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Building a Sustainable Future: Enhancing Construction Safety through Macro-Level Analysis

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Abstract: Accidents are events that occur unexpectedly during production or daily activities, causing personal injury or property damage. Analyzing accident trends and their influencing factors is crucial for policymakers to develop effective management systems and preventive measures, thereby significantly enhancing accident prevention strategies and promoting sustainability in construction practices. This study focuses on accidents in China's construction industry from 2008 to 2020, examining the macro factors that influence the growth rate of construction accidents and their underlying mechanisms. By employing a system dynamics model with incorporated delay functions, this study simulates the impact of 15 macro factors on the accident growth rate. The findings reveal that improvements in factors such as the power equipment rate and safety investments not only substantially reduce accident frequency, but also contribute to the sustainable development of construction practices by promoting safer and more resource-efficient methods. Furthermore, the introduction of delay functions validates the lag effects of various factors, emphasizing their long-term cumulative impact on both safety and sustainability. The simulation results demonstrate that the system dynamics model accurately reflects the actual growth trends of construction accidents, providing robust scientific evidence for policymakers. This study enhances the understanding of the mechanisms driving construction safety accidents and offers theoretical support for the formulation of effective and sustainable safety management policies.

Keywords: building construction; macro influencing factors; system dynamics; time-lag correlation analysis; scenario simulation

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1. Introduction

The construction industry is vital to China's national economy, significantly contributing to economic growth and development. It plays a crucial role in infrastructure development and urbanization processes in China, directly and indirectly stimulating employment and generating substantial income [1]. Statistical data indicate that the proportion of the construction industry in the national economy has been increasing annually, with its output value as a percentage of GDP continually rising, thus becoming one of the key drivers of economic growth [2]. However, with the rapid expansion of cities and the increase in construction activities, safety management measures in the construction industry have failed to improve in tandem. During the construction of building projects, safety accidents are frequently triggered by improper operation, equipment failures, mismanagement, and environmental factors, resulting in casualties and property losses, and causing great suffering to society and families [3,4].

In order to minimize workplace injuries and fatalities, while promoting sustainable practices that ensure the long-term health and viability of the construction industry, numerous scholars have conducted in-depth studies on construction safety issues, proposing various improvement measures and theoretical models. However, despite the development of accident research on a systematic level, current safety management studies still tend to focus on micro-level analyses of unsafe behaviors on construction sites [5]. Sanni-Anibire et al. [6] collected data from safety professionals at 15 large construction sites in the Eastern Province of Saudi Arabia. By employing pairwise comparison and rank-weighted survey methods, they developed a risk assessment method to enhance the safety performance in construction projects. The results indicated that "falling objects" posed the highest risk, primarily due to strong winds at the construction sites. Manzoor et al. [7] collected feedback data from contractors, clients, and consultants through questionnaires to identify the key safety factors leading to accidents in high-rise building projects in Malaysia. The findings revealed that "falls from roofs/floors" were the most critical safety factor, and recommendations were made to mitigate these factors' impact. Yılmaz [8] assessed the relationship between construction site safety measures and workers' actual and perceived knowledge of these measures through face-to-face questionnaires and bivariate correlation analysis. The study found that workers' knowledge of occupational health and safety measures was significantly lower than their perceived level, but certain protective measures could significantly enhance workers' safety awareness.

This research tendency neglects the discussion of macro-level accident-influencing factors, resulting in a lack of systematic and forward-looking overall safety management strategies [9]. The primary reason lies in the difficulties encountered in exploring macro-level accident-influencing factors, which mainly center around the numerous factors that need to be considered [10]. From the perspectives of economics, politics, society, culture, and ecological civilization, a considerable number of related elements can be extended [11], requiring interdisciplinary theoretical support and complex data analysis. Some studies have consciously shifted from the micro-level to the macro-level. Cai et al. [12] proposed a Bayesian integrated spatial collision frequency model, which links the number of collisions at the macro- and micro-levels based on spatial interactions, simultaneously identifying macro and micro factors that lead to collisions. Wang et al. [13] utilized time series data of human injuries and mortality rates to determine the causal factors of accident severity over time, evaluated the severity of traffic accidents in China from a macro perspective, and proposed effective countermeasures to reduce traffic accident fatalities. Lee and Abdel-Aty [14] used a multivariate Bayesian Poisson log-normal conditional autoregressive (CAR) model to identify factors influencing the locations of bicycle accidents and the residences of frequent accident-prone cyclists, providing a basis for implementing effective safety measures.

However, while the impact of macro-level accident-influencing factors on accidents is widely recognized [15], their effects differ from those at the micro-level and may not manifest immediately. For instance, economic indicators often precede accidents [16], with their impacts not being immediately apparent, but influencing future accidents, indicating a lag in their effects. Conversely, the effects can also be delayed in the other direction. The existing research has demonstrated that the impact of influencing factors on accidents changes over time, resulting in different short-term and long-term outcomes [17], echoing the principles of sustainability where long-term planning and impact assessments are crucial. Thus, understanding and determining whether a particular factor itself has a minimal impact on accidents or if the long cycle of its impact renders its effects less apparent becomes a significant challenge in the study of macro-level factors [18].

The emergence of system dynamics provides a powerful means to address the above-mentioned issues. This method eschews external disturbances or random events and employs the system science principle that "every system has a structure, and the structure of the system determines its function". It investigates the core issues from the perspective of causal feedback among internal elements within the system structure [19], making it an ideal approach to model the complex interrelations between construction safety and sustainability. Consequently, existing research has applied system dynamics theory to analyzing accident patterns, utilizing the findings for safety decision making, management, and control. For instance, Liu et al. [20] used system dynamics to simulate multi-player evolutionary games, examining the effectiveness of coal mine safety regulation through such games. They concluded that the coal mine safety performance is influenced not only by government safety regulations, but also, to some extent, by the game interactions of non-safety regulations within related internal and external industries. Zhang et al. [21] employed system dynamics methods and Vensim 9.2.3 software to establish causal mechanisms and loop diagrams for emergency processes, analyzing factors such as on-site material demand gaps, the number of people in safe zones, the number of vehicles in safe zones, the amount of disposal information, and system dynamic evolution behavior on the observed values. Similarly, Park and Park [22] utilized system dynamics to understand the process industries' complex socio-technical safety systems. They monitored and predicted the safety performance within organizations, identifying key components of the safety system through various scenarios and providing valuable safety insights for decision makers.

To address the complexity and time-lag effects of macro-level accident-influencing factors, this paper selects production safety accidents in the construction industry as the study's starting point. Using data on the number of construction safety accidents in China from 2008 to 2020, this study focuses on the growth rate of accident occurrences as the research subject and analyzes the factors influencing it. A dynamic model is constructed using system dynamics methods to simulate the interactions and feedback mechanisms between different influencing factors, thereby revealing the complex process of accident occurrence. A delay function is introduced by considering the differences in how macro-level factors in the construction production industry affect the number of accidents over time. This function analyzes how these indicators influence construction safety over time and simulates the impact results to uncover the accident mechanisms within macro-level factors. This study explores changes in various indicators that can reduce the growth rate of accidents, providing theoretical support for policy making, and aligning these policies with sustainable construction practices.

2. Materials and Methods

2.1. Analysis of Factors Influencing Accident Rate

In the early 21st century, many scholars conducted statistical analyses on China's safety production situation, exploring the intrinsic relationships between safety production and economic and social factors. These studies have provided a theoretical basis for selecting indicators related to construction industry accidents. The indicators primarily involve economic and policy aspects, but also include social and cultural factors [23]. Current research mainly focuses on economic development indicators, confirming a strong correlation between safety production and economic development [24]. By analyzing domestic and international research [25,26], it has been summarized that the most significant factors influencing the state of safety production include the economic development level, industrial structure, social structure, population employment, and policy intervention. Therefore, the macro-level regulation of these major relevant factors will be conducive to improving safety conditions and fostering sustainable growth in the construction sector.

The National Bureau of Statistics (NBS) has continuously recorded the number of building construction accidents in the country since 2008, and the number of accidents and the growth rate each year are shown in Table 1. This work selects 15 indicators affecting building construction accidents at the macro level from 2008 to 2020 as raw data, and their definitions and units are shown in Table 2. These 15 indicators can be divided into five different categories: economic and income-related indicators, construction production- and scale-related indicators, real estate development-related indicators, labor productivity-related indicators, and construction safety- and equipment-related indicators. This classification provides a comprehensive framework for analyzing the various factors affecting construction safety, including broad economic conditions, specific industry practices, and technological advancements.

Table 1. Number and Growth Rate of Building Construction Accidents in China, 2008–2020.

Time (Year)	Number of Accidents	Accident Growth Rate	Time (Year)	Number of Accidents	Accident Growth Rate
2008	778	0	2015	442	−0.153256705
2009	684	−0.113989637	2016	634	0.43438914
2010	627	−0.083333333	2017	692	0.09148265
2011	589	−0.060606061	2018	734	0.060693642
2012	487	−0.173174873	2019	773	0.053133515
2013	528	0.084188912	2020	689	−0.102199224
2014	522	−0.011363636			

Table 2. Definitions and units of selected indicators.

Indicators	Units	Definition
Gross Domestic Product (GDP)	CNY 100 million yuan	The total final output of all resident units in a country or region during a certain period, reflecting the economic situation of the country or region.
Monthly income of migrant construction workers	CNY	The monthly income of migrant construction workers refers to the total labor remuneration obtained by migrant workers engaged in the construction industry each month, including wages, bonuses, allowances, and subsidies. This indicator reflects the income level of workers in the construction industry.
Construction area of residential buildings in the construction industry	10,000 square meters	The construction area of residential buildings in the construction industry refers to the total area of houses under construction by construction enterprises during the reporting period, including new construction, expansion, and renovation. This indicator reflects the production scale and activity level of the construction industry.
Completed area of residential buildings in the construction industry	10,000 square meters	The completed area of residential buildings in the construction industry refers to the total area of houses completed and handed over for use by construction enterprises during the reporting period. This indicator reflects the actual output and completion status of the construction industry.
Land area purchased by real estate development enterprises	10,000 square meters	The land area purchased by real estate development enterprises refers to the land area obtained by real estate development enterprises through various means during the reporting period. This indicator reflects the activity of real estate development enterprises in the land market.
Land area awaiting development by real estate development enterprises	10,000 square meters	The land area awaiting development by real estate development enterprises refers to the land area that has been approved by relevant departments and obtained land use rights through various means, but has not yet started construction. This indicator reflects the future development potential and reserves of real estate development enterprises.
Gini coefficient of per capita disposable income of national residents	None	The Gini coefficient of per capita disposable income of national residents is an indicator that reflects the fairness of income distribution, with values ranging between 0 and 1.
Safety investment in the construction industry	CNY 100 million	Safety investment in the construction industry refers to various expenditures made by construction enterprises to ensure safe production during the production process, including safety training, purchase and maintenance of safety equipment, safety inspections, etc. This indicator reflects the importance and investment of enterprises in safe production.

Table 2. *Cont.*

Indicators	Units	Definition
Labor productivity of construction enterprises	CNY/person	Labor productivity of construction enterprises refers to the output value created by each employee of construction enterprises during a certain period. This indicator reflects the production efficiency of construction enterprises and the work efficiency of workers.
Total number of owned construction machinery and equipment	units	The total number of owned construction machinery and equipment refers to the total number of various types of construction machinery and equipment owned by construction enterprises. This indicator reflects the mechanization level and construction capacity of enterprises.
Total power of owned construction machinery and equipment	(Kw)	The total power of owned construction machinery and equipment refers to the total power of all construction machinery and equipment owned by construction enterprises. This indicator reflects the overall energy and construction capacity of enterprise machinery and equipment.
Technical equipment rate of construction enterprises	CNY/person	The technical equipment rate of construction enterprises is the value of mechanical equipment that belongs to fixed assets per person on average, reflecting the level of enterprise mechanical equipment. This indicator reflects the investment and technical level of enterprises in technical equipment.
Power equipment rate of construction enterprises	(Kw/person)	The power equipment rate of construction enterprises is the ratio of the total power of owned mechanical equipment at the end of the year to the number of all employees or workers at the end of the year. This indicator reflects the investment and technical level of enterprises in power equipment.
Total output value of the construction industry	CNY 100 million	The total output value of the construction industry refers to the total value of construction industry products and services produced by construction enterprises in a certain period, expressed in monetary terms. This indicator reflects the total output and economic contribution of the construction industry.
Value-added of the construction industry	CNY 100 million	The value-added of the construction industry refers to the final results of construction industry production and business activities expressed in monetary terms by construction enterprises during the reporting period. It is the new value created in the production process of enterprises. This indicator reflects the contribution of the construction industry to economic growth.

Each category plays a unique role in understanding and predicting construction safety accidents. Economic indicators provide the overall economic environment in which the construction industry operates [27]. Considering that the majority of front-line workers in China's construction industry are migrant workers [28], their income can represent the employees working on the front line. In the statistical reports published in China, the monthly income of migrant construction workers is also used as an important indicator. Therefore, considering China's national conditions, the Gross Domestic Product (GDP), the Gini coefficient of per capita disposable income of national residents, and the monthly income of migrant construction workers were selected. Construction production and scale indicators help to understand the activity level of the industry and the potential safety challenges associated with growth [29], selecting the construction area of residential buildings in the construction industry, completed area of residential buildings in the construction industry, total output value of the construction industry, and value-added of the construction industry. Real estate development indicators help to predict future construction activities and related risks [30], selecting land areas purchased by real estate development enterprises and land areas awaiting development by real estate development enterprises. Labor productivity indicators reveal the labor situation and its potential impact on safety practices [31], selecting the labor productivity of construction enterprises as an indicator. Construction safety and equipment indicators directly reflect the industry's commitment to safety measures and the level of mechanization and technological progress [32], selecting safety investment in the construction industry, the total number of owned construction machinery and equipment, the total power of owned construction machinery and equipment, the technical equipment rate of construction enterprises, and the power equipment rate of construction enterprises. These categories collectively provide a multi-faceted approach to analyzing construction safety from a macro perspective, representing economic, policy, and social development levels to a certain extent, allowing us to more comprehensively understand the factors leading to safety accidents in the construction industry.

As the economy and productivity develop, the scale of the construction industry continues to expand and the values of various indicators keep rising. Therefore, comparing absolute values lacks objectivity and generality. To address this, this paper employs the first-order growth rates of these indicators for the relevant research. By dimensionless processing, this approach more objectively reflects the correlation between various factors and construction accidents. The processed growth rate indicators are sequentially labeled as R1, R2..., and R15, and the growth rate of accident occurrences is labeled as R0.

The trends of various factor indicators (denoted as R1–R15) and the growth rate of accident occurrences (A) are shown in Figure 1. It can be observed that the growth rate of accident occurrences is highly volatile, with a notable spike in 2016. This spike is related to the fact that 2015 saw the lowest number of accidents in recent years. The "Regulations and Standards for Qualification Management of Construction Enterprises" issued at the beginning of 2015 inadvertently increased the pressure on enterprises. Although the construction enterprises obtained the corresponding qualifications, they did not necessarily meet the qualification standards in practice. The "qualification certificate renewal" process under the new standards required the formulation of new assessment criteria [33]. To ensure the validity of qualifications, enterprises paid more attention to safety production and strictly implemented various regulations, resulting in a moderately tense state across the industry, which reduced the probability of accidents. However, the "Notice on Issues Related to the Qualification Management of Construction Enterprises" issued in October of the same year simplified the reassessment process to a mere certificate renewal, quickly relieving the pressure on enterprises. The relaxation following this period of moderate pressure led to a surge in accidents in 2016.

Additionally, 2015 was a challenging year for construction enterprises, characterized by high personnel costs, difficulties in managing new and old projects, and a sluggish market, which exposed various problems within enterprises. Large and medium-sized enterprises faced bankruptcy and closure. Moreover, implementing the Public–Private Partnership (PPP) model, the nationwide unification of the construction market, industrialization, and major adjustments in leadership teams contributed to the historic low number of construction accidents in 2015, but also highlighted the need for sustainable practices to mitigate these systemic risks.

However, Figure 1 does not adequately demonstrate a strong correlation between the various indicators and the growth rate of accident occurrences. The possible reasons for this could be that the individual factors' trends have little correlation with construction accidents, meaning there is no inherent mutual influence. Another reason might be that the changes in these factors do not immediately impact accidents; their effects might only become evident over time, highlighting the need for sustainable, long-term safety strategies that consider the gradual influence of these indicators.

According to the relationship between the trajectories of different variables and the benchmark variable, statistical indicators can be categorized into leading, coincident, and lagging indicators. This paper aims to explore which category each of the 15 indicators falls into relative to the growth rate of construction safety accidents, the primary subject of this study, and to what extent they are correlated. This analysis supports sustainable decision making by identifying indicators that can predict or prevent accidents before they occur, promoting a proactive approach to safety management.

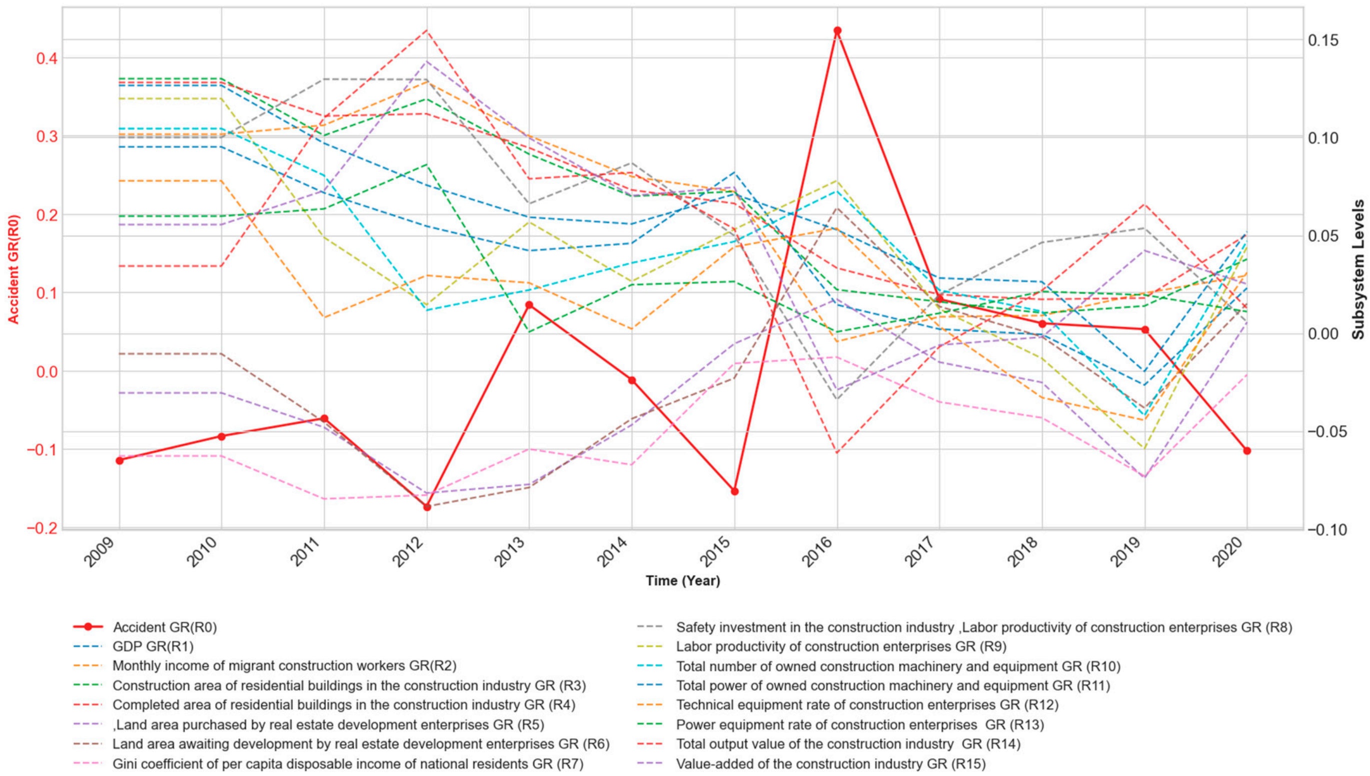

Figure 1. Trends of R1-R15 and R0 from 2009 to 2020.

2.2. Model Construction

Considering that there are also certain relationships among R1-R15 and that, from a macro perspective, they collectively influence R0, taking all these relationships into account will form a relatively complex system. System dynamics is suitable for analyzing complex system problems, where the research object is usually divided into multiple interrelated and interacting subsystems [34]. Since this study aims to design a system with all factors mutually related, its structure is unique and aligns with the characteristics of a complex system. Therefore, this section employs the system dynamics method to analyze in detail the logical relationships among different influencing factors and to simulate the changing trends of the accident occurrence growth rate, thereby deepening the study of variables that influence accident growth.

To establish an effective system dynamics model, the following three aspects need to be discussed: (1) Clarify the purpose of the system simulation and identify the key issues. (2) Determine the system boundaries to ensure that the system is neither influenced by external environmental factors nor controlled by internal factors. (3) Based on the boundary delineation, establish the assumptions of the model [35].

2.2.1. System Objectives

This study aims to analyze the factors influencing construction safety accidents and organize the factors within the influencing subsystems. This study examines the impact of multiple factors on the accident growth rate. Constructing a system dynamics model aims to comprehensively understand the process of changes in the accident occurrence rate and to analyze the relationships among the various factors involved in these changes. Additionally, this study explores the impact of the mutual constraints of these factors on the results. This approach provides guidance for the macro-level prediction of safety accidents, continuously optimizes prediction methods, and offers practical and effective analytical methods for the macro-level analysis of safety conditions.

2.2.2. System Boundaries

Defining the system boundaries influences the system structure and internal factors, and it is a critical aspect of system dynamics modeling. This step requires aligning with the modeling objectives and the research subject, focusing on the core issues. This study focuses on construction safety accidents in China, examining the interdependencies among 15 indicators potentially influencing accidents and their impact on the accident growth rate. Therefore, this study takes the changes in the accident growth rate from 2009 to 2020 as the core subject and the changes in each influencing indicator as the participating subjects. These form various subsystems, all included within the system boundaries.

2.2.3. Model Assumptions

Given the complexity and numerous factors influencing the model's construction, it is not feasible to include all influencing factors. To ensure the smooth operation of the model, the following basic assumptions are made in line with the system objectives and boundaries:

H1: *The change in the number of construction safety accidents nationwide is a continuously evolving dynamic process, driven by the interaction and feedback of the elements within the model.*

H2: *The data used in the model are processed growth rate data derived from the original raw data values. The growth rate of accident occurrences is the level variable, while the others are rate variables.*

H3: *The trend of the growth rate of accident occurrences is related to the 15 involved indicators, primarily considering economic and policy impacts and their implications for sustainable industry practices.*

H4: *The model is only influenced by factors within the system boundaries, excluding external factors (such as other economic indicators, policies, unforeseen events, etc.) that could cause disruptions or system collapse.*

2.3. Causal Relationships and Stock-Flow Diagrams

A causal loop diagram can visually represent the feedback relationships among various elements within a system [36]. Based on the analysis of causal relationships and relevant influencing factors, this paper depicts the changes in the accident growth rate influenced by 15 indicator factors. Initially, leading indicators are identified as causes and lagging indicators as effects, although there are mutual causal relationships among the indicators. Within the system boundaries, 15 subsystems are established. Each subsystem treats the growth rates of the 15 indicators as level variables, while other quantities are considered rate variables. Due to the complexity of the constructed stock-flow diagram, which includes numerous lines, it is challenging to clearly represent the relationships among the subsystems. Therefore, Figure 2a omits the connection lines of the influence changes on the subsystems for clarity, and Figure 2b uses a causal tree to simplify the representation of the multi-factor feedback process.

In this model, the red and blue arrows represent different causal relationships: red arrows indicate increments (pointing to Increment) or decrements (pointing to Decrement) in the growth rate of construction accidents. Red arrows pointing to Increment (such as R5) signify that an increase in a subsystem leads to an increase in the construction accident growth rate, whereas red arrows pointing to Decrement (such as R13) signify that an increase in a subsystem leads to a decrease in the construction accident growth rate. The blue arrows indicate the impact of growth rate changes in other subsystems on the

GDP growth rate (GDP GR r1), showing how changes in the subsystems feedback into the overall system by affecting the GDP growth rate. The impact of each subsystem on the overall system is indicated by "+" or "−", where "+" signifies that an increase in the subsystem leads to an increase in the growth rate, and "−" signifies that an increase in the subsystem leads to a decrease in the growth rate. Correctly understanding feedback loops is crucial for accurately describing system behavior and assessing sustainability. There are two main types of feedback loops: reinforcing loops and balancing loops. These loops are significant for the sustainability of the construction industry. Reinforcing loops refer to changes in a variable within the system that, through a series of causal relationships, ultimately feedback to it, further amplifying its change. For example, in the reinforcing loop of construction industry value-added growth, an increase in the GDP growth rate drives an increase in the construction area and gross construction output, which in turn increases the construction industry value added. This leads to a rise in the construction accident growth rate, prompting increased safety investment, which helps to reduce accident risk, thereby further promoting GDP growth, forming a complete reinforcing loop. Similarly, in the reinforcing loop of technical equipment rate growth, an increase in the GDP growth rate drives investment in and upgrading of technical equipment, enhancing the technical equipment level. This helps to reduce the construction accident growth rate, decrease the occurrence of accidents, and further promote GDP growth, also forming a complete reinforcing loop. These reinforcing loops not only promote economic growth, but also support the sustainability of the construction industry by improving the safety and technological levels, contributing to long-term economic growth and safe production. Balancing loops, on the other hand, refer to changes in a variable within the system that, through a series of causal relationships, ultimately feedback to it and inhibit its change, tending toward stability. For instance, in the resource consumption and regeneration loop, an increase in the GDP growth rate leads to an expansion in the construction area, but also results in the consumption of land resources. As the area of land awaiting development decreases, resource scarcity limits further growth in construction areas. With the reduction in land resources, the construction accident growth rate rises, further restricting the growth of construction areas, thereby inhibiting rapid GDP growth and forming a complete balancing loop. This balancing loop highlights the importance of resource management in the sustainable development of the construction industry, emphasizing the need to consider environmental carrying capacity while pursuing economic growth to ensure that the construction industry does not excessively consume resources or increase accident rates during expansion, thereby promoting sustainable development. By incorporating the construction accident growth rate into the causal chain and using a simplified causal tree representation, we can more comprehensively understand the feedback mechanisms within the system and the interactions between various subsystems. This provides a scientific basis for formulating effective policies and management measures. The analysis of this system dynamics model helps to understand and optimize sustainability strategies in the construction industry, ensuring the effective management of resources and safety risks while promoting economic growth. This offers comprehensive guidance and support for the long-term sustainable development of the construction industry.

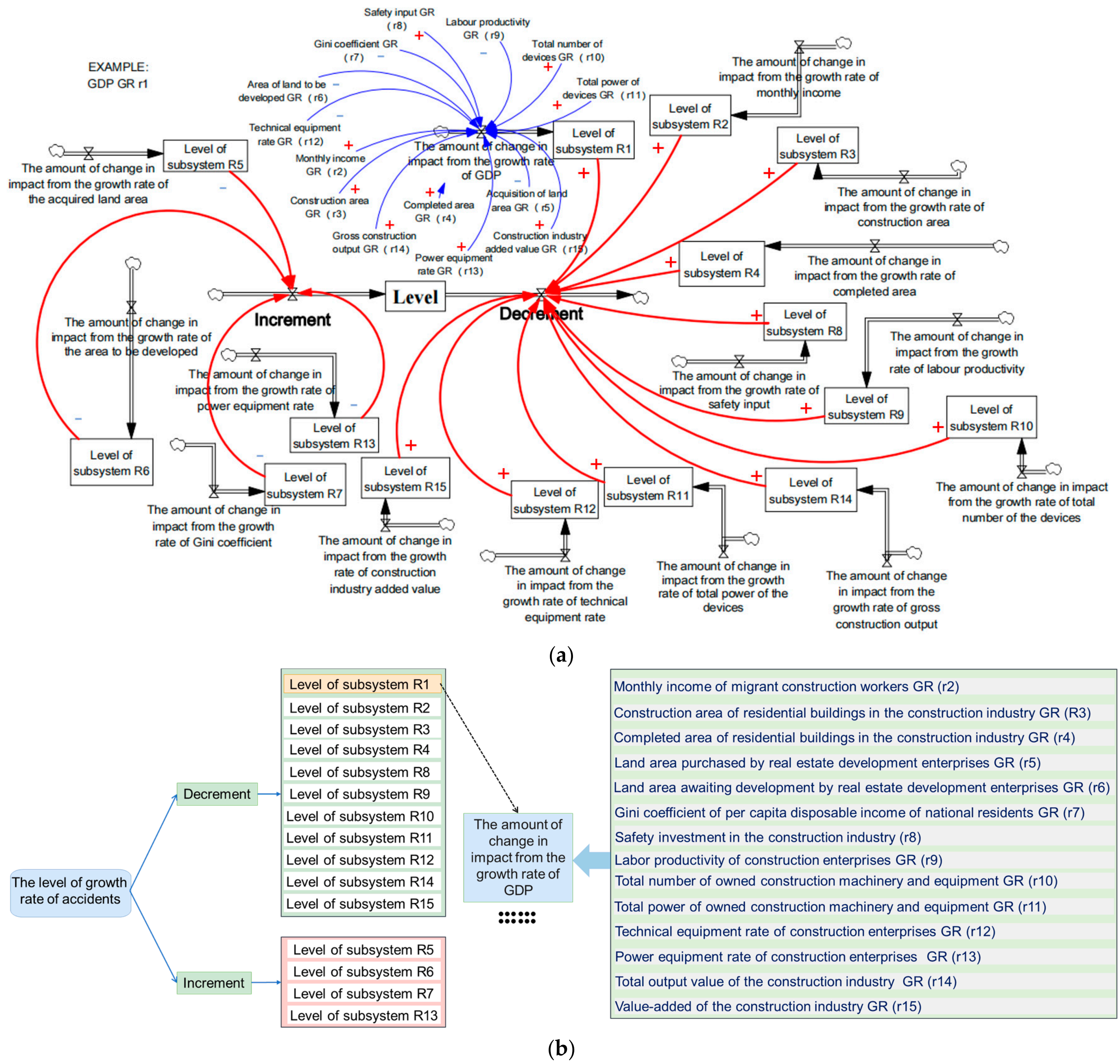

Figure 2. (**a**). Stock-Flow Diagram Example of GDP Growth Rate Impact Change (R1). (**b**). Causal Tree for Subsystem R1 and the Entire System.

3. System Dynamics Model Simulation

3.1. Calculation of Indicator Weights

This study utilizes the correlation coefficients between various indicators and the accident growth rate as a standard to analyze the growth rate data from 2009 to 2020. The highest correlation coefficient for each indicator with the accident growth rate is identified and its absolute value is used for weight allocation. Based on the causal relationships, positive and negative weights are assigned. The specific relationships are shown in Table 3. The normalized weights reflect the degree and direction of each indicator's impact on the accident growth rate.

Table 3. Calculation Results of Weights for R1–R15.

Evaluation Object	Absolute Value of Original Correlation Coefficient	Absolute Value of Correlation Coefficient	Change Magnitude	Lag Periods	Weight of Lag	Range	Composite Score	Normalized Weight (with Direction)
R1	0.081	0.299	0.218	3	0.1	0.189	0.233	−0.0330
R2	0.421	0.386	0.035	1	0.3	0.186	0.638	−0.0901
R3	0.344	0.409	0.065	1	0.3	0.211	0.650	−0.0919
R4	0.321	0.474	0.153	1	0.3	0.184	0.716	−0.1011
R5	0.282	0.271	0.011	3	0.1	0.569	0.278	0.0393
R6	0.211	0.246	0.035	3	0.1	0.600	0.269	0.0381
R7	0.404	0.244	0.16	3	0.1	0.042	0.225	0.0318
R8	0.516	0.309	0.207	1	0.3	0.401	0.795	−0.1123
R9	0.399	0.407	0.008	2	0.2	0.294	0.474	−0.0669
R10	0.238	0.296	0.058	3	0.1	0.350	0.236	−0.0334
R11	0.357	0.333	0.024	1	0.3	0.261	0.611	−0.0863
R12	0.082	0.407	0.325	3	0.1	0.372	0.401	−0.0567
R13	0.058	0.199	0.141	2	0.2	0.413	0.391	0.0552
R14	0.077	0.259	0.182	1	0.3	0.250	0.582	−0.0822
R15	0.007	0.246	0.239	1	0.3	0.221	0.579	−0.0818

Based on the principles of system dynamics, Vensim software is used for system simulation analysis. Taking subsystem R1 as an example, the input variable data are provided. The system dynamics equations are constructed as follows:

$$\begin{aligned}(GDPgrowth) = \ & \text{Lookup}[(2009,0)-(2020,0.3)],(2009,0.0855208),\\ & (2010,0.176881),(2011,0.216196),(2012,0.103783),\\ & (2013,0.100975),(2014,0.0853339),(2015,0.0703818),\\ & (2016,0.0835249),(2017,0.114739),(2018,0.104857),\\ & (2019,0.0731377),(2020,0.0274216)\end{aligned} \tag{1}$$

$$Accident\ growth\ rate = INTEG\ (Increment\text{–}Decrement) \tag{2}$$

In system dynamics, the $INTEG$ function is used to calculate state variables, where the equation implies that the level of accident growth rate is equal to the cumulative difference between the rate of increase and decrease. The $lookup$ table function is set to reflect the real changes in the growth rates of various indicators over the years, making the simulation more realistic. Similar lookup table functions are applied to other subsystem variables. The dynamic equations are shown in Table 4.

Table 4. System Dynamics Equations for Each Subsystem.

System	Variable Name	Type	System Dynamics Equations
Subsystem R1	GDP Growth Rate Impact Change	Rate	0.0850r2 + 0.0806r3 + 0.0817r4 − 0.0595r5 − 0.0846r6 − 0.1072r7 + 0.0646r8 − 0.0595r9 + 0.0411r10 + 0.0777r11 − 0.0495r12 + 0.0641r13 + 0.0737r14 + 0.071r15
Subsystem R2	Monthly Income Growth Rate Impact Change	Rate	0.0815r1 + 0.1103r3 + 0.1204r4 − 0.0405r5 − 0.0438r6 − 0.0537r7 + 0.0786r8 + 0.0772r9 + 0.064r10 + 0.0758r11 + 0.0578r12 + 0.0347r13 + 0.0872r14 + 0.0744r15
Subsystem R3	Construction Area Growth Rate Impact Change	Rate	0.0779r1 + 0.1112r2 + 0.1105r4 − 0.0604r5 − 0.0648r6 − 0.0438r7 + 0.0754r8 + 0.0744r9 + 0.035r10 + 0.0631r11 + 0.0529r12 + 0.0257r13 + 0.0996r14 + 0.1053r15
Subsystem R4	Completed Area Growth Rate Impact Change	Rate	0.0759r1 + 0.1167r2 + 0.1062r3 − 0.0643r5 − 0.0491r6 − 0.0639r7 + 0.0762r8 + 0.0782r9 + 0.0398r10 + 0.0574r11 + 0.0485r12 − 0.0358r13 + 0.0984r14 + 0.0897r15
Subsystem R5	Land Acquisition Area Growth Rate Impact Change	Rate	−0.0643r1 − 0.0456r2 − 0.0674r3 − 0.0747r4 − 0.0652r6 + 0.0484r7 + 0.0626r8 − 0.1373r9 − 0.0671r10 − 0.0575r11 − 0.1095r12 + 0.0525r13 + 0.0874r14 − 0.0606r15
Subsystem R6	Undeveloped Land Area Growth Rate Impact Change	Rate	−0.0827r1 − 0.0447r2 − 0.0655r3 − 0.0517r4 − 0.059r5 − 0.0744r7 − 0.0393r8 − 0.1237r9 − 0.0847r10 − 0.0904r11 − 0.0847r12 − 0.0662r13 + 0.0674r14 + 0.0656r15

Table 4. *Cont.*

System	Variable Name	Type	System Dynamics Equations
Subsystem R7	Gini Coefficient Growth Rate Impact Change	Rate	−0.1125r1 − 0.0587r2 − 0.0476r3 − 0.0721r4 + 0.047r5 − 0.0799r6 + 0.0448r8 − 0.0865r9 − 0.1163r10 + 0.0734r11 − 0.0675r12 + 0.0653r13 − 0.0419r14 − 0.0864r15
Subsystem R8	Safety Investment Growth Rate Impact Change	Rate	0.0737r1 + 0.0936r2 + 0.0889r3 + 0.0935r4 + 0.0662r5 − 0.0459r6 + 0.0487r7 + 0.0803r9 + 0.0728r10 + 0.059r11 + 0.0703r12 + 0.0347r13 + 0.0861r14 + 0.0862r15
Subsystem R9	Labor Productivity Growth Rate Impact Change	Rate	−0.0542r1 + 0.0733r2 + 0.0701r3 + 0.0767r4 − 0.1159r5 − 0.1153r6 − 0.0751r7 + 0.0641r8 − 0.0502r10 + 0.0502r11 − 0.0433r12 − 0.0591r13 + 0.0771r14 + 0.0754r15
Subsystem R10	Total Number of Owned Construction Machinery Growth Rate Impact Change	Rate	0.0461r1 + 0.075r2 + 0.0407r3 + 0.0481r4 − 0.0698r5 − 0.0973r6 − 0.1245r7 + 0.0716r8 − 0.0619r9 − 0.0342r11 − 0.0757r12 − 0.0663r13 + 0.0915r14 + 0.0975r15
Subsystem R11	Total Power of Owned Construction Machinery Growth Rate Impact Change	Rate	0.0796r1 + 0.0809r2 + 0.0668r3 + 0.0632r4 − 0.0545r5 − 0.0947r6 + 0.0715r7 + 0.053r8 + 0.0564r9 − 0.0311r10 − 0.0857r12 + 0.0443r13 + 0.0974r14 + 0.121r15
Subsystem R12	Technical Equipment Rate Growth Rate Impact Change	Rate	−0.0535r1 + 0.0651r2 + 0.0591r3 + 0.0563r4 − 0.1096r5 − 0.0935r6 − 0.0695r7 + 0.0666r8 − 0.0513r9 − 0.0729r10 − 0.0904r11 + 0.0919r13 + 0.0609r14 + 0.0593r15
Subsystem R13	Power Equipment Rate Growth Rate Impact Change	Rate	0.0836r1 + 0.0472r2 + 0.0347r3 − 0.0503r4 + 0.0635r5 − 0.0883r6 + 0.0811r7 + 0.0396r8 − 0.0845r9 − 0.0769r10 + 0.0565r11 + 0.111r12 + 0.0734r14 + 0.1094r15
Subsystem R14	Total Output Value of Construction Industry Growth Rate Impact Change	Rate	0.0688r1 + 0.0849r2 + 0.0962r3 + 0.0988r4 + 0.0756r5 + 0.0644r6 − 0.0373r7 + 0.0704r8 + 0.079r9 + 0.076r10 + 0.0888r11 + 0.0526r12 + 0.0525r13 + 0.0545r15
Subsystem R15	Value-Added Growth Rate of Construction Industry Growth Rate Impact Change	Rate	0.0634r1 + 0.0693r2 + 0.0972r3 + 0.0862r4 − 0.0501r5 + 0.0599r6 − 0.0735r7 + 0.0674r8 + 0.0738r9 + 0.0775r10 + 0.1055r11 + 0.049r12 + 0.0749r13 + 0.0521r14
Subsystem R5 + R6 + R7 + R13	Growth Rate Increase	Rate	0.0393R5 + 0.0381R6 + 0.0318R7 + 0.0552R13
Other Subsystems not Including Increase	Growth Rate Decrease	Rate	0.0330R1 + 0.0901R2 + 0.0919R3 + 0.1011R4 + 0.1123R8 + 0.0669R9 + 0.0334R10 + 0.0863R11 + 0.0567R12 + 0.0822R14 + 0.0818R15
Level	Accident Growth Rate Level	State	INTEG (Increase—Decrease)

3.2. Time-Lag Correlation Analysis

Time-lagged correlation analysis is a commonly used method to verify sequences' leading, coincident, or lagging relationships using correlation coefficients. Through this analysis method, one can determine the time dimension state at which the correlation between various factors and accidents reaches its maximum, and then compare it with the correlation coefficient in the original time dimension [37]. Suppose the obtained correlation degree is greater than the original correlation degree. In that case, it indicates that the impact of this indicator on the growth rate of construction accidents has a time difference and requires advance or lag operations to analyze its correlation and impact effect. If the obtained correlation degree is less than the original correlation degree, it indicates that the reason for the unclear relationship is not the time difference, but possibly that the indicator itself has little impact on the occurrence of accidents. Nevertheless, the impact of this indicator on the volatility of the accident development level still exists, so the discussion of this indicator needs to be retained.

Using the construction accident growth rate as the benchmark indicator, the 15 influencing factor indicators are treated as selected indicators. Each of these indicators is advanced or lagged by several periods, and their correlation coefficients are calculated.

The largest time-lag correlation coefficient is chosen to reflect the time-lag correlation relationship between the selected and benchmark indicators by comparing the correlation coefficients at different periods. The corresponding number of periods represents the number of periods by which the indicator is advanced or lagged. This method is derived from the cross-correlation method in time-series analysis [38], which is an extension of the Pearson correlation coefficient and is used for time-series data. The cross-correlation method is used to measure the similarity or dependence between two time series, taking into account the lag effect over time [39]. By using this method, the similarity or dependence between two time series can be measured, identifying and understanding the potential relationships between the growth rate of construction accidents and other influencing factors. The specific formula is as follows:

$$Ar_{\mathrm{xy}}(t) = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_{i+t} - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2(y_{i+t} - \overline{y})^2}} \quad (3)$$

where:

$r_{xy}(t)$ is the correlation coefficient at the time lag t.
x_i is the value of the benchmark indicator (accident growth rate) at time i.
y_{i+t} is the value of the selected indicator at time $i+t$.
$\overline{x}$ is the mean of the benchmark indicator values.
$\overline{y}$ is the mean of the selected indicator values.
n is the number of samples.

Using this formula, the correlation coefficients for different time lags or advances can be calculated, identifying the maximum correlation coefficient and its corresponding time lag. This reveals the time-difference impact of each indicator on the growth rate of construction accidents. At this point, the fluctuations of the selected indicators are closest to the benchmark indicator, and only those leading indicators with strong correlations can be used as predictive indicators for future forecasts. Table 5 shows the correlation coefficients of each indicator with the benchmark indicator before and after the time dimension changes, as well as the number of periods of change. R0 represents the benchmark indicator, namely the growth rate of accidents.

Table 5. Correlation Coefficients Between R1 and R15 and R0 Before and After Time Dimension Changes and the Corresponding Periods.

Baseline Indicator (R0)	Original Correlation Coefficient	Maximum Time-Lag Correlation Coefficient	Periods	Baseline Indicator (R0)	Original Correlation Coefficient	Maximum Time-Lag Correlation Coefficient	Periods
R1	−0.081	−0.299	−3	R9	−0.399	−0.407	−2
R2	−0.421	−0.386	1	R10	0.238	−0.296	−3
R3	−0.344	−0.409	1	R11	−0.357	−0.333	1
R4	−0.321	−0.474	−1	R12	−0.082	−0.407	−2
R5	0.282	0.271	−3	R13	−0.058	0.199	−2
R6	0.211	0.246	−3	R14	−0.077	−0.259	−1
R7	0.404	0.244	−3	R15	−0.007	−0.246	−1
R8	−0.516	−0.309	1				

By comparing the correlation relationships between various factors before and after time-lag correlation analysis, it was found that there are 11 leading indicators and 4 lagging indicators. Taking the GDP growth rate (R1) as an example of a leading indicator for the accident growth rate (R0), the impact of the GDP growth rate in 2009 needs to be lagged by 3 years to affect the accident data in 2012. After such an adjustment, the correlation coefficient between the two variables increased from −0.081 to −0.299, which aligns with the general rule that economic indicators typically precede safety events. As a lagging indicator, the growth rate of the construction area (R3) indicates that construction accidents affect the future construction area of residential buildings. By lagging the impact of the accident growth rate in 2009 by one year to affect the data in 2010, the correlation coefficient between the two variables increased from −0.344 to −0.409. This suggests that frequent safety accidents in the previous year may lead to a decrease in the construction area of residential buildings in the following year. Although the residential area is determined during the planning stage, the actual impact of the construction accident rate on the residential building area includes both the planned area and the actual construction area. An increase in accident rates will draw more attention from the government and enterprises towards safety. When accidents are reported or accident statistics are displayed by the government or enterprises, it inevitably affects construction activities, leading to a temporary reduction in the actual construction area. However, the planned construction area ultimately remains unchanged; the reduction in daily construction activities may extend the overall project timeline, thereby decreasing the annual total residential construction area. Additionally, in China, due to the rapid pace of infrastructure development, many buildings are completed in less than a year. Accidents not only affect the ongoing construction projects, but also influence government decisions regarding planned areas, which in turn affects the final indicators [40]. Thus, the impact of construction accidents is multifaceted, affecting not only the immediate construction activities, but also future planning and overall annual construction outcomes.

The correlation between most indicators and the accident growth rate has been somewhat enhanced with a few exceptions. Notably, as leading indicators, the total number of owned construction machinery and equipment (R10) and the growth rate of the power equipment ratio (R13) increased their correlation after lag adjustment and changed the direction of their correlation. The improvement in these two indicators represents an increased equipment quantity and a higher degree of automation, signifying technological progress in the construction industry. This advancement significantly reduces unsafe human behaviors and unsafe conditions of objects, thereby exerting a suppressive effect on the future number of accidents, which aligns with actual patterns. Figure 3 illustrates the trend of each indicator and the accident growth rate after the time-lag correlation analysis, displaying more significant correlations than Figure 1.

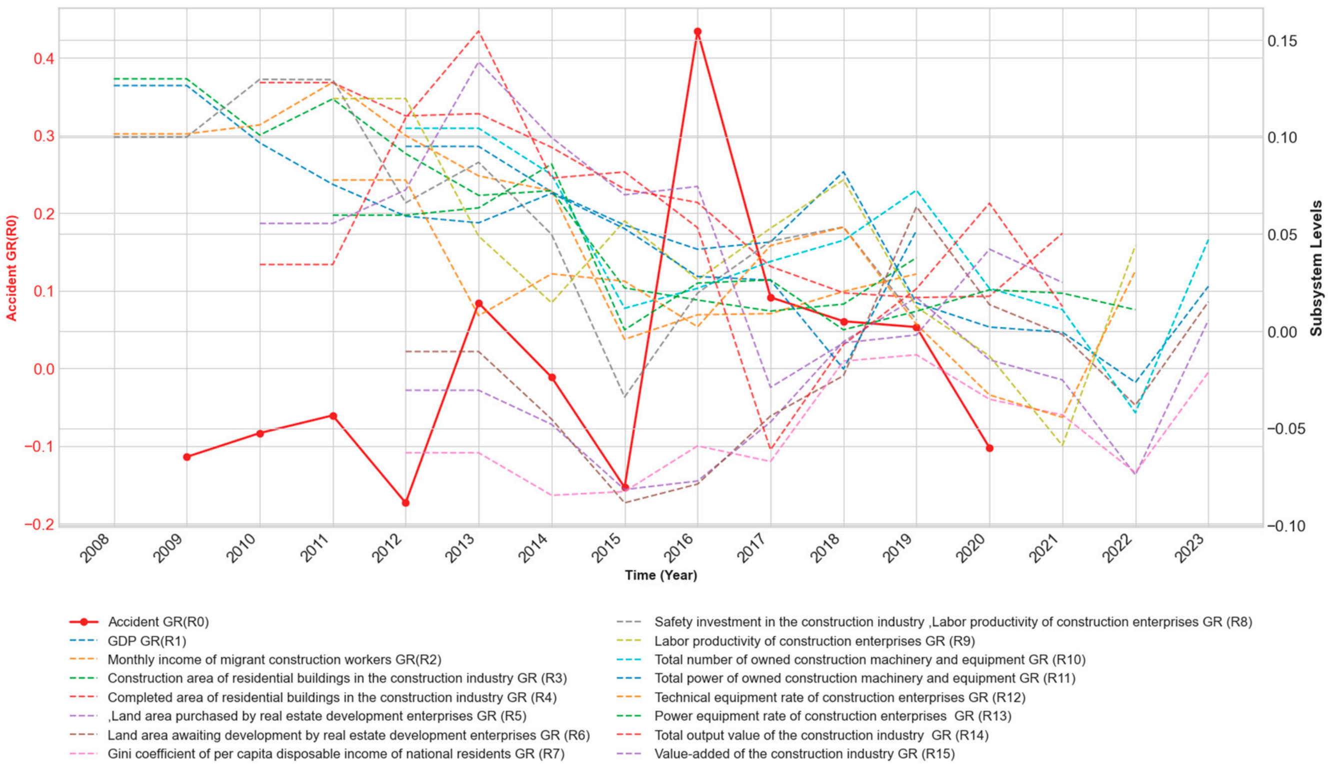

Figure 3. Trends of R1–R15 and R0 from 2009 to 2020 After Fluctuation Changes.

3.3. Formatting of Mathematical Components

In system dynamics, the changes in variables may require a certain period to respond, a phenomenon known as delay, and the function describing this phenomenon is called a delay function [41]. There are numerous instances of delay in systems, such as trainees needing time before their training has an effect or the incubation period of a disease. A delay in logistics flow is referred to as a logistics delay, while a delay in the information flow is called an information delay. In principle, all logistics and information flows experience delays, but only major delays are typically designed to balance system complexity and accuracy. Regarding the impact of lag, there are two approaches to choose from: material delay and information smoothing [42]. An information delay smooths the information to eliminate interfering information, such as spikes, by averaging information values at different time points. The larger the period, the better the smoothing effect, but the distortion also becomes more significant. Therefore, this study does not consider using smoothing, but instead uses the DELAY1 function to explore the level of each subsystem after a logistics delay.

$$\mathrm{DELAY1}(\{\mathrm{in}\}, \{\mathrm{dtime}\}, \{\mathrm{init}\}) \tag{4}$$

where:

{in}—the variable to be delayed.

{dtime}—the delay time.

{init}—the initial value of the variable.

By performing differential processing on the accumulated quantities corresponding to the levels of each subsystem, the real value of the change in the impact of each indicator under the influence of other indicators is obtained. Setting a time lag of 3 years and conducting a time-lag correlation analysis on these data yields the optimal correlation coefficient for each subsystem and its lead period, thus determining the number of periods it should lag relative to the accident growth rate. The results are shown in Table 6.

Table 6. Lag Periods and Correlation Coefficients of Each Subsystem.

Subsystem	Lag Periods	Correlation Coefficient	Subsystem	Lag Periods	Correlation Coefficient
R1	−3	−0.6347	R9	−3	−0.4190
R2	0	0.5106	R10	−3	0.3127
R3	0	−0.5217	R11	−3	−0.6373
R4	0	−0.5177	R12	−1	−0.4190
R5	−3	−0.2137	R13	−3	−0.5406
R6	0	−0.4473	R14	0	−0.3395
R7	0	−0.4211	R15	0	−0.4314
R8	0	−0.6373			

Table 6 shows that the indicators R1, R5, R9, R10, R11, R12, and R13 exhibit lag effects. Therefore, delay operations are performed on these indicators, as shown in Figure 4. After the delay, the accumulated levels of the subsystems become smoother compared to before, although the overall trends remain unchanged. The delayed subsystems are then integrated back into the original system to form a new complete system. Simulations of the increases and decreases are conducted to observe the changes in results.

After applying delay processing to the impact effects of each subsystem, the volatility was reduced to varying degrees. However, the peak characteristics were preserved, avoiding distortion caused by peak suppression. Since the delayed data more accurately reflect the actual impact, analyzing the generated comparison charts can reveal the changing patterns of the impact effects of each subsystem.

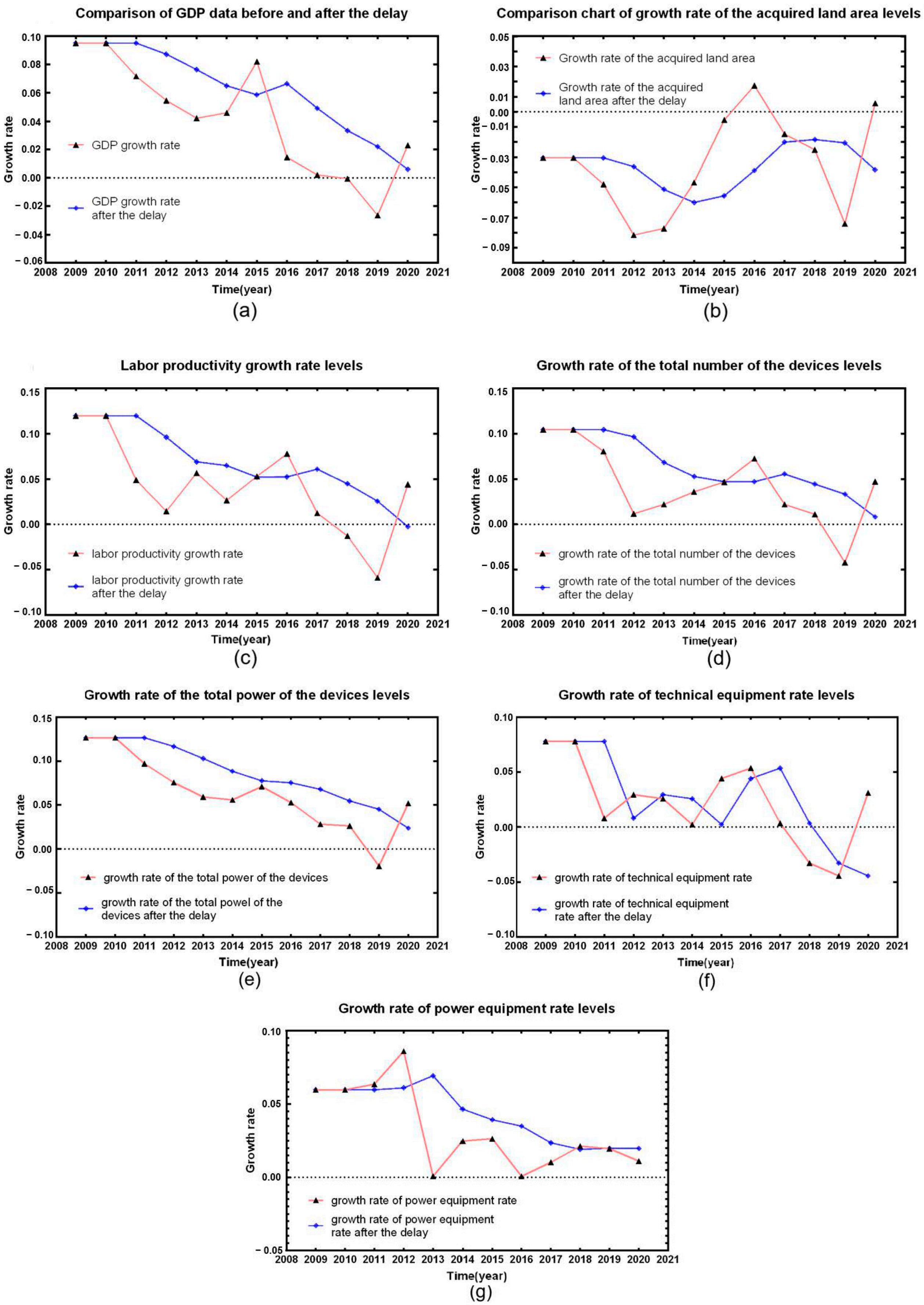

Figure 4. Comparison of Subsystem Levels After Delay Operations.

Specifically, after delaying the impact effect of GDP by 3 years, the overall level shows a declining trend, and the original spike in 2019–2020 is postponed, with the local peak shifting from 2015 to 2016. After delaying the impact effect of the land acquisition area by 3 years, the overall fluctuation becomes smoother, with the original low point in 2012 and high point in 2016 being postponed to 2014 and 2018, respectively, and the low point in 2019 being postponed to after 2020. The impact effects of labor productivity, the total number of owned construction machinery and equipment, and total power, after being delayed by 3 years, all show a declining trend in their overall levels, with the correlation coefficient increasing from around 0.9 to above 0.95. The local maxima and minima are also correspondingly delayed. The impact effect of the technical equipment rate, after a 1-year delay, maintains the same volatility as the original state, only being postponed by one year in terms of time. After delaying the impact effect of the power equipment rate by 3 years, the overall level shows a declining trend, with the local peak shifting from 2012 to 2013. Overall, the cumulative levels of the subsystems after delay processing become smoother compared to before, but the trends remain unchanged. This further verifies the lag effect of the impacts and provides a more reliable basis for analysis.

4. Discussion

4.1. Single Subsystem Simulation

After establishing a complete system dynamics model, we need to individually manipulate each subsystem to study its impact on the accident growth rate. The specific operations are as follows: reduce the level of subsystems that influence the increase in accident occurrences by 20% and reduce the level of subsystems that influence the decrease in accident occurrences by 50%. This approach allows us to explore the impact of changes in subsystem levels on the accident growth rate, highlighting sustainable practices that contribute to long-term safety improvements. Figure 5 shows that changes in the levels of specific subsystems (R5, R6, R7, and R13) significantly impact the accident growth rate. Among these, the reduction in the level of R13 has a notable suppressive effect on the increase in accident occurrences, thereby lowering the accident growth rate. This phenomenon is because the reduction in R13 corresponds to a slowdown in the growth rate of the power–equipment ratio. Despite this, the power–equipment ratio itself continues to increase. The increase in the power–equipment ratio indicates a higher level of mechanization in construction activities. A higher level of mechanization can reduce dependence on manual labor, lower the error rate in operations, and enhance the stability and safety of construction processes, promoting not only immediate safety, but also sustainable construction practices by reducing resource consumption and minimizing the environmental impact. Therefore, even if the growth rate of the power–equipment ratio slows down, it can still effectively reduce safety accidents during construction, thus suppressing the increase in the number of accidents.

Additionally, the slowdown in the growth rate of the power–equipment ratio also means that workers have more time to adapt to and familiarize themselves with new equipment and technologies. This increased adaptation period helps workers better master the operation and safe use of equipment, further reducing operational errors and safety accidents. This factor not only contributes to immediate safety improvements, but also builds a foundation for long-term sustainable safety practices, as well-trained workers are less likely to engage in practices that could lead to resource wastage and environmental damage.

On the other hand, the reduction in the levels of the other three subsystems (R5, R6, and R7) has instead promoted an increase in the number of accidents, with their impact ranked as R7 > R5 > R6. This indicates that the slowdown in the rate of the income disparity reduction has the greatest promoting effect on the accident growth rate, followed by the reduction in the land acquisition area, and the impact of changes in the area of land awaiting development is the smallest. Previous research has found a relationship between income disparity and accident rates in the transportation sector.

Studies have shown that in low-income areas, the accident rate for pedestrians and cyclists is higher [43]. As income increases, the traffic accident mortality rate significantly decreases, indicating that low-income groups face higher traffic accident risks [44]. Anbarci et al. [45] explored the relationship between income inequality and traffic accidents, concluding that income inequality increases accident rates. These studies collectively support the conclusion that the existence and expansion of income disparity may lead to unbalanced economic development, which in turn can cause social instability and ultimately increase the risk of safety accidents. The reduction in the land acquisition area may affect the planning and execution of construction projects, thereby impacting safety management [46]. Changes in the area of land awaiting development have a relatively smaller impact, possibly because it is less directly related to actual construction operations. Therefore, in subsequent simulations, we need to increase the levels of these three subsystems (R5, R6, and R7) and pay attention to their weight distribution to achieve the goal of suppressing the growth in the number of accidents.

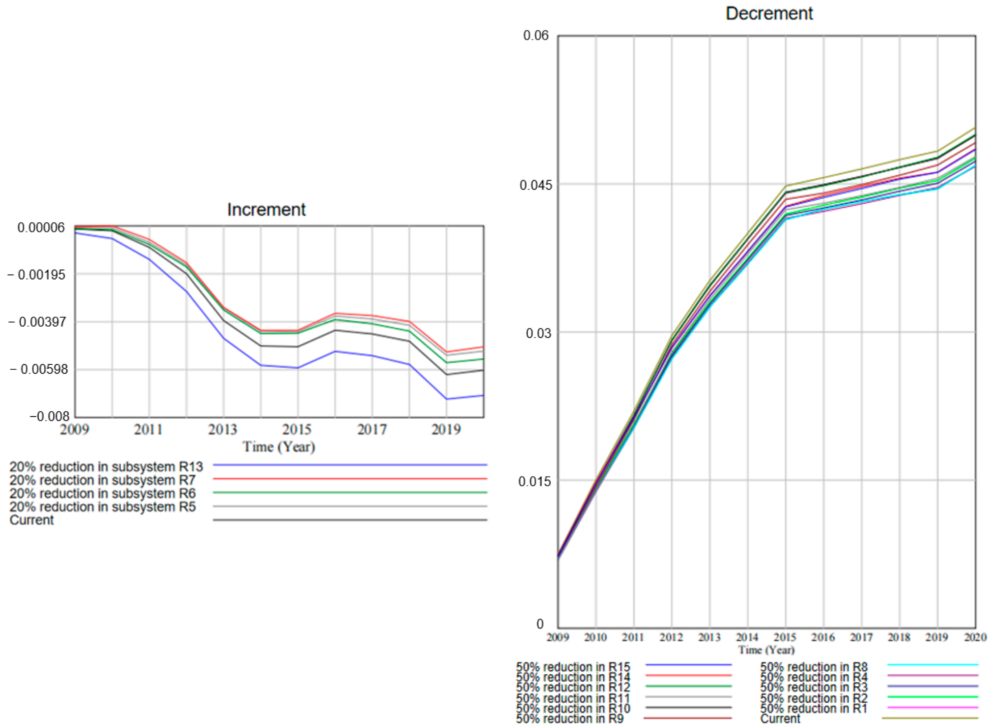

Figure 5. Simulation Results of Subsystem Levels for R1–R15.

On the other hand, for the other group of subsystems (R1, R2, R3, R4, R8, R9, R10, R11, R12, R14, and R15), reducing their levels decreases the reduction in the number of accidents, thereby increasing the growth rate of accident occurrences. Among these subsystems, the reduction in the level of R4 has the greatest suppressive effect on the reduction in the number of accidents. The impact size ranking is as follows: R4 > R3 > R8 > R11 > R2 > R9 > R15 > R12 > R10 > R1 > R14. This indicates that the continuous increase in the completed area significantly reduces the number of accidents, while the total output value of the construction industry has the smallest impact. The increase in the completed area usually signifies the successful completion and quality assurance of construction projects, indicating that safety management measures during the construction process were effective, thereby significantly reducing the occurrence of accidents. On the other hand, while the total output value of the construction industry reflects the overall scale of the industry, it has less of an impact on the safety management of specific construction projects, thus having the smallest influence.

To minimize the growth rate of accident occurrences, apart from reducing the level of subsystem R13, the levels of other subsystems should be correspondingly increased. Since multiple other indicators influence the levels of each subsystem, it is necessary to assign simulated growth rates to these indicators for the next two years to obtain the simulation results for each subsystem level.

First, use the r1–r15 indicator data from 2009 to 2020 as input, assuming that the indicator values for 2021 and 2022 remain the same as in 2020, i.e., no change. This will yield the initial change in impact and the cumulative effect of each indicator's growth rate on subsystem levels. Next, apply an increase and decrease of 10%, 20%, and 50% to the values of each indicator for the next two years to evaluate the impact of these changes on subsystem levels. Specifically, the r13 indicator should only be decreased while the other indicators are increased. This method generates images under various change scenarios and verifies the reasonableness of the assumptions.

In this process, the impact effect of the subsystem is calculated by summing the impact effects of each indicator within the subsystem and applying the predetermined weight distribution. Figure 6 shows the changes in the levels of the R1–R15 subsystems. In subsystems R1–R13, the increase or decrease of each influencing indicator is positively correlated with the overall subsystem level change, meaning that appropriate adjustments can increase the reduction level of the accident growth rate and decrease the increase level of the accident growth rate.

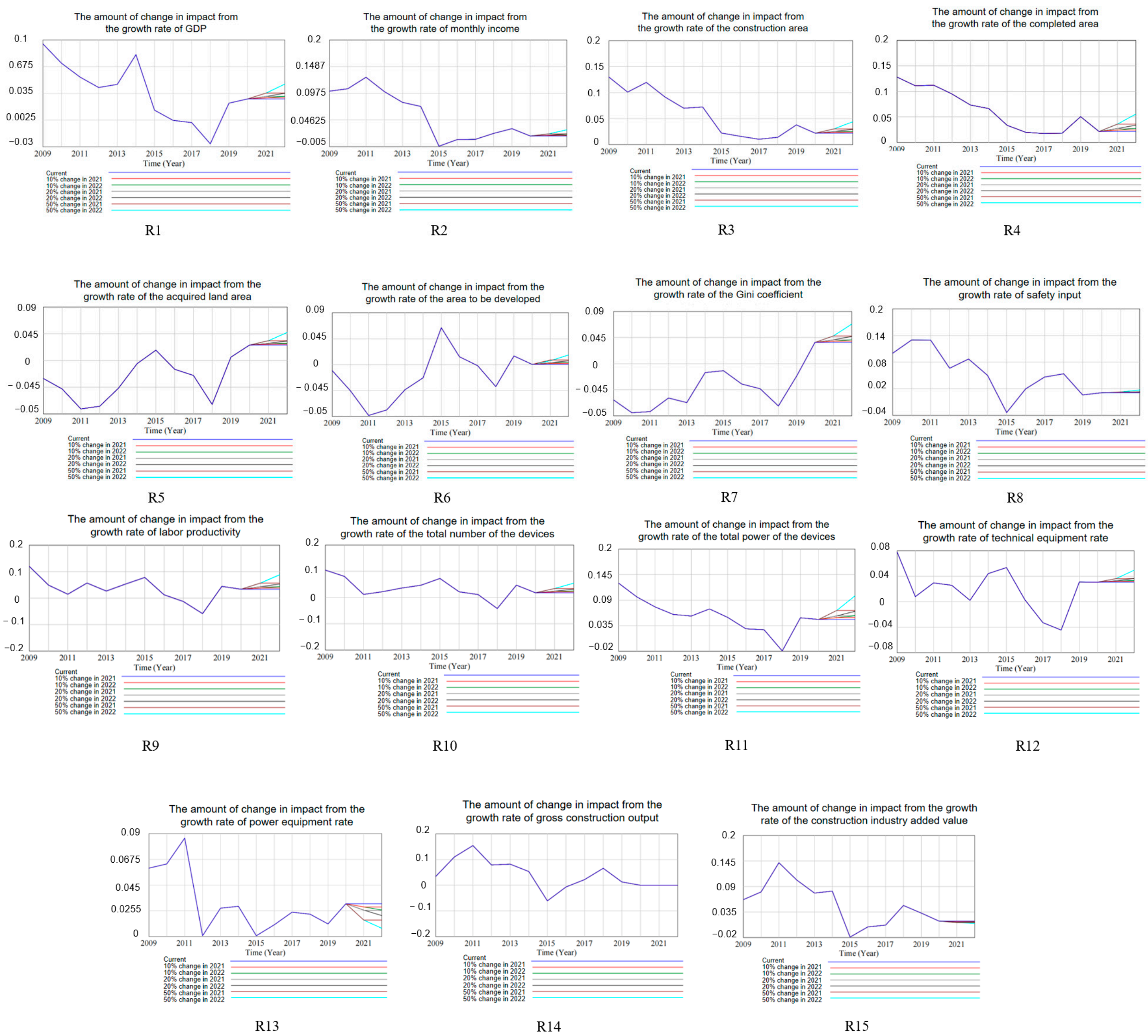

Figure 6. Images of Subsystem Level Changes for R1–R15.

However, regardless of changes made to other indicators, the levels of subsystems R14 and R15, representing the growth rate of the total output value and value-added growth rate of the construction industry, respectively, will decrease. This will lead to a reduction in the level of accident growth rate reduction, thereby increasing the accident occurrence growth rate. Based on the overall system analysis, the subsystem level of the construction industry's total output value growth rate (R14) ranks lowest in terms of contribution to reduction, with a smaller impact; the subsystem level of the construction industry's value-added growth rate (R15) ranks moderate, with a certain impact. Therefore, in subsequent scenario settings, special attention should be paid to the special cases in the above simulation results.

For example, the safety investment (R8) growth rate is not significantly affected by the other 14 indicators. However, its subsystem level ranks high regarding contribution to reduction, indicating that other indicators and even small changes do not easily influence the level of safety investment and can significantly impact the growth rate of accident occurrences. Therefore, the level of the R8 subsystem should be maximized; the reduction in the level of the R15 subsystem should be minimized; and for the R14 subsystem, the reduction in its level should also be minimized, but restrictions can be lifted if necessary.

4.2. Full System Level Simulation

After simulating the level of a single subsystem, we obtained the impact of changes in indicators within each subsystem on the subsystem level and further explored the impact of subsystem levels on the study subject (i.e., the accident growth rate level). The specific operations are as follows: by reducing the level of increases by 5%, 10%, 20%, and 50%, and increasing the level of decreases by 5%, 10%, 20%, and 50%, we simulated the cumulative value of the accident growth rate level and performed differential processing. The results are shown in Figure 7. As the magnitude of changes in the levels of the impact on the increase and decrease in accident occurrences increases, the cumulative effect on the accident growth rate level also further increases. When analyzing the trend of accident growth rate changes from 2009 to 2020, it was found that making corresponding adjustments to the subsystems can effectively reduce the accident growth rate and lower the increase in the accident growth rate, thereby suppressing the accident growth rate. Specifically, when the increase is reduced, the speed at which accidents increase slows down; when the decrease is increased, the speed at which accidents decrease accelerates. This method of adjusting accident rates is aligned with sustainable safety management practices, which aim to create a balance between operational productivity and safety, thereby enhancing the overall resilience of construction projects against potential disruptions. Therefore, by reasonably adjusting the increases and decreases of subsystems, the goal of controlling the accident growth rate can be achieved. This strategic approach not only addresses the immediate needs for accident reduction, but also aligns with sustainable development goals by promoting safer, more efficient, and environmentally friendly construction practices.

By comparing the original data with the simulation results of an overall 5% change in subsystem levels, it was found that during this period, the range of the accident growth rate increased from 0.0469 to 0.0487, an increase of 3.69% year-on-year; when the change was 10%, the range increased to 0.0504, a year-on-year increase of 7.39%; with a 20% change, the range increased to 0.0539, a year-on-year increase of 14.78%; and with a 50% change, the range increased to 0.0643, a year-on-year increase of 36.95%. This indicates that even small adjustments in subsystems not only impact the immediate accident rates, but also foster long-term sustainability by establishing safer and more resilient operational practices. The effective expression of this impact in the model reached 73.9%. This demonstrates that changes in subsystem indicators have a cumulative effect, and even small adjustments can significantly impact the accident growth rate. Therefore, policymakers can gradually achieve the goal of reducing the accident growth rate by fine-tuning subsystem indicators to align with sustainability goals that include reducing environmental impacts and ensuring worker safety.

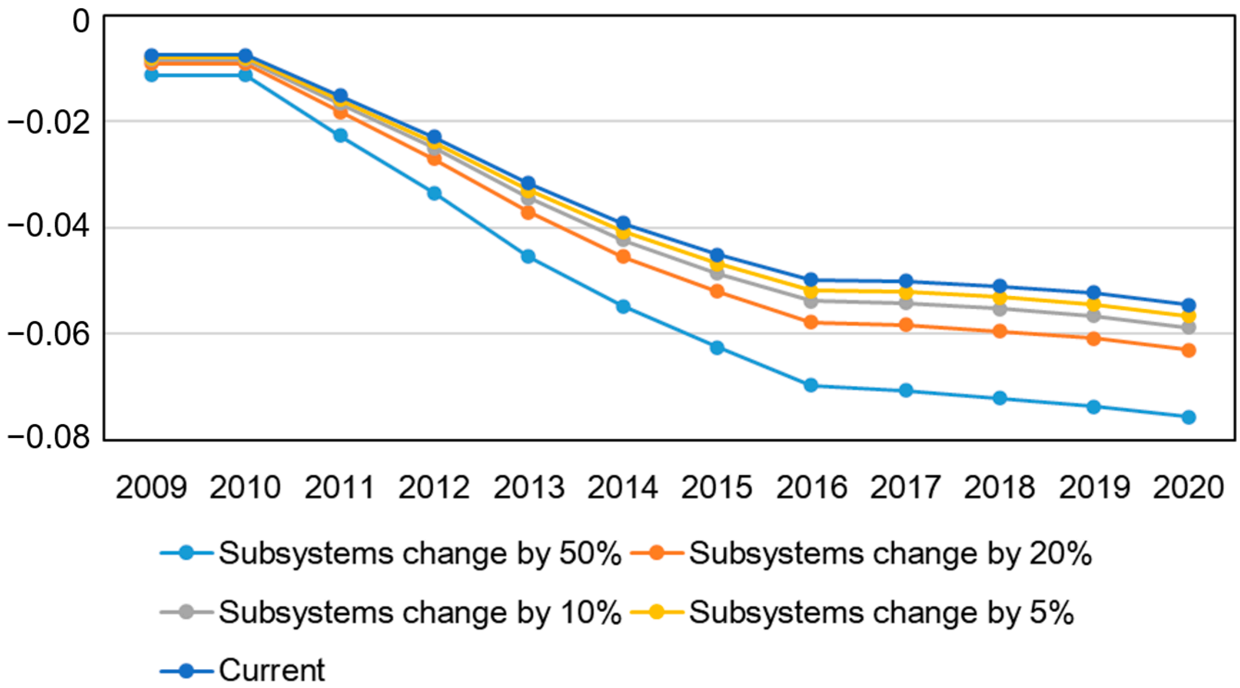

Figure 7. Impact of Subsystem Changes on Overall System Simulation Results.

Using the system dynamics model corrected by the delay function, further level simulations were conducted for single subsystems and the entire system. The simulation results for single subsystems are shown in Figures 8 and 9. From Figure 8, it can be seen that the impact effect of reducing the system level on the decrease in the increase amount is ranked as follows: R13 > overall reduction > original > R5, indicating that reducing the power equipment rate has the strongest suppressive effect on the increase in the accident growth rate. However, for land acquisition areas, reducing it would instead exacerbate the occurrence of accidents. Under their combined effect, the increase in the number of accidents was somewhat controlled. This suggests that the fluctuation of the power equipment rate has a greater impact on production safety accidents and should receive more attention. This means that increasing the power equipment rate is one of the key measures to control the accident growth rate. On the other hand, reducing the land acquisition area might lead to fewer construction projects, resulting in insufficient investment in safety management by construction companies, thus increasing the likelihood of accidents. If the levels of the five subsystems affecting the decrease amount are reduced, it can be seen that lowering their levels would exacerbate the increase in the number of accidents, with the impact ranking as follows: R11 > R9 > R10 > R1 > R12. This means that reducing the levels of these systems suppresses the reduction in the accident growth rate. Suppressing the total power of owned construction machinery for single systems would significantly increase the probability of accidents. Therefore, it is necessary to jointly enhance the levels of the total power of owned construction machinery, labor productivity, the total number of owned construction machinery, GDP, and the technical equipment rate to reduce the probability of accidents. These findings indicate that increasing the levels of these subsystems is an important strategy to reduce the number of accidents. Specifically, enhancing the total power of owned construction machinery and labor productivity can directly improve the safety and efficiency of the construction process, thereby significantly reducing the occurrence of accidents.

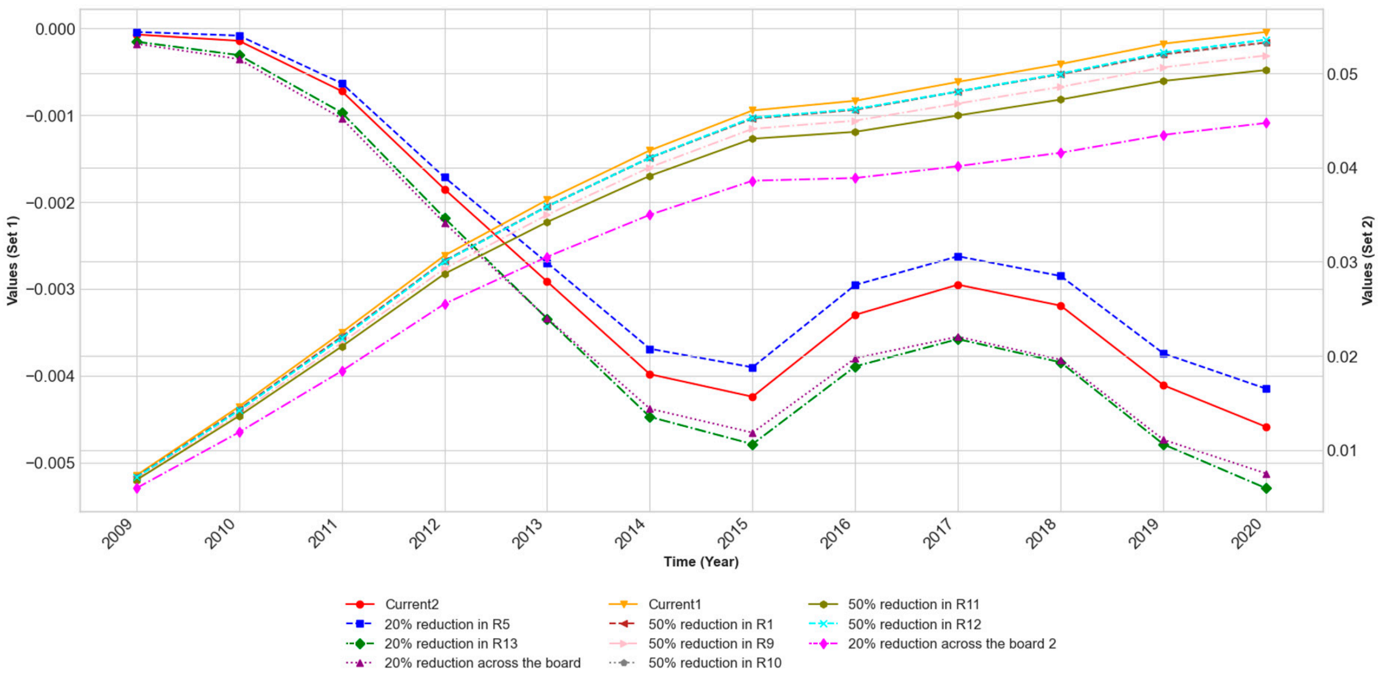

Figure 8. Simulation Results of Corrected Subsystem Levels for R1–R15.

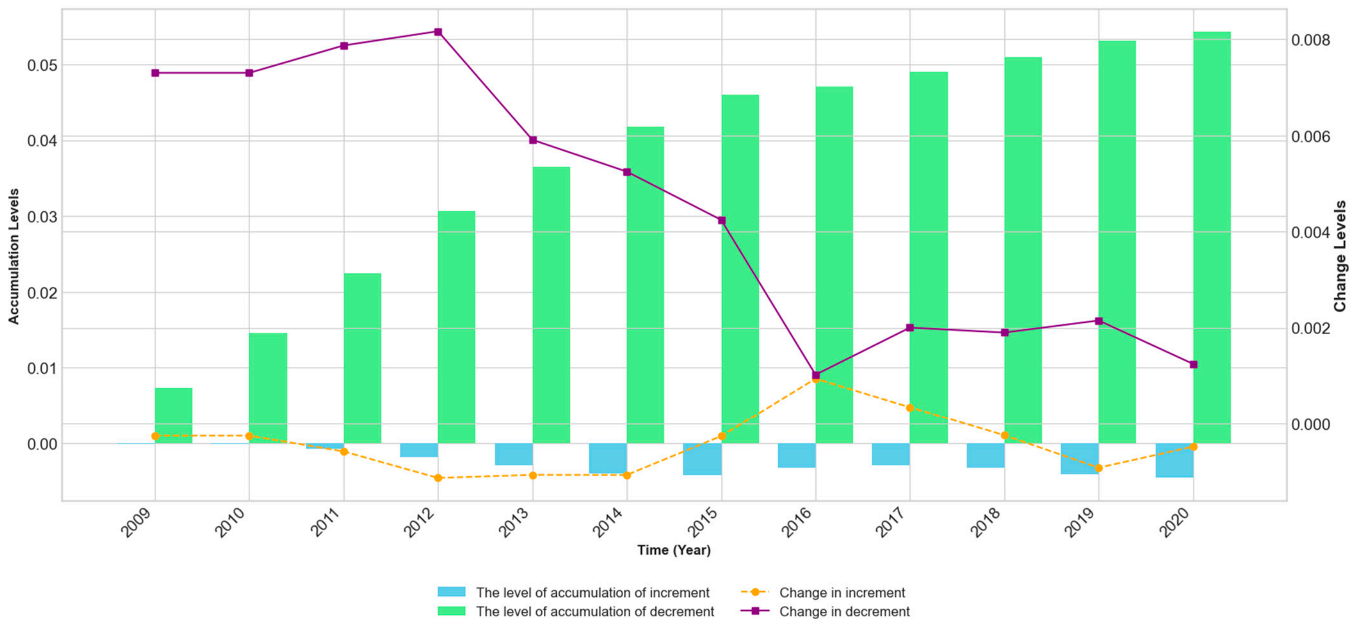

Figure 9. Simulation Results of Corrected Growth Rate Increase and Decrease Levels.

Figure 9 shows that the corrected simulation results for the increase and decrease levels of the growth rate generally follow the same trend as before the correction, but the overall variation is smoother. In 2012, the increase in the accident growth rate reached its minimum, and the decrease reached its maximum, indicating that the number of accidents in 2012 significantly decreased compared to 2011. There were 589 construction safety accidents in 2011 and 487 in 2012, a year-on-year decrease of 17.3%, the largest drop in the past decade. Conversely, in 2016, the increase in the accident growth rate reached its maximum, and the decrease reached its minimum, indicating that the number of accidents in 2016 significantly increased compared to 2015. There were 442 construction safety accidents in 2015 and 634 in 2016, a year-on-year increase of 43.4%, the largest rise in the past decade. This confirms that the results obtained from the corrected system dynamics model are consistent with actual situations, validating the model's effectiveness. By comparing with actual data, the model's simulation results accurately reflect the trend of accident occurrences, demonstrating the model's reliability in predicting accident growth rates. This provides strong support for further policy making and safety management. Adopting a sustainable approach in these policies ensures that the industry not only aims to reduce accident rates, but also enhances overall project sustainability, contributing to safer conscious construction environments

By exploring the impact of subsystem levels on the study subject (accident growth rate level) using the corrected model, we simulated the cumulative value of the accident growth rate level and performed differential processing. The results are shown in Figure 10. By comparing the corrected original data with the simulation results of a 5% overall change in subsystem levels during this period, the range of the accident growth rate increased from 0.0511 to 0.0533, a year-on-year increase of 4.34%; with a 10% change, the range increased to 0.0556, a year-on-year increase of 8.68%; with a 20% change, the range increased to 0.0600, a year-on-year increase of 17.37%; and with a 50% change, the range increased to 0.0733, a year-on-year increase of 43.42%. By comparing this with the data before correction, it was found that in the corrected model, changes in subsystem indicators had an impact on the overall accident growth rate level that was closer to the simulated change values. The effective expression of this impact increased to 86.8%. The corrected model demonstrated higher accuracy and consistency in predicting the impact of subsystem changes on the accident growth rate. This further indicates that considering the time effects of macro indicators is necessary when studying construction safety accidents. It further validates that, when exploring the factors affecting construction safety accidents, the time effects of these macro indicators must be considered. Using the time-lag correlation between indicators as a basis and introducing delay functions can effectively correct the result deviations caused by the time lag of different indicators' impacts. The correction method of introducing delay functions effectively addresses the time-lag effect problem of different indicators, making the model more accurately reflect actual situations. This is significant for improving prediction accuracy and formulating effective safety management policies.

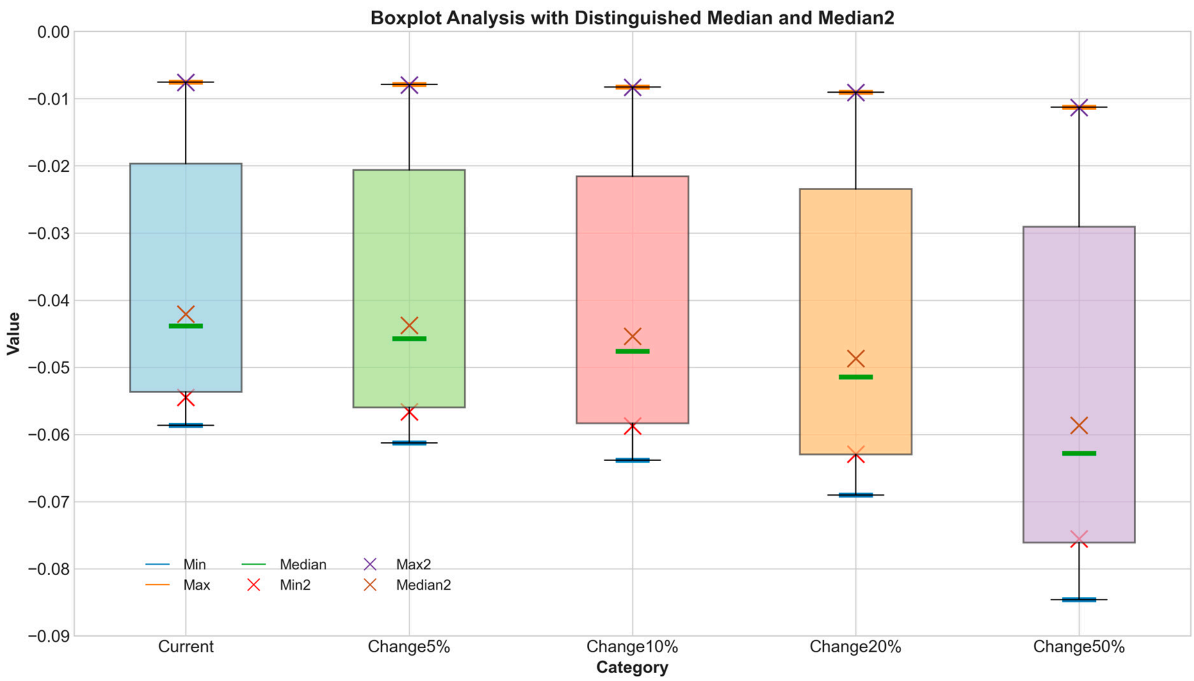

Figure 10. Impact of Corrected Subsystem Changes on Overall System Simulation Results.

4.3. Policy Recommendations

By analyzing the system dynamics model of construction safety accidents and its simulation results, we gained a deep understanding of the impact of macro factors on accident occurrence rates. To reduce the occurrence of construction safety accidents, policy makers should focus on the following aspects: Firstly, the power equipment rate (R13) should be increased, meaning the use of modern and automated equipment should be expanded. The government can encourage enterprises to introduce advanced equipment through policy formulation, tax reductions, and subsidies, while also strengthening technical training to improve equipment operation and maintenance levels, ensuring equipment safety performance, and thereby reducing safety accidents caused by equipment failures [47]. This approach not only enhances safety, but also supports sustainable construction practices by reducing reliance on labor-intensive methods and minimizing environmental impacts through efficient resource use. Increasing safety investment (R8) [48] is another effective measure. The government should mandate a minimum safety investment ratio for construction enterprises and provide special funds or low-interest loans to support enterprises' safety equipment and training investments. Enhancing safety education and training for workers can improve their safety awareness and operational skills, effectively reducing accidents caused by human errors while also promoting a culture of safety that aligns with sustainable employment practices. These two aspects are often related in practice; the increase in the power equipment rate requires corresponding safety investment to introduce safer equipment, ensure equipment maintenance, and provide operational training. Only in this way can the potential of modern equipment in reducing accidents be maximized.

Regulating the completed area (R4) is also crucial. A reasonable construction schedule and planning of the completed area can reduce safety hazards caused by rushing projects [49]. The government can require enterprises to formulate reasonable construction plans, limit the excessive growth of the completed area, and strictly enforce construction quality acceptance systems to ensure safety and quality at every construction stage.

To control income disparity (R7), it is recommended that a fair remuneration system be established to narrow the income gap among construction workers and enhance their work enthusiasm and safety awareness. Improving the social security system by providing basic medical, pension, and work injury insurance can alleviate workers' concerns. Additionally, strengthening the supervision of labor contract signing and fulfillment can safeguard workers' legal rights. These measures can boost workers' enthusiasm and sense of responsibility, thereby reducing safety accidents caused by psychological pressure or dissatisfaction, while also contributing to a sustainable workforce that feels valued and protected.

5. Conclusions

This study takes construction safety accidents as an example to investigate 15 macro-level factors affecting the growth rate of construction accidents and their impact patterns. By constructing a system dynamics model and introducing delay functions, the time-dimensional differences and their effects on the accident growth rate were simulated and analyzed, leading to the following conclusions:

(1) Macro factors significantly influence the accident growth rate. Factors such as the power equipment rate (R13), completed area (R4), and safety investment (R8) notably affect the growth rate of construction accidents. In particular, increasing the power equipment rate and safety investment can significantly reduce the frequency of accidents. This not only enhances immediate operational safety, but also contributes to the long-term sustainability of construction practices by ensuring that modern, efficient, and safer methods are adopted.

(2) Introducing delay functions validated the lag effect of different macro factors on the accident growth rate. This indicates that the impact of some factors is not immediate, but gradually unfolds over time. For example, although the improvement in the power equipment rate might not show significant effects in the short term, it has a notable impact on reducing accidents in the long term. Such delayed effects underscore the importance of planning for sustainability in safety practices, where long-term benefits are realized through consistent and sustained efforts.

(3) The simulation results demonstrate that the system dynamics model can accurately reflect the actual growth trends of construction accidents. Adjusting the increases and decreases in subsystem levels can effectively control the growth rate of accidents. The model validation shows high reliability in predicting accident occurrence rates.
(4) This study found that slight adjustments in subsystem indicators can have significant cumulative effects over the long term. Even small changes can notably impact the control of the accident growth rate. This provides policymakers with a theoretical basis for gradually improving safety management measures. Such incremental adjustments align with sustainable development principles, where ongoing minor improvements can lead to substantial enhancements in safety and efficiency.

This study reveals the significant influence of macro factors on construction safety accidents through the system dynamics model, validating the importance of time effects and cumulative effects, and providing scientific evidence for policymakers. However, the study primarily focuses on macro-level factors, neglecting the role of micro factors such as on-site management and individual behavior in accident occurrences. Future research should combine micro-behavior analysis with macro models to provide more comprehensive safety management strategies that integrate both immediate and long-term sustainability goals.

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