convenience, and employee-friendly workplaces;
2. Policymaking should consider the impacts of operations, production, and services on the public, society, and the environment. It should incorporate relevant technologies and innovations to reduce various wastes generated throughout these processes, aiming for the ultimate goal of social and environmental sustainability;
3. Industrial development should be accompanied by human capital development, emphasizing progress and knowledge enhancement, skills, abilities, and understanding related to modern technologies and innovations. This generates income, improves living standards, and promotes social equality. Additionally, it must be developed in tandem with environmental considerations to ensure clarity and concreteness;
4. Policies should serve as guidelines for designing a new economic model, such as the circular economy or green economy, as well as developing business models suitable for each industry's characteristics. Moreover, there should be a new approach to supply chain management alongside support for research and innovation aligned with sustainability. Climate and environmental changes should also be taken into account;
5. Achieving sustainability in Thailand's management requires essential tools that operate concurrently in the economic, social, and environmental aspects rather than segregating management as in the past. Segregated management lacks efficiency.

The limitation of this research is that Thailand lacks research in this area, and the government has earnestly promoted only economic and social aspects, neglecting the environment. Thus, developing Thailand to align with the Thailand 5.0 vision is challenging. Moreover, there is a shortage of environmental personnel and suitable organizations, including specialized administrative personnel, to manage efficiently and sustainably.

**Author Contributions:** Conceptualization, P.S. and Y.B.; methodology, P.S. and G.M.; software, P.S. and V.V.; validation, P.S. and V.V.; formal analysis, P.S., V.V. and Y.B.; investigation, P.S. and H.M.; resources, Y.B., P.S. and H.M.; data curation, G.M., P.S. and V.V.; writing original draft preparation, P.S. and H.M.; writing review and editing, Y.B., G.M. and H.M.; visualization, P.S.; supervision, Y.B. and G.M.; project administration, Y.B., G.M. and H.M. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** All data used in this study are publicly available and mentioned in the paper.

**Conflicts of Interest:** The authors declare no conflict of interest.

## References


1. Javaid, M.; Haleem, A.; Singh, R.P.; Suman, R.; Gonzalez, E.S. Understanding the adoption of Industry 4.0 technologies in improving environmental sustainability. *Sustain. Oper. Comput.* **2022**, *3*, 203–217. [CrossRef]
2. Bag, S.; Pretorius, J.H.C. Relationships between industry 4.0, sustainable manufacturing and circular economy: Proposal of a research framework. *Int. J. Organ. Anal.* **2022**, *30*, 864–898. [CrossRef]
3. Liu, L.; Song, W.; Liu, Y. Leveraging digital capabilities toward a circular economy: Reinforcing sustainable supply chain management with Industry 4.0 technologies. *Comput. Ind. Eng.* **2023**, *178*, 109113. [CrossRef]
4. Department of Alternative Energy Development and Efficiency. Available online: https://www.dede.go.th/ (accessed on 20 February 2022).
5. National Statistic Office of Thailand. Available online: https://www.nso.go.th/nsoweb/index?set_lang=en (accessed on 25 February 2024).
6. Sutthichaimethee, P.; Kubaha, K. The Efficiency of Long-Term Forecasting Model on Final Energy Consumption in Thailand's Petroleum Industries Sector: Enriching the LT-ARIMAXS Model under a Sustainability Policy. *Energies* **2018**, *11*, 2063. [CrossRef]
7. Sutthichaimethee, P.; Chatchorfa, A.; Suyaprom, S. A Forecasting Model for Economic Growth and $CO_2$ Emission Based on Industry 4.0 Political Policy under the Government Power: Adapting a Second-Order Autoregressive-SEM. *J. Open Innov. Technol. Mark. Complex.* **2019**, *5*, 69. [CrossRef]
8. Sutthichaimethee, P. A Framework on Setting Strategies for Enhancing the Efficiency of State Power use in Thailand's Pursuit of a Green Economy. *Int. J. Energy Econ. Policy* **2024**, *14*, 108–120. [CrossRef]
9. United Nations Framework Convention on Climate Change, UNFCCC, Bonn, Germany. The Paris Agreement: An Early Assessment. *Environ. Policy Law* **2014**, *44*, 485–488.
10. United Nations Framework Convention on Climate Change, UNFCCC, Bonn, Germany. Global Progress in Environmental Law. *Environ. Policy Law* **2016**, *46*, 23–27.
11. Sutthichaimethee, P. Forecasting Economic, Social and Environmental Growth in the Sanitary and Service Sector Based on Thailand's Sustainable Development Policy. *J. Ecol. Eng.* **2018**, *19*, 205–210. [CrossRef]
12. Pollution Control Department. Ministry of Natural Resources and Environment. Enhancement and Conservation of National Environmental Quality Act, B.E. 2535. Available online: https://www.pcd.go.th/laws/5406/ (accessed on 25 February 2024).
13. Pollution Control Department. Ministry of Natural Resources and Environment. Navigation of Thai Waterways Act, B.E. 2546. Available online: https://www.pcd.go.th/waters/%E0%B9%80%E0%B8%AD%E0%B8%81%E0%B8%AA%E0%B8%B2%E0%B8%A3-water-quality-management-in-thailand// (accessed on 25 February 2024).
14. Pollution Control Department. Ministry of Natural Resources and Environment. Principle 4: In Order to Achieve Sustainable Development, Environmental Protection Shall Constitute an Integral Part of the Development Process and Cannot Be Considered in Isolation from It. Available online: https://www.pcd.go.th/laws/ (accessed on 25 February 2024).
15. Mishchuk, H.; Bilan, Y.; Androniceanu, A.; Krol, V. Social capital: Evaluating its roles in competitiveness and ensuring human development. *J. Competitiveness* **2023**, *15*, 1–17. [CrossRef]
16. Chytilová, E.; Talíř, M.; Straková, J.; Dobrovič, J. Impact of digital procurement on economic resilience of enterprises during COVID-19. *J. Int. Stud.* **2024**, *17*, 188–204. [CrossRef]

17. Sutthichaimethee, P.; Ariyasajjakorn, D. Forecasting Model of GHG Emission in Manufacturing Sectors of Thailand. *J. Ecol. Eng.* **2017**, *18*, 18–24. [CrossRef]
18. Łucjan, K.; Szostek, D.; Balcerzak, A.P.; Rogalska, E. Relationships between leadership style and organizational commitment: The moderating role of the system of work. *Econ. Sociol.* **2023**, *16*, 11–39. [CrossRef]
19. Oliinyk, O.; Mishchuk, H.; Vasa, L.; Kozma, K. Social Responsibility: Opportunities for Integral Assessment and Analysis of Connections with Business Innovation. *Sustainability* **2023**, *15*, 5608. [CrossRef]
20. Office of the National Economic and Social Development Council (NESDC). Available online: https://www.nesdc.go.th/nesdb_en/main.php?filename=index (accessed on 10 February 2024).
21. Sutthichaimethee, P.; Ariyasajjakorn, D. A Forecasting Model on Carrying Capacity for Government's Controlling Measure under Environmental Law in Thailand: Adapting Non-recursive Autoregression Based on the Var-X Model. *Int. J. Energy Econ. Policy* **2020**, *10*, 645–655. [CrossRef]
22. Sutthichaimethee, P.; Kubaha, K. A Relational Analysis Model of the Causal Factors Influencing $CO_2$ in Thailand's Industrial Sector under a Sustainability Policy Adapting the VARIMAX-ECM Model. *Energies* **2018**, *11*, 1704. [CrossRef]
23. Štreimikienė, D. Externalities of power generation in Visegrad countries and their integration through support of renewables. *Econ. Sociol.* **2021**, *14*, 89–102. [CrossRef]
24. Pracucci, A.; Vandi, L.; Belletti, F.; Melo, A.R.A.; Vlachos, M.; Amditis, A.; Calcagni, M.T.; Esteves, D.S. Integration of Piezoelectric Energy Harvesting Systems into Building Envelopes for Structural Health Monitoring with Fiber Optic Sensing Technology. *Energies* **2024**, *17*, 1789. [CrossRef]
25. Bahrami, A.; Soltanifar, F.; Fallahi, P.; Meschi, S.S.; Sohani, A. Energy and Economic Advantages of Using Solar Stills for Renewable Energy-Based Multi-Generation of Power and Hydrogen for Residential Buildings. *Buildings* **2024**, *14*, 1041. [CrossRef]
26. Huang, K. Positive Rail Voltage Rise Behavior and Inhibition Analysis of Regenerative Braking of Medium–Low-Speed Maglev Train. *Energies* **2024**, *17*, 1782. [CrossRef]
27. Rami, Y.; Allouhi, A. Design, Economic, and Environmental Accounting Assessment of a Solar-Powered Cold Room for Fish Storage in Traditional Markets. *Sustainability* **2024**, *16*, 3080. [CrossRef]
28. Prasad, R.D. School Electricity Consumption in a Small Island Country: The Case of Fiji. *Energies* **2024**, *17*, 1727. [CrossRef]
29. Hao, J.; Huang, T.; Sun, Y.; Zhan, X.; Zhang, Y.; Wu, P. Optimal Prosumer Operation with Consideration for Bounded Rationality in Peer-to-Peer Energy Trading Systems. *Energies* **2024**, *17*, 1724. [CrossRef]
30. Silvestri, L.; Forcina, A.; Silvestri, C.; Arcese, G.; Falcone, D. Exploring the Environmental Benefits of an Open-Loop Circular Economy Strategy for Automotive Batteries in Industrial Applications. *Energies* **2024**, *17*, 1720. [CrossRef]
31. Schnidrig, J.; Chuat, A.; Terrier, C.; Maréchal, F.; Margni, M. Power to the People: On the Role of Districts in Decentralized Energy Systems. *Energies* **2024**, *17*, 1718. [CrossRef]
32. De Oliveira, D.E.P.; Miranda, A.C.; Junior, M.V.; Santana, J.C.C.; Tambourgi, E.B.; Facchini, F.; Iavagnilio, R.; Pinto, L.F.R. Economic and Environmental Feasibility of Cogeneration from Food Waste: A Case Study in S.o Paulo City. *Sustainability* **2024**, *16*, 2979. [CrossRef]
33. Gedvilaite, D.; Ginevicius, R. Assessment of the technological efficiency of production and consumption of EU countries in the context of circular economy. *J. Int. Stud.* **2024**, *17*, 83–96. [CrossRef]
34. Vasile, V.; Iordache, V.; Radu, V.M.; Dragomir, C.-S. The Relationship between Mechanical Ventilation, Indoor Air Quality Classes, and Energy Classes in a Romanian Context. *Atmosphere* **2024**, *15*, 444. [CrossRef]
35. Anušauskas, J.; Grigas, A.; Lekavičienė, K.; Zaleckas, E.; Paulikienė, S.; Steponavičius, D. Energy and Environmental Assessment of Bacteria-Inoculated Mineral Fertilizer Used in Spring Barley Cultivation Technologies. *Agriculture* **2024**, *14*, 569. [CrossRef]
36. Altun, Y.E.; Kutlar, O.A. Energy Management Systems' Modeling and Optimization in Hybrid Electric Vehicles. *Energies* **2024**, *17*, 1696. [CrossRef]
37. Dragonetti, L.; Papadaki, D.; Assimakopoulos, M.-N.; Ferrante, A.; Iannantuono, M. Environmental and Economic Assessment of Energy Renovation in Buildings, a Case Study in Greece. *Buildings* **2024**, *14*, 942. [CrossRef]
38. Peta, K.; Suszyński, M.; Wiśniewski, M.; Mitek, M. Analysis of Energy Consumption of Robotic Welding Stations. *Sustainability* **2024**, *16*, 2837. [CrossRef]
39. Jamshidi, F.; Ghiasi, M.; Mehrandezh, M.; Wang, Z.; Paranjape, R. Optimizing Energy Consumption in Agricultural Greenhouses: A Smart Energy Management Approach. *Smart Cities* **2024**, *7*, 859–879. [CrossRef]
40. Yang, C.; Huang, J.; Jiao, M.; Yang, Q. The Effects of Urbanization on Urban Land Green Use Efficiency of Yangtze River Delta Urban Agglomeration: Mechanism from the Technological Innovation. *Sustainability* **2024**, *16*, 2812. [CrossRef]
41. Liang, J.; Ding, R.; Ma, X.; Peng, L.; Wang, K.; Xiao, W. The Carbon Emission Reduction Effect and Spatio-Temporal Heterogeneity of the Science and Technology Finance Network: The Combined Perspective of Complex Network Analysis and Econometric Models. *Systems* **2024**, *12*, 110. [CrossRef]
42. Vallati, A.; Di Matteo, M.; Pompei, L.; Nardecchia, F.; Fiorini, C.V. Mitigation of Renewable Energy Source Production Variability in Residential Stock through Small-Scale Gas–Liquid Energy Storage Technology Application. *Processes* **2024**, *12*, 655. [CrossRef]
43. Ping, Q.; Wu, S.; Li, X.; Xu, Y.; Hu, J.; Sun, S. Dynamic and Energy Consumption Characteristics of Sandstone Ring Specimens under Dry and Wet Cycling. *Appl. Sci.* **2024**, *14*, 2646. [CrossRef]
44. Bao, H.; Knights, P.; Kizil, M.; Nehring, M. Energy Consumption and Battery Size of Battery Trolley Electric Trucks in Surface Mines. *Energies* **2024**, *17*, 1494. [CrossRef]

45. Richter, L.; Bender, T.; Lenk, S.; Bretschneider, P. Generating Synthetic Electricity Load Time Series at District Scale Using Probabilistic Forecasts. *Energies* **2024**, *17*, 1634. [CrossRef]
46. Postawa, K.; Czarnecki, M.; Wrzesińska-Jędrusiak, E.; Łyskawiński, W.; Kułażyński, M. Cascade-Forward, Multi-Parameter Artificial Neural Networks for Predicting the Energy Efficiency of Photovoltaic Modules in Temperate Climate. *Appl. Sci.* **2024**, *14*, 2764. [CrossRef]
47. Osawa, J. Evaluation of Technological Configurations of Residential Energy Systems Considering Bidirectional Power Supply by Vehicles in Japan. *Energies* **2024**, *17*, 1574. [CrossRef]
48. Senyapar, H.N.D.; Aksoz, A. Empowering Sustainability: A Consumer-Centric Analysis Based on Advanced Electricity Consumption Predictions. *Sustainability* **2024**, *16*, 2958. [CrossRef]
49. Zhao, M.; Gomez-Rosero, S.; Nouraei, H.; Zych, C.; Capretz, M.A.M.; Sadhu, A. Toward Prediction of Energy Consumption Peaks and Timestamping in Commercial Supermarkets Using Deep Learning. *Energies* **2024**, *17*, 1672. [CrossRef]
50. Mystakidis, A.; Koukaras, P.; Tsalikidis, N.; Ioannidis, D.; Tjortjis, C. Energy Forecasting: A Comprehensive Review of Techniques and Technologies. *Energies* **2024**, *17*, 1662. [CrossRef]
51. Koukaras, P.; Mustapha, A.; Mystakidis, A.; Tjortjis, C. Optimizing Building Short-Term Load Forecasting: A Comparative Analysis of Machine Learning Models. *Energies* **2024**, *17*, 1450. [CrossRef]
52. Bhuiyan, M.H.; Sakib, A.N.; Alawee, S.I.; Razzaghi, T. Fueling the Future: A Comprehensive Analysis and Forecast of Fuel Consumption Trends in U.S. Electricity Generation. *Sustainability* **2024**, *16*, 2388. [CrossRef]
53. Parizad, B.; Ranjbarzadeh, H.; Jamali, A.; Khayyam, H. An Intelligent Hybrid Machine Learning Model for Sustainable Forecasting of Home Energy Demand and Electricity Price. *Sustainability* **2024**, *16*, 2328. [CrossRef]
54. Raudys, A.; Gaidukevičius, J. Forecasting Solar Energy Generation and Household Energy Usage for Efficient Utilisation. *Energies* **2024**, *17*, 1256. [CrossRef]
55. Tian, Z.; Chen, D.; Zhao, L. Short-Term Energy Consumption Prediction of Large Public Buildings Combined with Data Feature Engineering and Bilstm-Attention. *Appl. Sci.* **2024**, *14*, 2137. [CrossRef]
56. El-Gohary, M.; El-Abed, R.; Omar, O. Prediction of an Efficient Energy-Consumption Model for Existing Residential Buildings in Lebanon Using an Artificial Neural Network as a Digital Twin in the Era of Climate Change. *Buildings* **2023**, *13*, 3074. [CrossRef]
57. Al-Jamimi, H.A.; BinMakhashen, G.M.; Worku, M.Y.; Hassan, M.A. Advancements in Household Load Forecasting: Deep Learning Model with Hyperparameter Optimization. *Electronics* **2023**, *12*, 4909. [CrossRef]
58. Alharbi, F.R.; Csala, D. A Seasonal Autoregressive Integrated Moving Average with Exogenous Factors (SARIMAX) Forecasting Model-Based Time Series Approach. *Inventions* **2022**, *7*, 94. [CrossRef]
59. Durand, D.; Aguilar, J.; R-Moreno, M.D. An Analysis of the Energy Consumption Forecasting Problem in Smart Buildings Using LSTM. *Sustainability* **2022**, *14*, 13358. [CrossRef]
60. Albatayneh, A.; Assaf, M.N.; Albadaineh, R.; Juaidi, A.; Abdallah, R.; Zabalo, A.; Manzano-Agugliaro, F. Reducing the Operating Energy of Buildings in Arid Climates through an Adaptive Approach. *Sustainability* **2022**, *14*, 13504. [CrossRef]
61. Ding, Z.; Wang, Z.; Hu, T.; Wang, H. A Comprehensive Study on Integrating Clustering with Regression for Short-Term Forecasting of Building Energy Consumption: Case Study of a Green Building. *Buildings* **2022**, *12*, 1701. [CrossRef]
62. Poczeta, K.; Papageorgiou, E.I. Energy Use Forecasting with the Use of a Nested Structure Based on Fuzzy Cognitive Maps and Artificial Neural Networks. *Energies* **2022**, *15*, 7542. [CrossRef]
63. Zawodnik, V.; Schwaiger, F.C.; Sorger, C.; Kienberger, T. Tackling Uncertainty: Forecasting the Energy Consumption and Demand of an Electric Arc Furnace with Limited Knowledge on Process Parameters. *Energies* **2024**, *17*, 1326. [CrossRef]
64. Chaganti, R.; Rustam, F.; Daghriri, T.; Díez, I.d.l.T.; Mazón, J.L.V.; Rodríguez, C.L.; Ashraf, I. Building Heating and Cooling Load Prediction Using Ensemble Machine Learning Model. *Sensors* **2022**, *22*, 7692. [CrossRef] [PubMed]
65. Chreng, K.; Lee, H.S.; Tuy, S. A Hybrid Model for Electricity Demand Forecast Using Improved Ensemble Empirical Mode Decomposition and Recurrent Neural Networks with ERA5 Climate Variables. *Energies* **2022**, *15*, 7434. [CrossRef]
66. Huang, J.; Algahtani, M.; Kaewunruen, S. Energy Forecasting in a Public Building: A Benchmarking Analysis on Long Short-Term Memory (LSTM), Support Vector Regression (SVR), and Extreme Gradient Boosting (XGBoost) Networks. *Appl. Sci.* **2022**, *12*, 9788. [CrossRef]
67. Pu, X.; Yao, J.; Zheng, R. Forecast of energy consumption and carbon emissions in China's building sector to 2060. *Energies* **2022**, *15*, 4950. [CrossRef]
68. Soyler, I.; Izgi, E. Electricity Demand Forecasting of Hospital Buildings in Istanbul. *Sustainability* **2022**, *14*, 8187. [CrossRef]
69. Henzel, J.; Wróbel, Ł.; Fice, M.; Sikora, M. Energy Consumption Forecasting for the Digital-Twin Model of the Building. *Energies* **2022**, *15*, 4318. [CrossRef]
70. Enders, W. *Applied Econometrics Time Series*; Wiley Series in Probability and Statistics; University of Alabama: Tuscaloosa, AL, USA, 2010.
71. Harvey, A.C. *Forecasting, Structural Time Series Models and the Kalman Filter*; Cambridge University Press: Cambridge, UK, 1989.
72. Velos, S.P.; Go, M.B.; Bate, G.P.; Joyohoy, E.B. A Seasonal Autoregressive Integrated Moving Average (SARIMA) Model to Forecasting Tourist Arrival in the Philippines: A Case Study in Moalboal, Cebu (Philippines). *Recoletos Multidiscip. Res. J.* **2020**, *8*, 67–78. [CrossRef]
73. Dickey, D.A.; Fuller, W.A. Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root. *Econometrica* **1981**, *49*, 1057–1072. [CrossRef]

74. MacKinnon, J. *Critical Values for Cointegration Test in Long-Run Economic Relationships*; Engle, R., Granger, C., Eds.; Oxford University Press: Oxford, UK, 1991.
75. Johansen, S. *Likelihood-Based Inference in Cointegrated Vector Autoregressive Models*; Oxford University Press: New York, NY, USA, 1995.
76. Johansen, S.; Juselius, K. Maximum likelihood estimation and inference on cointegration with applications to the demand for money. *Oxf. Bull. Econ. Stat.* **1990**, *52*, 169–210. [CrossRef]