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Data- and Model-Driven Crude Oil Supply Risk Assessment of China Considering Maritime Transportation Factors

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Abstract: Effective supply-chain risk assessment is the basis for developing sustainable supply policies, and it has received growing attention in global oil supply system management. Dynamical modeling and data-driven modeling are two main risk assessment technologies that have been applied in crude oil supply networks. Dynamical risk modeling and data-driven risk modeling offer distinct advantages in capturing the complexities and dynamics of the system. Considering their complementary strengths, a hybrid modeling framework combining system dynamics and data-driven neural networks is proposed for risk assessment of crude oil transportation network. Specifically, the system dynamics module is to capture and interpret the underlying dynamics and mechanisms of the transportation network, while the deep neural networks module is to discover the nonlinear patterns and dependencies of risk factors from various inputs. Based on joint training, the hybrid model can ultimately develop the capability of risk prediction with a small amount of data. In addition, it can consider the dynamic nature of crude oil transportation networks to interpret the predicted results of the risk level for decision-makers to make specific risk-mitigating policies. Extensive experiments based on China's scenario have been conducted to demonstrate the effectiveness of the proposed hybrid model, and the results show that our model achieves higher accuracy in risk prediction compared to the current state of the art. The results also present an explanation for China's policy change of building a resilient crude oil transportation system.

Keywords: hybrid modeling; risk assessment; crude oil supply; system dynamics

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1. Introduction

Sustainable maritime transportation aims to minimize environmental impacts and enhance shipping safety and resilience [1,2]. In recent years, it has played a more crucial role in global crude oil supply as there is a growing variety of risks and uncertainties, including geopolitical conflicts, natural disasters, human accidents, and disruptions in infrastructure or logistics [3,4]. These risks arising from different sources could lead to severe social, environmental, and economic consequences [5]. In this situation, systematic risk assessments that focus on identifying and quantifying the major risk sources and critical vulnerabilities have attracted growing research attention [5,6]. Risk assessment can provide comprehensive information and insights for decision-makers to develop resilient policies to mitigate risks and enhance the sustainability of the crude oil transportation system. China, as the world's largest energy consumer and crude oil importer, relies heavily on the global crude oil transportation network and supply chain. In the past decades, the risks of its global crude oil transportation have greatly influenced China's policy making and operation of building a sustainable oil supply network [7]. The complexity and requirement of risk assessment for China's oil supply system underscores the importance of developing effective and comprehensive risk assessment frameworks and methods [8].

When assessing the risk of a crude oil supply system, the main difficulties lie in the complexity and interconnectedness of transportation networks [9]. For example, China's international and domestic crude oil supply relies on various transport modes, including ships, pipelines, tankers, and trucks, and involves different stakeholders, such as producers, shippers, and receivers [10]. Furthermore, the risks involved span multiple dimensions, including technical, environmental, and social factors. These factors interact with each other in a variety of ways and often change over time, increasing the complexity of quantifying and assessing and managing risks [11]. In this case, the key challenge in the risk assessment of a global oil supply network is how to incorporate the complex dynamics and uncertainties of the supply network in a comprehensive risk modeling framework.

In the past decades, researchers have developed several risk assessment models in crude oil supply networks, mainly including the event tree model (ETM), failure mode and effective analysis (FMEA), the system dynamics (SD) model, and the neural network (NN) model. From the view of system modeling, existing risk assessment models can be roughly grouped into two categories: dynamical modeling and data-driven modeling. Each of them applies different methods to describe key factors and their complex, nonlinear dynamics for quantitatively assessing or predicting the system risk.

The first category is the dynamical model, which has been studied for many years. Dynamical models are generally defined with a set of mathematical formulas with specified parameters or a series of related indicators of risk. A typical instance is the SD model, which involves building multi-dynamic models for simulating the interactive behaviors of components of the supply system over time [12]. It captures the interconnectedness and feedback loops between various components, typically considering multiple factors such as supply and demand fluctuation, the topological structure of transportation network, the capacity of transport facility, and price volatility. These factors are represented as different variables and parameters within the system, and their interactions are defined by a series of differential equations, thereby allowing for the quantitative analysis of risk evolution [13]. By integrating input parameters or introducing different policy variables into an SD model, we can estimate the risk and predict the influences of different policies on the crude oil supply system. In addition, an SD model, as the result of dynamical modeling, uses known dynamical models to quantitatively describe the chains of causal relationships of various factors [14]. Thus, it can consider the interconnected dynamic changes related to supply and demand, feedback mechanisms, time delays, and other factors and reveal the characteristics and patterns of risk evolution of the system. However, dynamics-related risk assessment models rely on a number of pre-defined parameters, functions, or equations that are mostly derived from decision-makers' subjective understanding, empirical assumptions, and simplifications that might not fully capture real-world complexities, making them difficult to be applied to accurately assess novel risks and predict potential influences.

Another category is the data-driven risk prediction model that has attracted great attention in recent years. It focuses on applying machine learning methods such as deep neural networks to recognize and classify data by learning the mapping from input to output [15]. The input of this type of model is a set of historical state data of the system of interest, and the output is often the risk level or risk value. In the analysis of global crude oil supply problems, neural-network-based models are successfully used to predict the risk of pipeline, vessel failures, and supply shortage [9]. Data-driven risk prediction models can learn complex patterns and nonlinear relationships of risk factors within the system if there are enough data, making them particularly suitable for capturing the intricate dynamics of system. Additionally, they have the ability to adapt and generalize well to novel phenomena or changes in the system [16]. Despite the capabilities of risk prediction and classification, such data-driven models heavily rely on the number and quality of training datasets, which are mostly limited or biased in the global oil transportation field [9,17]. For example, there are only dozens of annual data samples of the crude oil import and export for China. Additionally, such types of models have weak interpretability of risk prediction results, as the weights and parameters in neural network models are difficult to interpret.

Without fully understanding causal relationships of risk factors, it will be difficult to formulate responsive strategies or policies.

Dynamical risk modeling and data-driven risk modeling offer distinct advantages in capturing the complexities and dynamics of the systems. Considering their complementary strengths, this paper aims to develop and validate a data- and model-driven hybrid risk assessment model that combines system dynamics and artificial neural networks to predict the risk of China's crude oil supply system. In this paper, we establish an SD model and neural network for the system of interest and define the hybrid modeling process as a joint risk prediction and parameter optimization problem. The trained hybrid model can capture complex, nonlinear patterns of various risk factors using small amounts of data [18]. In addition, it can interpret predicted oil supply risk results from the underlying dynamics for decision-makers to make specific risk-mitigating policies.

This paper focuses on China's global crude-oil supply system and successfully uses a small set of historical data to train a hybrid risk assessment model. The main contributions are summarized as follows.

- To capture the dynamics of risk evolution of the crude oil supply system, the main potential risk factors and their casual relationships are identified. An SD model considering multiple risk factors is developed.
- To achieve accurate risk prediction and interpretation, a novel hybrid model that combines system dynamics and multilayer neural networks is proposed.
- Simulation experiments under different oil supply scenarios for China have been conducted to demonstrate the effectiveness of the hybrid model. Some important conclusions were draw from the simulation results for optimizing the policy of resilient crude-oil supply.

The rest of the paper is organized as follows. Section 2 reviews the existing literature on risk assessment of the global oil transportation and supply. Section 3 presents the implementation and testing of the proposed hybrid model, including the system dynamics model, neural network model, and the hybrid modeling problem. Section 4 provides case studies and experiments to evaluate the performance and effectiveness of the hybrid framework. Finally, Section 5 concludes the paper and discusses future research directions.

2. Related Work

Our research is connected to two areas of study in the literature: the application of system dynamics and the use of neural network methods in maritime transportation network research.

The maritime transportation system is a complex system that involves interactions among various participants, such as ocean carriers, terminal operators, shippers, freight forwarders, inland logistics service providers, and governments. System dynamics can effectively describe the nonlinear relationships in the maritime transportation market by placing emphasis on feedback mechanisms and dynamic evolution. Oztanriseven et al. provide a summary of the applications of system dynamics in maritime disruption, port operations, vessel-related decisions, and other relationships [19]. Engelen et al. develop a system dynamics model to investigate the relationship between freight rates in the dry bulk markets [20]. Jeon et al. examine the cyclical characteristics of the container shipping freight index by utilizing system dynamics to analyze the relationship between supply and demand [21]. Wan et al. propose a system dynamics framework to investigate the risk in inland waterway transportation, considering both intelligent ships and traditional ships [22]. Kong et al. construct a system dynamics carbon abatement model that explores the interaction between different factors from a supply chain perspective, with a case study conducted at Shanghai Port in China [23]. Nursyamsi et al. analyze the impact of government policies on the maritime economy and industry in Indonesia [24]. Carlucci et al. present a system-dynamics-based simulation model that studies the effects of maritime transportation development on port cities, aiming to support government policy decision-making [25].

The neural network method has been widely applied in the transportation field for a considerable amount of time, with Dougherty (1995) providing a comprehensive review of its applications in transportation research. Within maritime transportation, neural networks are commonly used to predict various aspects such as vessel time series, cargo volume, freight rates, and fuel consumption [26–29]. These predictions assist shipping companies in making accurate ship scheduling and freight planning decisions, leading to improved transport efficiency and resource utilization. Additionally, neural networks have the capability to forecast the future position and behavior of ships by learning from historical vessel trajectory data and relevant environmental conditions [30–33]. This information is crucial for dynamic vessel positioning, route optimization, and risk management. Neural networks are also capable of analyzing and predicting marine environment and climate conditions to provide marine and climate change monitoring [34,35]. This enhances marine risk management capability.

In addition to the abovementioned two methods, other methods are also used for risk assessment in maritime transportation [11,36,37]. From the literature review, we find that both system dynamics and neural networks have been applied in risk analysis or risk management in the maritime transportation system. System dynamics can provide explanations for the internal structure and behavior of systems, analyzing the relationships and interactions between various components of the system. Neural networks, through learning from large amounts of data and pattern recognition, can offer explanations for the correlations among complex data. In this paper, we combine these two approaches from a new angle to propose a hybrid modeling framework to better understand the operational mechanisms and influencing factors of the crude oil supply system of China. This combination makes the model more flexible and effective in dealing with uncertainties and changes in supply risk assessment.

3. Methodology

Risk is the potential for loss or damage resulting from exposure to uncertain events or circumstances. It is generally conceptualized as a rate describing the likelihood (or probability) of an event happening with negative consequences [38]. In a risk assessment model, risk can be formulated as Equation (1):

$$r = f(\boldsymbol{X}, \boldsymbol{C}), \tag{1}$$

where f is a quantitative function, r is the risk rate or level, $\boldsymbol{X} = \{x_1, x_2, \ldots, x_n\}$ is the set of potential risk factors (i.e., variables) denoted by x, and $\boldsymbol{C} = \{c_1, c_2, \ldots, c_m\}$ is the set of possible negative consequences. China's oil supply system involves multiple risk factors with complex interactions, increasing the complexity of defining an appropriate risk assessment function. To address this issue, we have developed a hybrid model for risk assessment. Specifically, we first develop a system dynamics model to describe critical risk factors and their causal relations. Building on this, we define a set of important state variables as inputs to design a neural network and ultimately train the network with the system dynamics model jointly to construct a hybrid model. In this section, we present the implementation of the above models.

3.1. Development of a System Dynamics Model

A crude oil supply system for a country involves various components and risk factors. To capture its dynamics, we adopt the SD methodology to describe the inherent non-linear system behaviors and their changes by modeling the causal structure of the key factors. The causal structure mainly consists of multi variables and a chain of cause-and-effect relations. These relations shape several feedback loops whose interactions form the dynamics of the system of interest. In our work, we firstly identify the key risk factors and their causal relations by investigating China's global crude oil transportation system and then define the overall feedback structure of the system.

3.1.1. Identification of Critical Risk Factors

Over the last few decades, China's crude oil supply has been divided into two parts: domestic supply and international supply. The oil supply system comprises two subsystems accordingly, each with its own set of risk factors. From the perspective of supply chain security, we try to identify critical factors that may pose security risks to sustainability of oil supply for each subsystem. In addition to routine risk factors directly influencing the volume of oil supply and demand, we also consider more factors that have significant indirect impacts on supply–demand balance and long-term sustainability.

(1) Risk factors in domestic supply

texless Due to long-term dependence on overseas imports, China has made efforts to increase domestic supply, which serves as the cornerstone of sustainable oil supply, particularly in crisis situations. Currently, there are three primary factors that pose risks to domestic supply.

- texless Transport disruption, which mainly considers the possibility and potential consequence of transport line disruption. In the mainland of China, local oil transport mostly relies on pipelines and ships, and the potential disruptions are mostly due to natural hazards, particularly the earthquakes that may occur along pipelines and transshipment sites. Routine accidents are ignored here because of their little impact. The lower the probability of natural disaster is, the lower the risk of transport disruption is.
- Supply shortage, which could be caused by domestic oil underproduction and insufficient oil reserves. This part of risk is characterized by the national resource security level, the reserve-to-production ratio, and the safety level of the stockpile compared to the suggested security level in the Agreement on an International Energy Programme (I.E.P.) The higher the oil production and reserves are, the lower the oil supply shortage is.
- Technological threats, which mainly arise from the current technological competition among countries and cybersecurity. These non-energy-related factors are becoming growing concerns for the energy supply system. Since key techniques and equipment for China's oil exploitation and further processing are dependent on oversea imports, the technological blockade from other countries could limit the efficiency and sustainability of local oil production. Such risk can be represented by the gap between domestic and foreign technology levels in core equipment manufacturing and innovation capability. Cybersecurity threats refer to potential cyberattacks on physical facilities, which have arisen quickly in recent years. They can be determined by the likelihood of cyberattacks and critical facility resilience. In general, the lower the technological competition and cybersecurity risks are, the lower the oil production and supply risk are.

(2) Risk factors in international supply

China became the primary importer of crude oil in 1993 and has heavily relied on international sources to meet its oil demand. This has also exposed China to multiple supply risk factors related to politics, finances, and technologies. Based on our theoretical investigation and collected data, these factors can be briefly summarized into three parts.

- Procurement risk, which refers to the potential for unfavorable outcomes or disruptions when purchasing crude oil from the third-party countries or regions. Such risk mainly arises from geopolitics. We defined it from three aspects: the local political stability of oil-exporting countries, the stability of bilateral relationships, and the concentration of sources of oil imports. The local political stability of a source is evaluated empirically depending on its domestic situation. The concentration is represented by the external dependency ratio on different sources, and the bilateral relationship is quantified by the current bilateral relationship development scores that are calculated through analyzing thousands of diplomatic matters. Diverse oil suppliers and stable bilateral relationships will lead to a low procurement risk.

- Maritime transport disruption, which mainly involves international oil transport lines. During China's maritime oil transport, this means the political stability of countries along transport lines and the crisis response capability of building temporary lines. The former is mainly determined by the stability of transport lines. The political stability of international oil transport lines can be indicated with political stability indices provided by international organizations.
- Finance threats, which are considered from the perspectives of oil prices and the national oil pricing capabilities. In recent years, China has opened more crude oil futures trading, enhancing the connectedness between oil and finance. International oil price fluctuations pose growing influence on China's crude oil market, especially on the overseas oil procurement costs and volume, ultimately threatening domestic oil supply sustainability. Oil price fluctuations are generally quantified by the variance of oil export prices. The smaller the variance is, the more stable the international oil trade price is, and the lower the financial risk is. Additionally, oil pricing ability depends on the renminbi (RMB) internationalization and bargaining power. The higher the internationalization index is, the higher the discourse power that leads to a lower oil procurement cost is.

The above discusses several critical risk factors. Indeed, there are many other factors that may directly or indirectly impact the oil supply of China. Table 1 summarizes the main risk sources and their corresponding micro factors that we identified in a hierarchical manner. The whole crude-oil supply system exists with different layers of risk sources. After disregarding some minor risk factors, there are a total of 12 remaining risk factors contributing to the overall risk. Additionally, potential quantitative indices have been specified to provide potential measurement of these factors.

Table 1. The main risk factors in China's crude oil supply system.

Subsystems	Risk Sources	Critical Factors	Indices
Domestic supply	Local transport risk	Line disruption caused by natural hazards	Pipeline disruption probability
	Supply shortage	Oil underproduction	Reserve/production ratio
			Resource security degree
		Oil reserves insufficiency	Strategic oil reserve safety level
	Technological threats	Technology competition and blockade	Equipment manufacturing level
			Technological innovation index
		Cybersecurity attacks	Cybersecurity risk index
International supply	Maritime transport risk	Crisis response capability	Capability of opening temporary lines
		Stability of oil maritime transport lines	Transport channels stability index
	Procurement risk	Political stability of oil-exporting countries	Political stability index
		Concentration of oil suppliers	External dependency ratio on different importers
		Stability of international relations	Bilateral relation scores
	Finance threats	International oil price fluctuation	Variance in oil export price
		Oil pricing capability	RMB internationalization index
			Bargaining power index

3.1.2. Definition of Causal Relation and Stock-Flow Diagram

To analyze how the critical risk factors interact with each other, this paper establishes a system dynamics (SD) model to depict their potential causal relationships. The boundaries and subsystems of the SD model are identified, leading to the construction of a causal loop diagram. As illustrated in Figure 1, there are positive and negative influences among the variables, which could lead to causal loops. There are in total nine feedback loops in the causal relation diagram, each of which specifies a relation of cause to effect. For example, the overall oil supply is determined by both the volume of crude oil imports and domestic supply. To maintain supply–demand balance, an increase in China's domestic oil supply will reduce crude oil imports and vice versa, resulting in negative feedback loop between them. Another example is that increasing crude oil imports from international markets causes fluctuations in oil prices, which in turn enhances China's bargaining power in oil procurement. The increased bargaining power further promotes oil import, resulting in positive feedback. In theory, feedback loops reveal the dynamics of the risk evolution of the oil supply system. There is a real case to prove these feedback loops. During the COVID-19 pandemic, international oil prices plunged due to reduced demand for energy. However, China increased its oil imports at that time because of extremely low overseas oil prices. This, in turn, led to a significant short-term contraction of domestic oil production capacity. The constructed causal relation diagram provides the basis for interpreting risk assessment results.

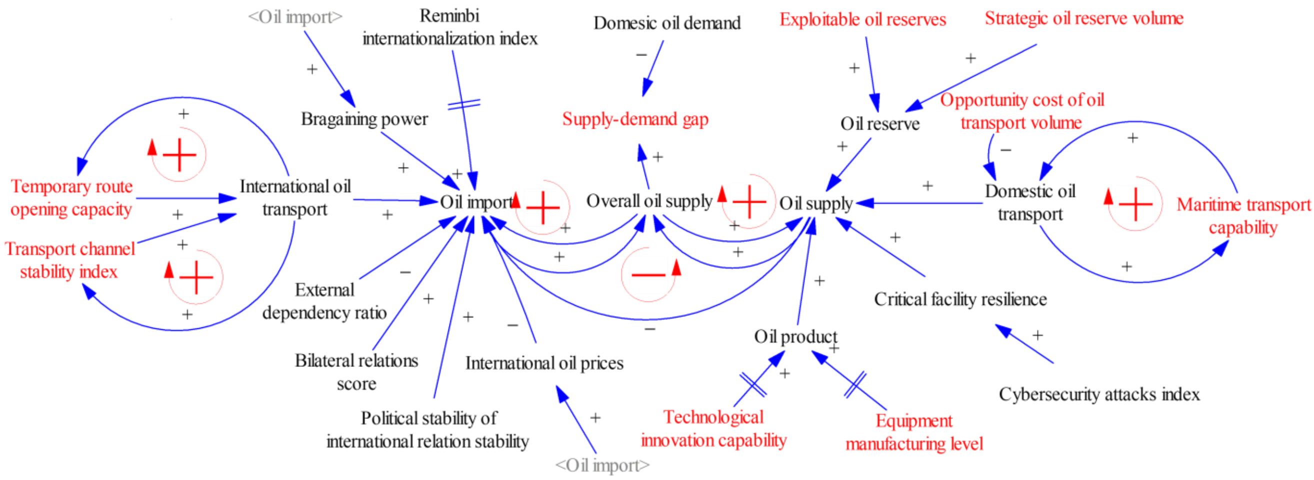


Figure 1. The causal relation diagram for China's crude oil supply.

The feedback loops in the causal relation diagram define multiple self-reinforcing and balancing feedback mechanisms of critical factors. Building on this, we further construct a stock-flow diagram to quantitatively analyze dynamical behaviors of the system. A stock-flow structure is a graphical representation of the system's components, their interconnections, and the flows between them. The stock-flow structure consists of stocks, representing accumulations of variables, and flows, representing the rates at which these variables change over time. Stocks are akin to reservoirs, while flows correspond to the inflows and outflows into and out of these reservoirs. Let us have a stock variable represented as φ_i, which has inflows $\boldsymbol{I}_i$ and outflows O_i. The change in stock over time is determined by the governing equation $d\varphi_i/dt = g(\boldsymbol{I}_i, O_i)$, where g is a function specifying the relations the stock and other relevant variables. By specifying these variables and governing equation in the stock-flow structure, we can simulate the behavior of the system and gain insights into its long-term dynamics.

Figure 2 presents the stock-flow structure of China's crude oil supply system. The system dynamics are quantitatively defined by time-varying differential variables and governing equations. There are five stock variables: domestic oil transport volume (DV_{t}), domestic oil reserves (RV), domestic oil production (DV_{p}), international oil imports volume (IV), and international transport volume (IV_t). They represent the quantities that accumulate over time. There are also many flow variables with auxiliary variables. When formulating stock-flow structures, the information about variable relations in causal loops is transferred into governing equations. To set up reasonable equations for expressing different causal relations, we searched dozens of publications from different disciplines. In this SD model, there are 19 governing equations, listed in Appendix B. The notable one is the mathematical equation for quantifying the overall risk of the oil supply system, which is the most important output. From the view of sustainable supply, we defined the risk in two parts at the system level: supply–demand imbalance and external dependence [31]. The specific formula is a weighted function, as shown in Equations (2)–(4),

$$r = \omega_1(1 - r_d) + \omega_2 r_i,\ w \in [0, 1] \tag{2}$$

$$r_d = \begin{cases} 1 & ,\ IV + DV_p \geq D \\ \frac{IV + DV_p}{D} & ,\ \text{else} \end{cases} \tag{3}$$

$$r_i = \frac{IV}{IV + DV_p} \tag{4}$$

where r is the measurement of risk level, $r \in [0,\ 1]$, ω_1 and ω_2 are the risk-aversion coefficients, r_d is the degree of imbalance of oil supply and demand, r_i is the ratio of the volume of international oil imports to the total supply, and D is the overall domestic demand. In practice, the accuracy of governing equations that together determine the dynamics of the oil supply system completely depends on the knowledge and expertise of modelers.

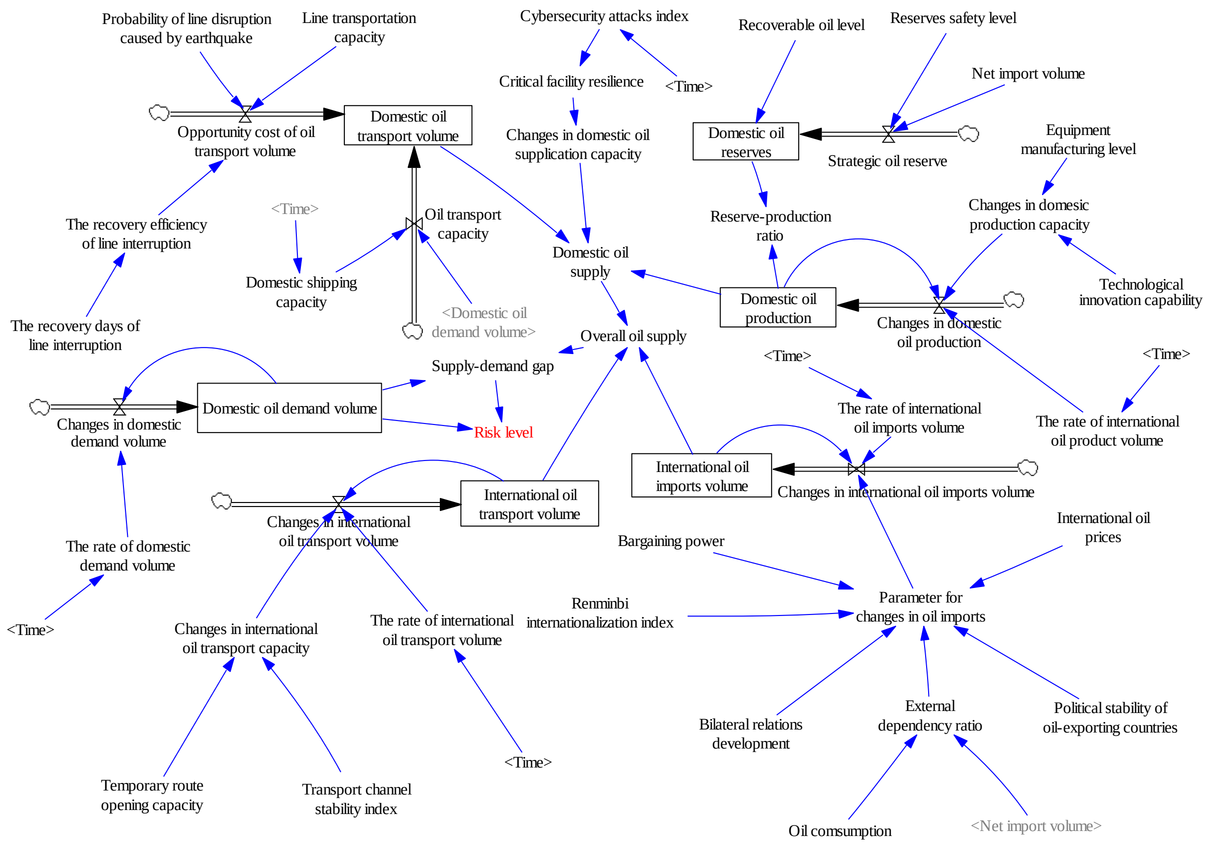


Figure 2. The stock-flow diagram of China's crude oil supply.

A dozen governing equations in the SD model involve lots of unknown parameters that need to be calibrated. In this paper, we try to calibrate these unknown parameters by searching for the potential value range from the literature and collecting multi-source statistical data to validate them from the reports or yearbooks of international and domestic organizations. To be specific, we calibrated key parameters by solving equations fitting the historical data for stock variables. However, there are some parameters that have not been predefined or observed before, such as bilateral relation indexes between China and its oil-importing countries or areas. Extra investigations on parameter calibration are thus required. For example, to acquire the bilateral relation indexes, an event-based effect analysis is applied to collect 1174 diplomatic matters happening between related countries. The recent development of bilateral relations can be evaluated through a scoring system based on a statistical analysis of both negative and positive events that have affected the national relations. Mathematical description is presented in Appendix C. The results are ultimately compared with historical situations. As shown in Figure 3, the bilateral relations scores between China and the main oil-exporting countries in the world has increased gradually in the most recent twenty years. This is consistent with what has been known about the status of China's energy diplomacy, which is committed to improving multilateral relations.

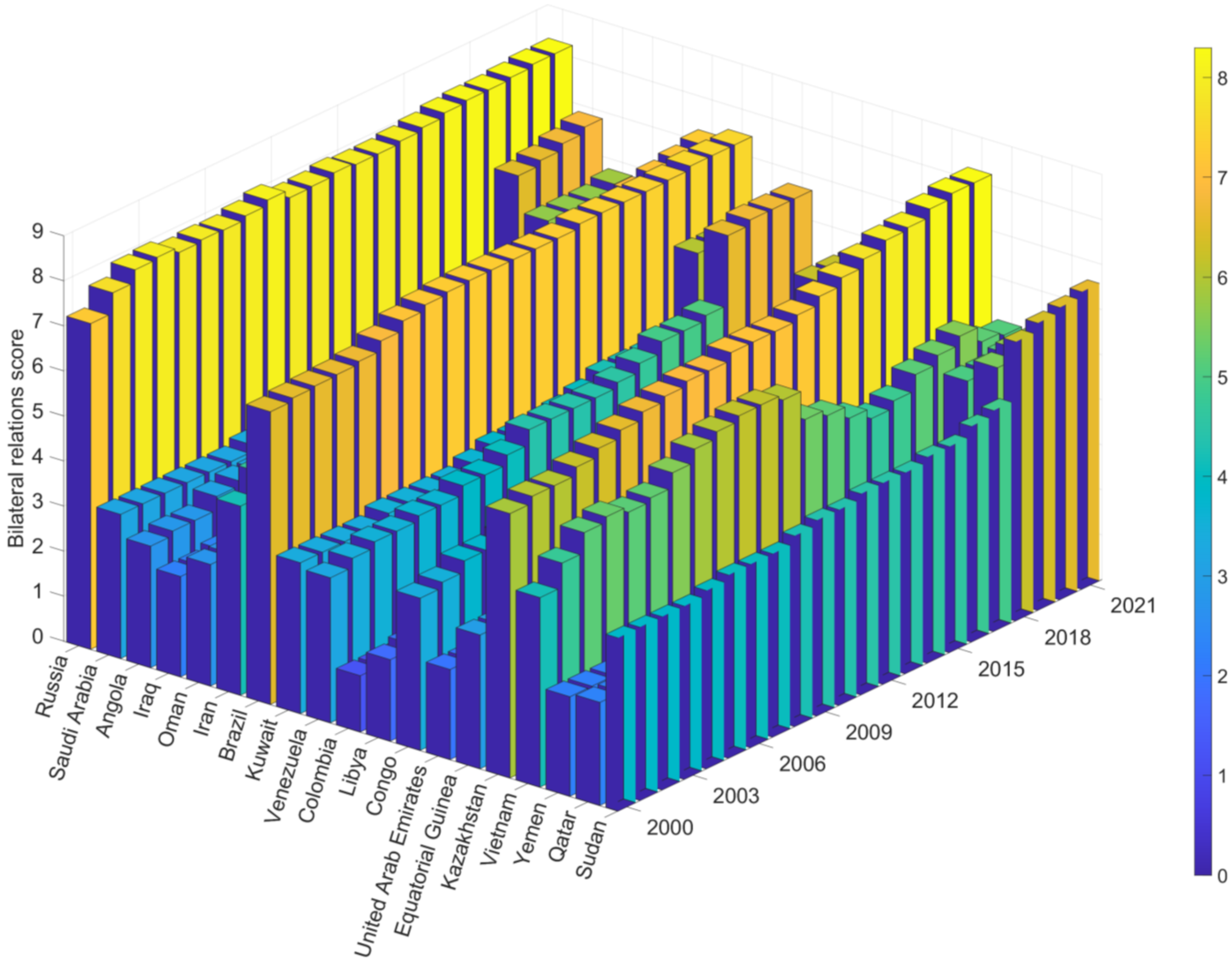


Figure 3. The recent development of China's bilateral relations with its oil-supplying countries.

After parameter calibration, one can run the stock-flow model for prediction. The dynamics of variables are defined by the set of equations underlying the model. By varying the values of variables, the effect of these variations on the output is observed. In this way, we can run the model for predicting unknown changes in stock variables and assessing the overall risk by setting up scenarios for various oil supply situations. This makes the model become a useful tool for developing the relevant policies of resilient and sustainable oil supply management. However, an oil supply system is an open complex system in which many factors can impact the equations and their parameters. While it is feasible to calibrate them, doing so requires significant disciplinary knowledge and manual work. Furthermore, the calibrated parameter values may not be the unique optimal solution, and even the best parameter value could vary as the system evolves. As a result, it is hard for the SD model to capture complete dynamics and accurately predict the future in the long term.

3.2. Design of a Hybrid Risk Assessment Model

When putting it into practice on an oil supply risk assessment, the SD model is capable of interpreting predicted results but weak for capturing the complex, time-varying dynamics of the system. To tackle this issue, we combine neural networks with the system dynamics model to develop a hybrid model to achieve a better prediction in oil supply risk assessment. The hybrid model can use observed data to adjust parameters, thereby saving lots of manual work. In addition, it can also generate various explanatory scenarios for policy assessment.

3.2.1. Problem Statement

Risk assessment for oil supply systems aims to build a risk measurement function. In general, a neural network represents a function to be approximated, $f : x \to y$. Given a finite sequence of variables, $\boldsymbol{s} = \{x_1, x_2, \ldots, x_n\}$ and the marginal result vector $\boldsymbol{r}$, a neural network is formulated as a mapping function, $\boldsymbol{r} = f(\boldsymbol{s}|\boldsymbol{w})$, where $\boldsymbol{w}$ is a hyperparameter vector of the network. When training a neural network, the adjustment of weight parameters relies on pre-assigned training data. Defining two complementary state sets, $\boldsymbol{O} = \{\hat{\boldsymbol{s}}_1, \hat{\boldsymbol{s}}_2, \ldots, \hat{\boldsymbol{s}}_{N_o}\}$ and $\boldsymbol{C} = \{\boldsymbol{s}_1, \boldsymbol{s}_2, \ldots, \boldsymbol{s}_{N_c}\}$ respectively represent the observed state space and the collocation state space, where N_o and N_c are the size of this two-state set. The observed state set contains historical observed state data of the system of interest, and the collocation (unobserved) state set contains state data obtained through system dynamics simulations and stochastic sampling-based known parameter distributions. It provides additional information that can help train the model. Denote r as the risk level assessed by a set of variables $\{x_1, x_2, \ldots, x_n\}$, which is divided into K levels, and the level K means the highest risk. To acquire risk observation results, the expert scoring method is applied to assess a risk level for each element of the observed state set. Denote $\boldsymbol{r_o}$ as the observed risk set, $\boldsymbol{r}_o = \{\hat{r}_i, \ i = 1, 2 \ldots, N_o\}$, which has the same size as the observation state set. The final observation data consists of pairwise observed state and risk level, denoted as $\{\hat{\boldsymbol{s}}_i, \hat{\boldsymbol{r}}_i | i = 1, 2, \ldots, N_o\}$. In practice, experts have diverse understanding of potential threats and uncertainties of the oil supply system, so there could be different risk level assessments for the same state. Instead of averaging the results, we argue that diverse risk assessment results can better reflect the risky situation of a complex, uncertain oil supply system. Thus, we need to build a one-to-many mapping in the neural network. In this paper, we define risk assessment as a multi-classification task that generates a probability distribution for describing the potential risk level in a given system state.

Assume we have an SD model for a crude-oil supply system with given stock-flow structure. As defined in Section 3.1.2, the output of the model is a risk value that is mainly determined by the governing equations with a set of parameters, denoting these parameters as vector $\boldsymbol{\theta}$. Thus, we have $r = g(\boldsymbol{s}|\boldsymbol{\theta})$. Similarly, the risk value r will be mapped to a risk level to keep consistent with the output of the neural network. The prediction accuracy of the SD model is mainly influenced by the parameter vector $\boldsymbol{\theta}$.

With the above notations, we provide a problem statement for a hybrid framework to assess the risk of an oil supply system. Assume we select a neural network parameterized with weight vector $\boldsymbol{w}$ and have already built a system dynamics model with parameter vector $\boldsymbol{\theta}$, and there are the observed state set $\boldsymbol{O}$, the collocation state set $\boldsymbol{C}$, and the observed risk set $\boldsymbol{r_o}$. The neural network model maps a set of observed states to a risk level, denoted as $f(\hat{\boldsymbol{s}}_i|\boldsymbol{w}) : \hat{\boldsymbol{s}}_i \to \hat{r}_i$. Building on this, we further define risk assessment of the hybrid model as a joint risk classification and parameter-discovery problem, which can be specifically formulated as an optimization problem:

$$\begin{aligned} \min_{\boldsymbol{w},\boldsymbol{\theta}} \quad & -\sum_{i=1}^{N}\sum_{k=1}^{K} r_{i,k} log(p_{i,k}) \\ \text{s.t.} \quad & p_{i,k} = f(\hat{\mathbf{s}}_i|\boldsymbol{w},\boldsymbol{\theta}), \hat{\mathbf{s}}_i \in \boldsymbol{O}, \text{and } \boldsymbol{\theta} \subseteq \boldsymbol{\Theta}, \end{aligned} \tag{5}$$

where $p_{i,k}$ is the predicted probability of risk level k ($r_{i,k}$, viewed as a true label) with inputs of $\hat{\mathbf{s}}_i$, and $\boldsymbol{\Theta}$ is the solution space of unknown parameter $\boldsymbol{\theta}$ of the SD model. Note that, in practice, the parameters of $\boldsymbol{\theta}$ should be trainable to adapt to dynamic updates during model training.

3.2.2. The Hybrid Architecture

As highlighted before, the hybrid risk assessment should combine a mechanistic module and a data-based learning module. In this paper, the hybrid model we designed consists of an SD model and an artificial neural network (ANN). As illustrated in the structure in Figure 4, the upper module is the SD model that has been defined in Section 3.1. It takes collocation states as inputs and outputs a risk level. Considering the lack of sufficient training data, we have pre-calibrated the key model parameters based on empirical knowledge and information so that the parameters can be trained using small-sample observation data during joint training. The bottom module is the ANN associated with neurons and edges, and each edge involves a weight parameter that needs to be specified during model training with observation data. The ANN includes both observation states and collocation states as inputs, and it uses a SOFTMAX [39] function as output layer to generate a probability distribution of different risk levels. It is necessary to note that other types of neural networks, like deep neural networks, are also applicable but may require more training data.

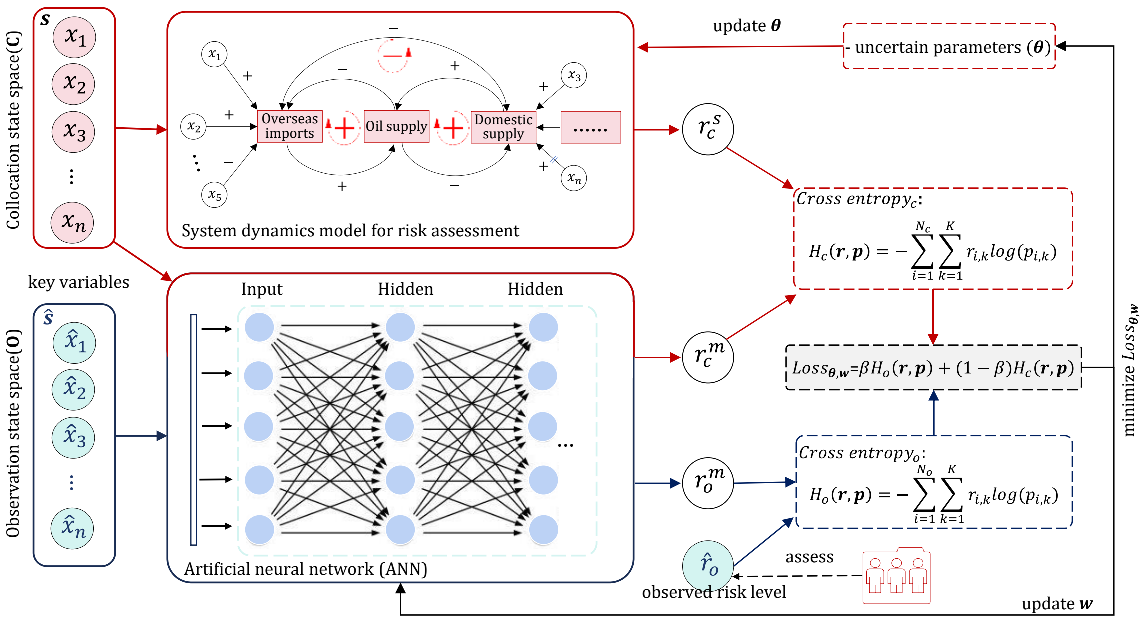


Figure 4. Generic structure of a hybrid model for risk assessment of oil supply system.

(1) Inputs variable and state data

Observation and collocation states set are the basis for training a hybrid model. Observed data contain a set of state–risk pairs. In practice, independent system variables shall be set as observed state variables for the hybrid model. In terms of the oil supply system of China, for example, there are nineteen key independent variables (i.e., the non-stock variables), as presented in Figure 1, which describes the underlying risk factors. These state variable values are extracted from the annual global oil trade data and national statistical data in the petroleum industry, allowing us to obtain the observed states of the oil supply system for different years. Subsequently, domain experts are invited to assess the oil supply security situation each year and provide an assessment of the annual risk value that is within [0, 1]. The risk value is divided into five levels from low risk to high risk by equally splitting the risk value range, as explained in Table 2. Here, in the questionnaire survey results, experts show different risk perceptions for the same situation, thereby leading to a probability distribution of observed risk levels. A specific oil supply state and corresponding risk level are assessed by an expert form an observation data sample $\{\hat{\boldsymbol{s}}_i, \hat{\boldsymbol{r}}_i\}$. Different from extracting an observed state from reality, the collocation state is considered as the situation that has not been observed. This means there is no existing observed result for a collocation state. In this case, there are few constraints for collocation states, so they can be discovered based on available mechanism-related knowledge. In the oil supply management context, the collocation states can be produced by defining changes in the non-stock variables, like adding fluctuation to constant variables with a statistical distribution to form multiple plausible situations. After running the pre-calibrated SD model, the risk level for one collocation state is acquired. Thus, we can define collocation data samples $\{\boldsymbol{s}_i, r^s_{i,c}\}$. It is important to note that the available observation data on the oil supply situation are quite limited on an annual basis. Introducing collocation data is necessary and will significantly improve the accuracy of model training.

Table 2. The risk level classification for a crude oil supply system.

Range	**[0, 0.2)**	**[0.2, 0.4)**	**[0.4, 0.6)**	**[0.6, 0.8)**	**[0.8, 1]**
Risk level	Low	Medium–low	Medium	Medium–high	High

(2) Loss function selection

When inputting state data into the hybrid model during training, the SD model will predict a risk level denoted as r^s_c, but the ANN will generate probabilities for each potential risk level. In this situation, we introduce cross-entropy as the loss function. In fact, to achieve accurate prediction and simultaneously calibrate unknown parameters for the SD model, we need to minimize two components of risk assessment discrepancy. One is the difference between the observed risk level and the ANN-predicted risk level (r^m_o), and the other is the difference between the SD model predictions (denoted as r^m_c) and the ANN predictions (denoted as r^m_c) using collocation data. Risk assessment discrepancies are computed using the cross-entropy formula. To consider both components of the discrepancies together, we introduce a weighted loss function as follows:

$$\begin{aligned} Loss_{\boldsymbol{\theta},\boldsymbol{w}} &= \beta H_o(\boldsymbol{r}, \boldsymbol{p}) + (1-\beta) H_c(\boldsymbol{r}, \boldsymbol{p}) \\ &= -\sum_{i=1}^{N_o} \sum_{k=1}^{K} r_{i,k} \log(p_{i,k}) - \sum_{i=1}^{N_c} \sum_{k=1}^{K} r_{i,k} \log(p_{i,k}), \end{aligned} \tag{6}$$

where β is the weight referring to the importance of the two parts of the discrepancy, H is the cross-entropy function. In each training epoch, the loss value is calculated and used to determine the gradients of the parameter corrections. Decision-makers can also define a threshold of loss value for terminating training process.

(3) Training algorithm and final outputs

In our work, a multilayer neural network with two hidden layers and nine nodes in each hidden layer was chosen after comparative validation. Since the loss function is cross-entropy, the Adam optimizer [40] is used in our work to train the model and optimize parameters. During training, $Loss_{\boldsymbol{\theta},\boldsymbol{w}}$ will be calculated to simultaneously update the system dynamics parameter $\boldsymbol{\theta}$ and the neural network parameter $\boldsymbol{w}$ in a gradient descent algorithm. As the key parameters of the SD model have been preliminarily calibrated in advance, it could converge quicker than the ANN. It is hence necessary to define different learning rates for the two modules.

The final output of the joint training process is a learned neural network and a learned SD model with new estimated parameters. When assessing the risk of an oil supply situation, the ANN is responsible to predict probabilities for potential risk levels, and the SD model is mainly to produce the changes in stock variables of the oil supply system. We calculate the expectation of risk level by multiplying each possible risk level by its respective probabilities as the final risk assessment result, and in addition, we further analyze the state changes of stock variables via the SD model to interpret the evolution dynamics of the risk and its impacts on the oil supply chain. That is to say, the hybrid model can provide risk prediction results that carry physical meanings well.

3.3. Test and Performance Evaluation

By employing data-driven joint parameter training, the hybrid model enables us to capture the complex nonlinear relationships among the various risk factors of an oil supply system. As a result, it could provide accurate risk prediction and result interpretation, thereby enhancing risk assessment reliability. To test the hybrid model, we firstly collected the state data of the key variables for China's crude oil supply system from 2001 to 2021 and defined a collocation state dataset. The twelve identified critical risk factors involve fifteen independent variables (n = 15). The risk is divided into five levels, as mentioned above. Next, we invited experts from the fields of supply chain management and national security to provide subjective assessment on the risk level of different states. The observation data and its risk level assessments are attached in Appendix D. Half of the observation data and all collocation data have been used as training data. So, only the rest of the observation data from 2012 to 2021 are taken as test data. The test data are used to evaluate the hybrid model performance on risk assessment. In this section, risk prediction and result interpretation experiments are conducted.

Risk assessment in the hybrid model is a risk classification task. When given an input, the model can output a probability distribution of five risk levels through the SOFTMAX layer, and the expected risk value can be calculated from this probability distribution. The range of the SOFTMAX function is [0, 1]. That is why we normalize the risk value to a range of 0 to 1 in our work. Figure 5 presents the expectation of predicted risk levels and the mean estimate of "true risk levels" assessed by experts for the most recent ten years. The risk value on the right vertical axis is within [0, 1]. The bigger the value is, the higher the risk level is. It is obvious that the predictions fit the true values well in different years, showing a high classification precision and recall. This indicates that the hybrid model can produce risk estimates that are consistent with the domain experts' assessments.

In addition to risk prediction, the hybrid model also supports risk interpretation. According to the international experience, a 50% dependence on imported oil is taken as a "safety warning line" that corresponds to a medium risk level. According to Figure 5, the risk level of China's oil supply has consistently remained at a medium to high level and has shown a continuous increase from 2012 to 2021. To identify potential causes, the state values of four important stock variables of the oil supply system are predicted by the SD module, which are domestic oil transport volume (DV_{t}), domestic oil production $\left(DV_{\mathrm{p}}\right)$, international oil transport volume (IV_t), and international oil imports (IV). These four stock variables directly determine the oil supply risk, and their state changes can represent the compensative effects of various risk factors and their interactions on oil supply. As listed in Appendix D, the predicted stock state values have very few errors compared to the observed data. From 2012 to 2021, China's international oil imports kept increasing significantly, but the growth rate of domestic oil transport and production lags far behind. In 2021, China's external dependency on crude oil even reached 72%. This provides an explanation of why the risk of China's oil supply has grown significantly for a long time. In fact, we can conduct more cause–effect analyses on predicted risk results, such as the growing technological competition between China and the United States, which has increased the oil supply risk in China since 2019. The above results demonstrate that the hybrid model not only provides accurate risk predictions but also supports result interpretation.

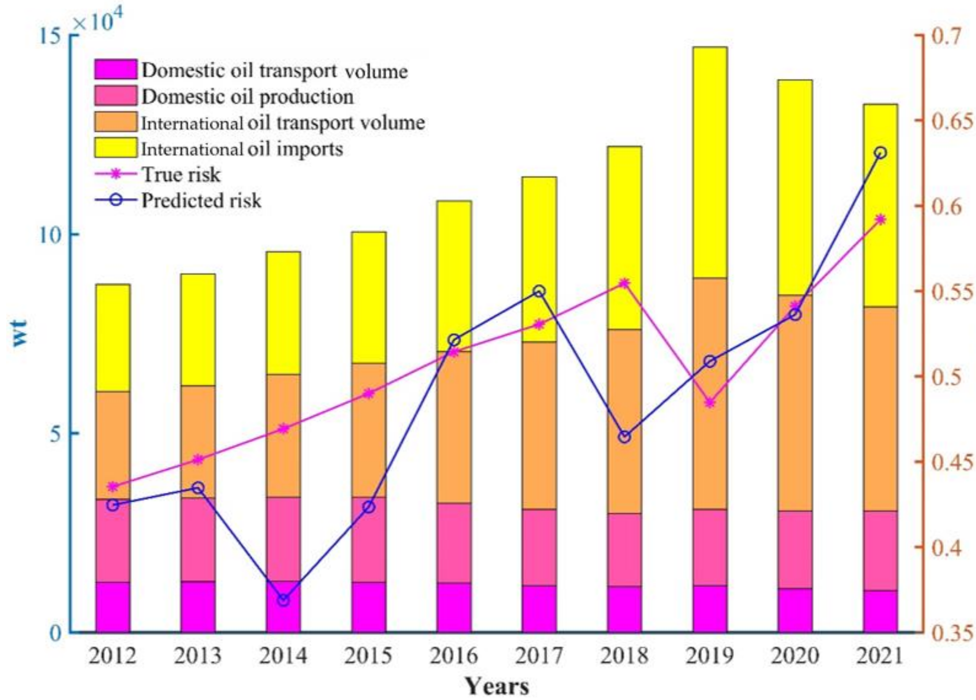


Figure 5. The predicted results of China's oil system risk and stock states in recent years.

4. Scenario Analysis for China's Crude Oil Supply System

This paper employs a system dynamics simulation to conduct sensitivity analysis on various factors affecting the overall oil supply risk in China at four levels of variation: 2%, 4%, 6%, and 8%. The analyzed factors include the interruption probability of crude oil pipelines, the safety level of reserves, technological innovation capabilities, the stability index of transportation channels, and the development of bilateral relations. These factors have been considered as critical uncertain factors in China's crude oil supply chain. Five simulation scenarios are proposed to explore the changes in China's crude oil supply volume and potential risk.

This section focuses on studying the impact of individual indicator variations on crude oil supply security. The oil supply risk is measured by the expected risk generated by the hybrid model. The risk level classification that a risk value specifies has been elaborated in Table 2. According to this classification, if the change in risk value caused by an uncertain factor is greater than 0.2, there would be a step change in the risk level, suggesting significant attention to the insecurity factor. The results of the policy simulation scenarios are presented below.

(1) Scenario simulation based on reduced line transportation capacity

Transportation capacity in this context refers to the capacity of the transportation pipeline that intersects with the primary seismic zone in China. The greater the transportation capacity of this pipeline, the higher the potential for opportunity loss in oil transportation, resulting in a decrease in total transportation volume and an increase in transportation risk. As shown in Figure 6, when lowering the interruption probability of pipelines intersecting with earthquake-prone zones, the overall risk of the oil supply can be diminished, although the extent of the reduction is relatively small. Consequently, it can be inferred that China needs to enhance infrastructure resilience to ensure the stability of domestic oil transport.

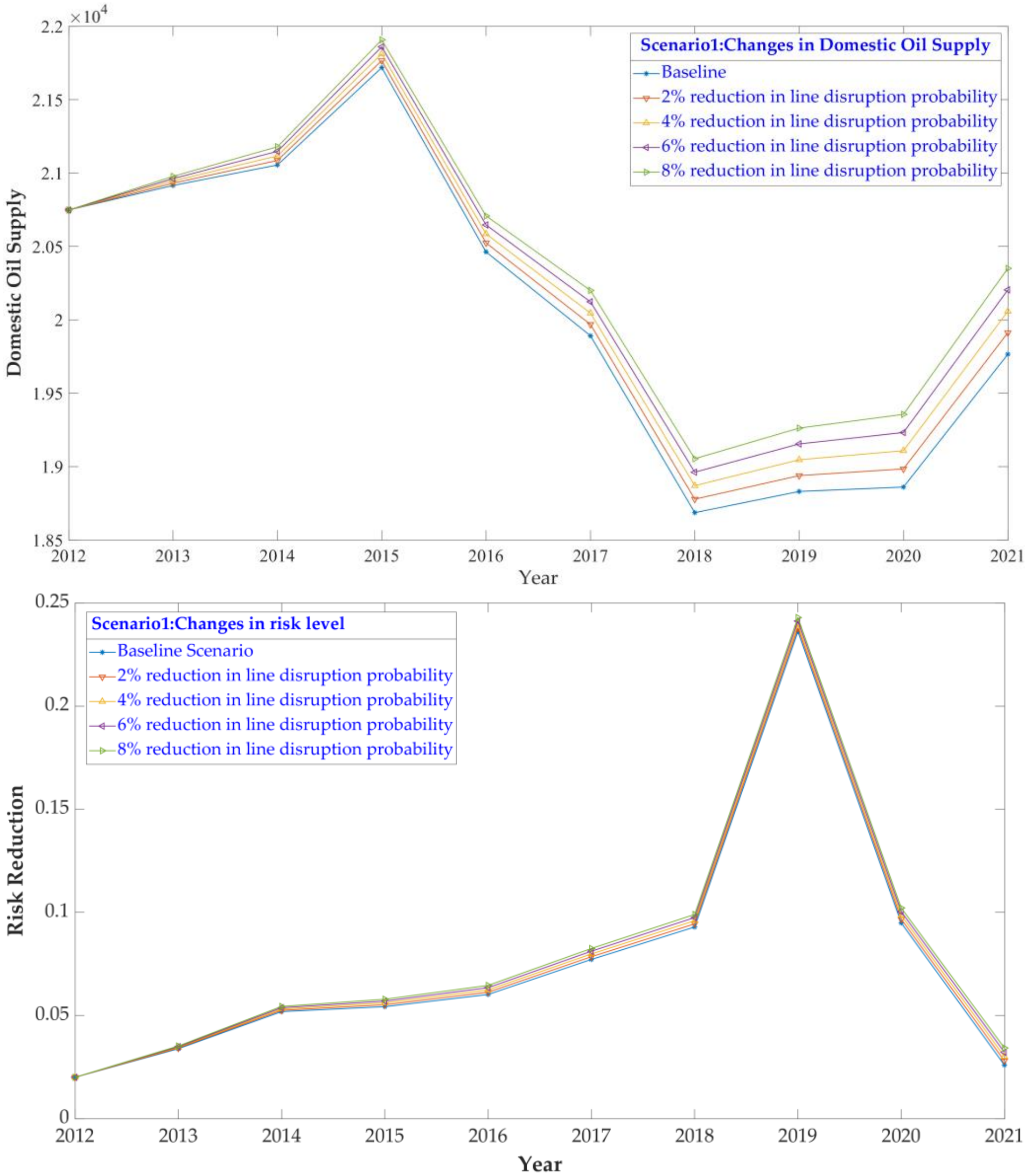
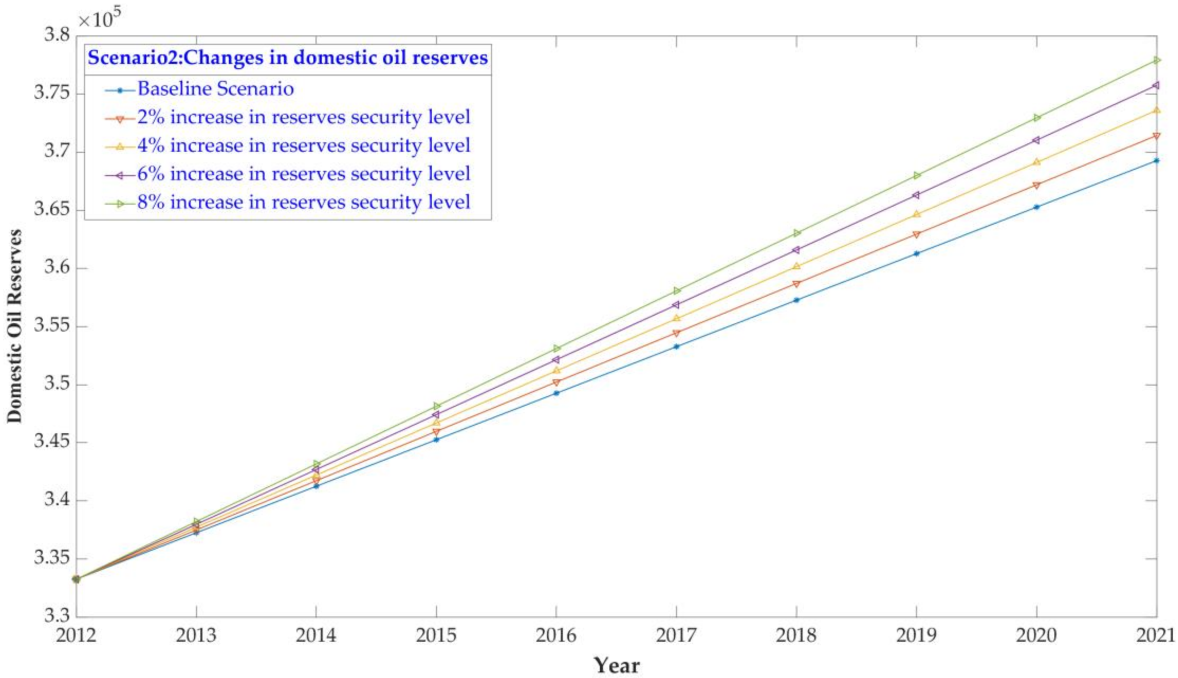


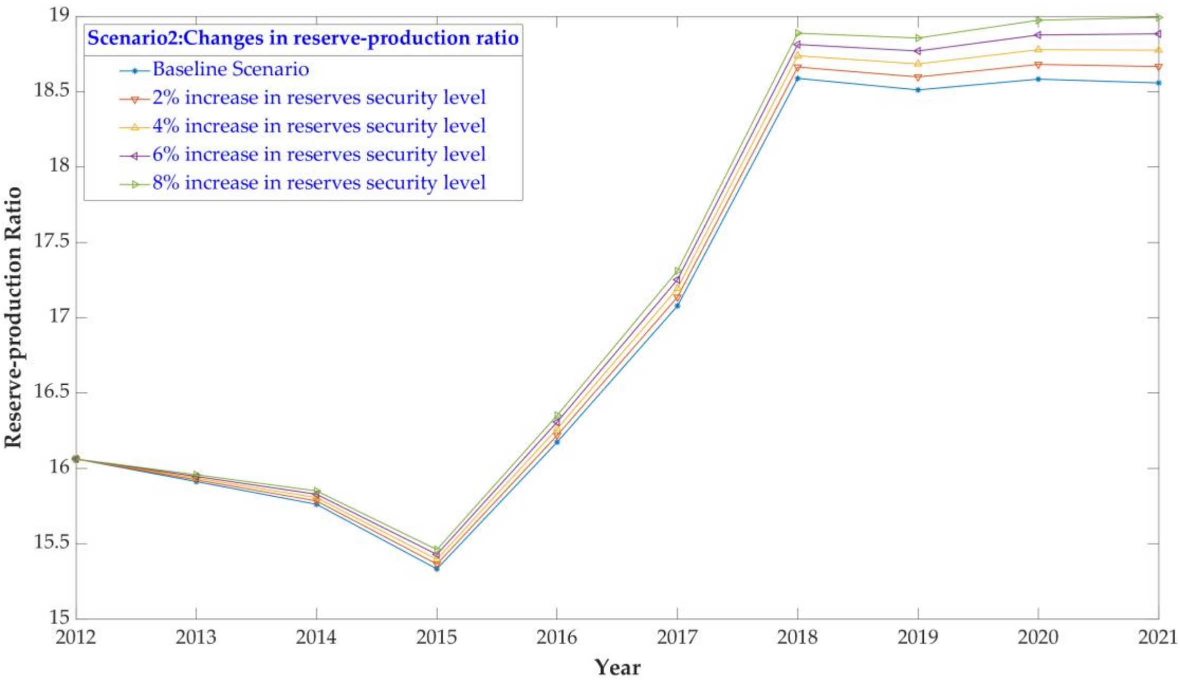
Figure 6. Simulation results under different reductions in transport line disruption probability.

(2) Scenario simulation based on improving the security level of oil reserve

The strategic crude oil reserves play an important role in China's oil supply system, especially under crisis situations. The higher the security level of the oil reserve is, the larger the domestic oil reserves are, leading to increased total supply capability and reduced transportation risk. Figure 7 presents the simulated changes of the domestic oil reserves and reserve/production ratio over recent years when adjusting the reserve security level. It is obvious that enhancing the security level of domestic oil reserves leads to an increase in the domestic oil reserves, which will consequently improve the oil supply capability during crises (Figure 7a). Similarly, an increase in the reserve-to-production ratio can be observed in Figure 7b. texless The reserve-to-production ratio, measured by the ratio of domestic oil reserves to exploitation, reflects the potential exploitation years for domestic oil. The above simulation results indicate that enhancing the security level of oil reserves can improve both short-term emergency supply capability and long-term supply sustainability.



(a)



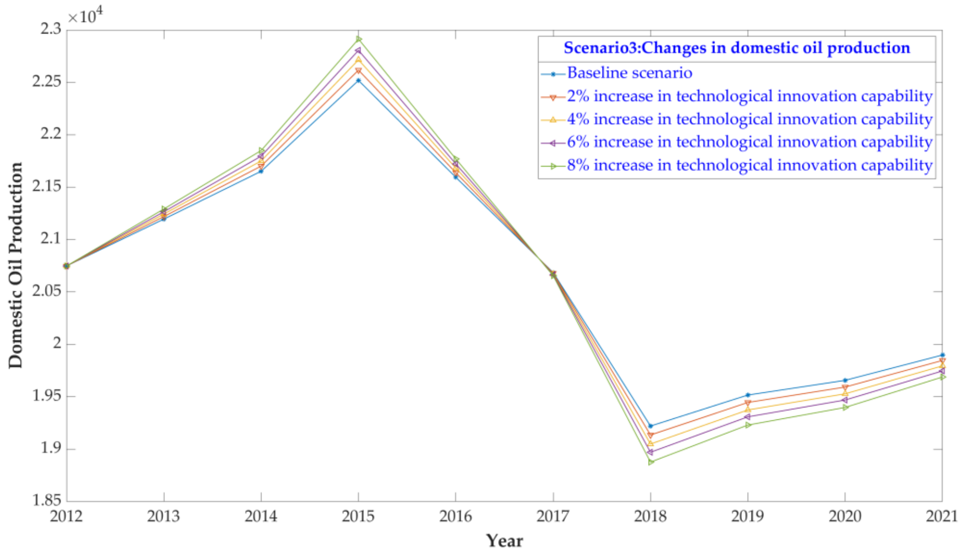
(b)

Figure 7. Scenario simulation results for increasing oil reserve security levels.

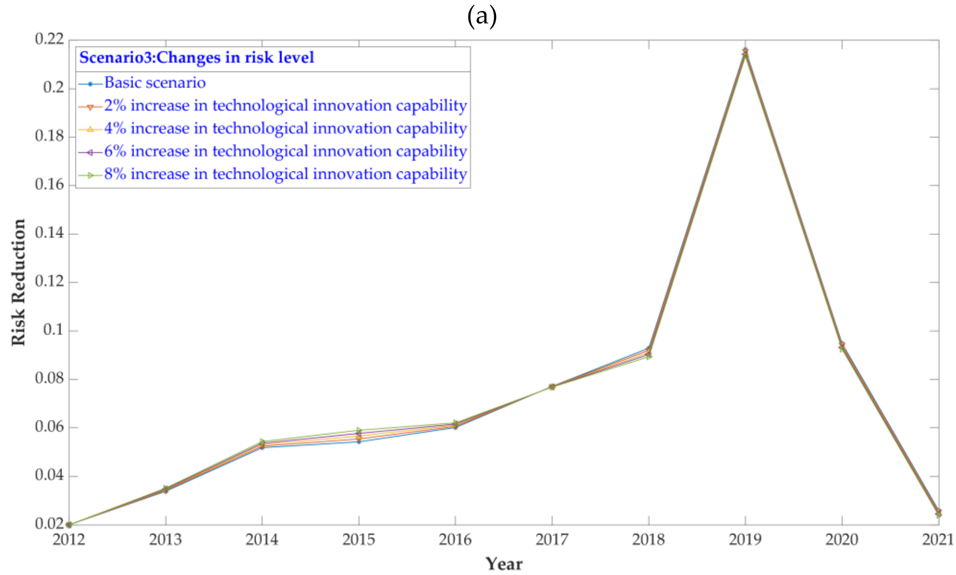
(3) Scenario simulation for improving technological innovation capability

The term "technological innovation capacity" in this context mainly refers to the innovation capacity of domestic oil exploitation and production technology. The greater the technological innovation capacity is, the higher the domestic oil production is, leading to increased total supply and a reduction in the overall supply risk. Considering the current situation, China's technological innovation capacity index in petrochemical equipment and technologies stands at a moderate level worldwide. By setting different increases in the index, we can simulate the influences of technological innovation capability on oil production and overall supply risk.

As shown in Figure 8a, enhancing the technological innovation capability will increase the volume of domestic oil production, resulting in an overall boost in oil supply. Although technological innovation capability primarily influences the changes in domestic oil production, the increase in domestic oil production could indirectly lead to a reduction in international oil imports. That is to say, the improvement of technological innovation capacity could help reduce oil import dependence and hence mitigate the overall oil supply risk. This conclusion can be indicated in Figure 8b, where the risk obtains a bigger reduction for a larger increase in technological innovation capability.



(a)



(b)

Figure 8. Scenario simulation results for improving technological innovation capacity.

(4) Scenario simulation based on enhancing transport channel stability

China heavily relies on maritime shipping routes, pipelines, and other transport infrastructure for the efficient and reliable transport of crude oil from global suppliers. Ensuring the stability of these international oil transportation channels is crucial for its oil supply security. In our work, we quantify the stability of the transport channels using an index. Based on the current situation, the primary international oil transport channels, notably the Strait of Hormuz, experience frequent geopolitical conflicts, significantly impacting global oil transport. By changing the transport channel stability index during simulations, as shown in Figure 9a, it can be observed that enhancing the stability of transport channels can lead to a significant increase in the international oil transport volume. This could be simply because a higher transport channel stability brings a lesser disturbance in transport capability, which ultimately results in a reduction in transport disruption risk. This can be indicated in Figure 9b. The bigger increase in the transport channel stability index will lead to a larger reduction in the overall supply risk. The above results show that international transport channel stability is a sensitive factor and enhancing this stability would effectively mitigate the oil supply risk and contribute to a more stable oil supply chain.

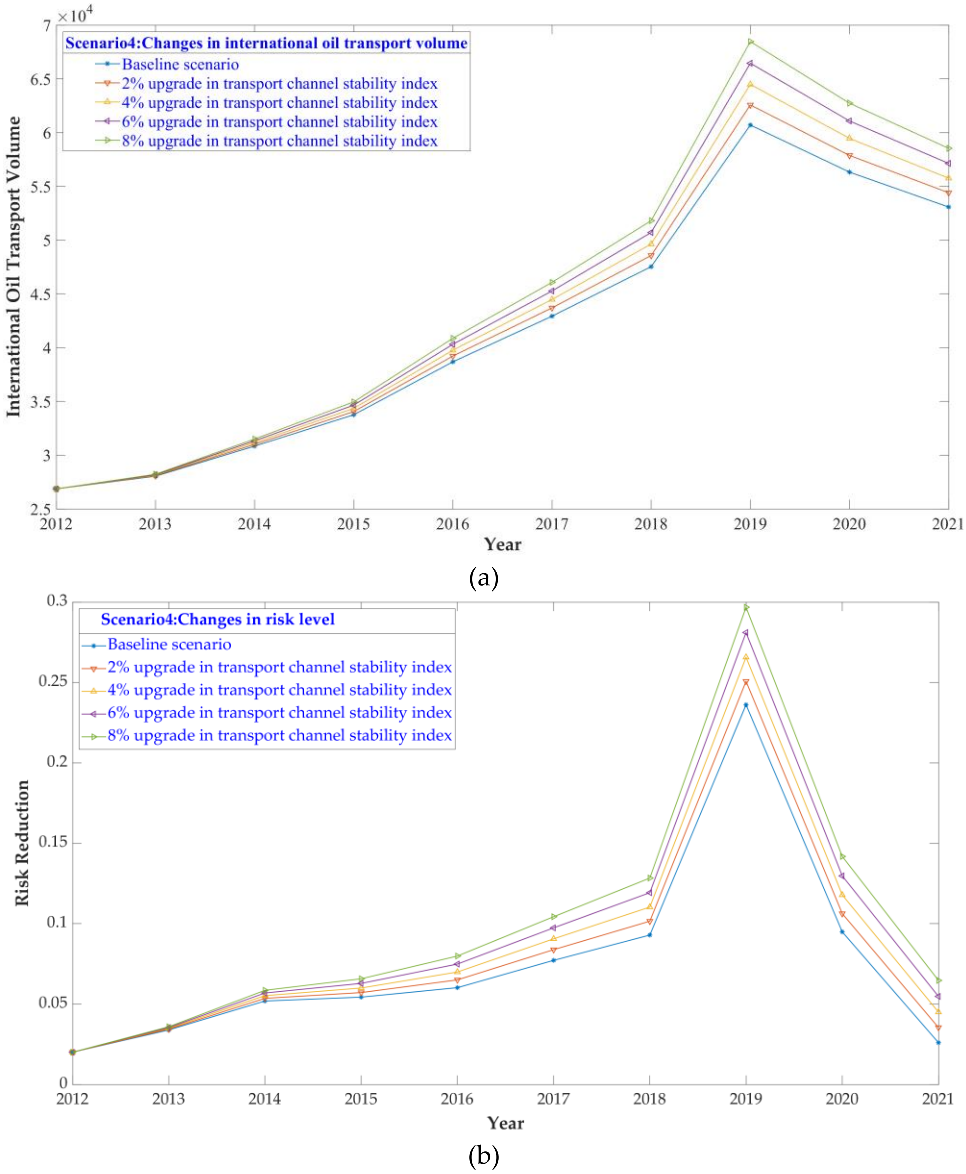
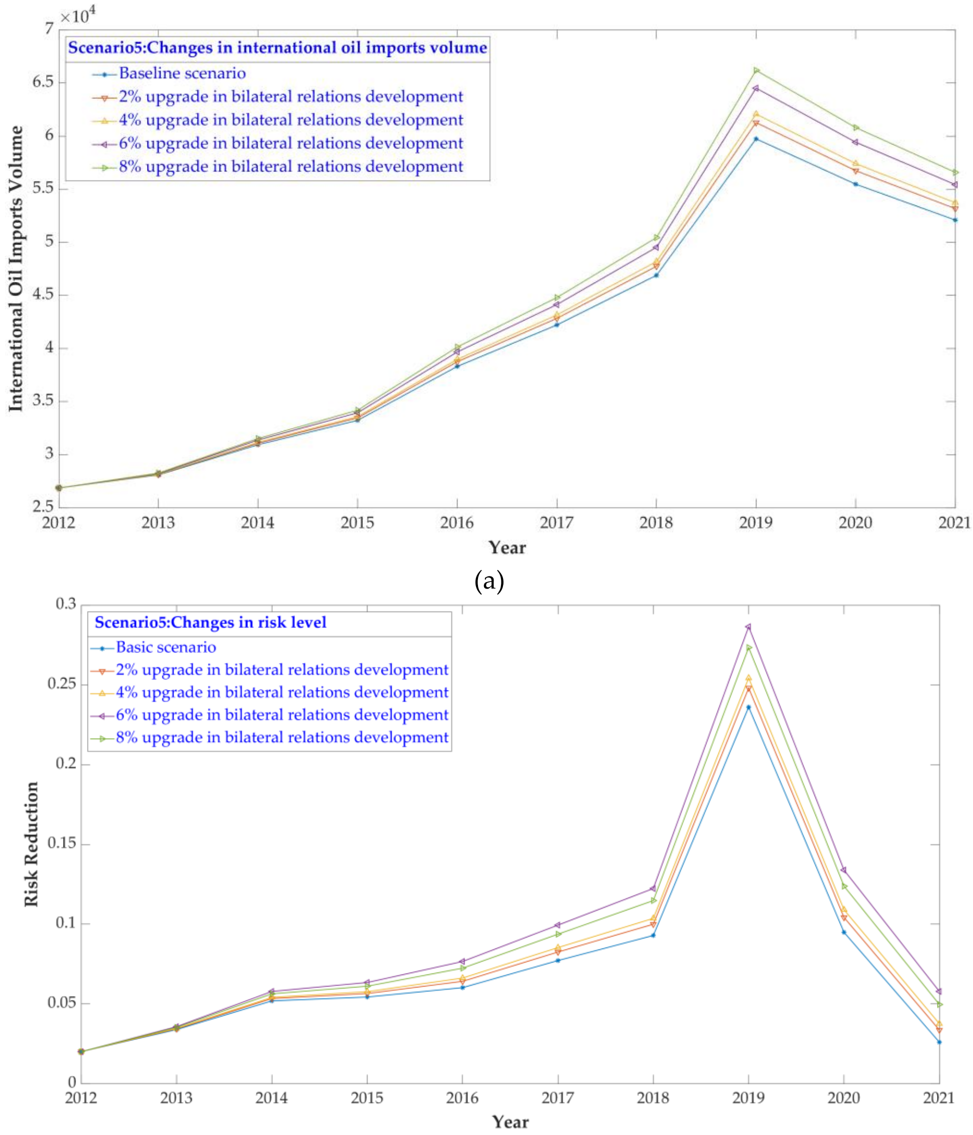


Figure 9. Simulation results for improving the stability index of international transport channels.

(5) Scenario simulation based on improved bilateral relations with oil-trading countries

The bilateral relation scores are used to quantify the stability of China's international relationships with the oil-trading countries, as discussed before. In the current diplomatic situation of China, the measured average score of bilateral relation development is 3.96 (i.e., a moderate level). We set different scenarios for bilateral relation improvements to explore the changing patterns of the oil supply system risk.

According to the simulation results, improving bilateral relationships with oil-trading countries can bring a positive impact on reducing oil supply risk. Figure 10a illustrates that a higher score in bilateral relations leads to a greater increase in international oil imports. Furthermore, Figure 10b shows a similar trend, as a stronger improvement in bilateral relations development results in a larger reduction in overall supply risk. Therefore, it can be concluded that closer bilateral relations contribute to lower oil supply risks. In practical terms, establishing close and stable bilateral relations with oil-trading countries helps to mitigate the risks associated with crude oil procurement and transportation. This is achieved through a reduction in accidents and trade disputes occurring in the oil trading process.



(a) (b)

Figure 10. Simulation results for improving bilateral relations.

5. Conclusions

Risk assessment plays a vital role in formulating sustainable crude-oil supply policies. However, the global crude-oil supply system is a complex system that involves various risk factors, which significantly increases the complexity of risk assessment. In this paper, we conduct a data- and model-driven crude oil supply risk assessment of China considering maritime transportation factors. A hybrid modeling framework combining system dynamics and data-driven neural networks is proposed to assess the risk. The hybrid model proposed can leverage the advantages of both dynamic modeling and data-based modeling.

It can capture the complex, nonlinear relationships of the risk factors of the oil supply system with limited data and in the meantime allow for the interpretability of the underlying dynamics. Computational experiments based on China's scenario have been conducted to demonstrate the effectiveness of the proposed hybrid model, and the results provide some management insights: (1) The government needs to enhance infrastructure resilience, especially to ensure the stability of domestic oil supply. (2) By improving the safety level of domestic oil reserves, the overall risk of oil supply can be reduced. (3) Improving the innovation capacity of oil extraction technologies helps mitigate the overall risk associated with oil supply. (4) By improving the development of bilateral relations with oil-trading countries, the overall oil supply risk will be decreased.

In our study, we have only collected China's oil supply data for recent decades and used a combination of a relatively simple system dynamics and neural networks to assess the risks associated with crude oil supply. We did not compare the effectiveness of our method with other methods, nor did we take into account the specific ocean transportation conditions of the crude oil. Even so, we think that the advantages of the hybrid models make it as a promising approach for more applications in maritime fields. In future research, the following aspects could be considered to extend the hybrid model: (1) The impacts of different types of ocean transportation vehicles could be studied. (2) Multi-modal transportation could be included in the import schemes of crude oil. (3) Other data- and model-driven approaches could be integrated together to conduct similar risk assessments.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. The definition of symbols.

Symbols		Symbols	
P_{pipe}	Pipeline interruption probability caused by natura hazards	λ_{ship}	Domestic shipping transport ratio
κ	Reserve/production ratio	S_{line}	Stability of global oil transport lines
L_{res}	Crude oil reserve safety level	S_{pol}	Political stability index of exporting countries
I_{eq}	Equipment manufacturing level	d_{con}	Degree of concentration of oil import sources
C_{tech}	Technological innovation capability	I_{rel}	International relation stability index
I_{cs}	Cybersecurity risk index	I_{bp}	Bargaining power index
C_{open}	Temporary line opening capacity	D	Domestic oil demand
I_{re}	Critical facilities resilience index	DC_t	Domestic oil transport capacity
λ_{ed}	External dependency ratio	IC_t	International maritime transport capacity
I_{br}	Bilateral relations index	RV_{str}	Strategic oil reserves
var_p	Variance of oil export prices	NI	Daily net imports
I_{RMB}	RMB internationalization index	RV	Domestic oil reserve volume

Table A1. *Cont.*

Symbols		Symbols	
DV_t	Domestic oil transport volume	RV_{exp}	Exploitable oil reserve volume
C_t	Line transport capacity	IV	International oil import volume
η	Interruption recovery efficiency	ΔIV	Changes in international oil imports
DV_{pro}	Domestic oil production volume	μ	Annual average oil imports
ΔV_d	Changes in domestic oil production	τ_m	Rate of change in international oil imports
ΔP_d	Changes in domestic oil productivity	τ_d	Rate of change in domestic oil supply
λ_{pro}	Oil productivity fluctuation ratio	IV_t	International oil transport volume
DV	Domestic supply volume	ΔV_t	Changes in international oil transport volume
V	The overall oil supply	ω	Oil-importing risk aversion degree

Appendix B

Table A2. The main governing equations of the system dynamics model for China's crude oil supply.

Variables	Types	Unit	Equations
Opportunity loss of oil transport volume	A	Wt/Year	$Loss_T = C_T P_{pipe} I_{\mathrm{re}}\ \eta$
Critical facility resilience	A	Dmnl	I_{re} = *WITH LOOKUP* (<Time * Unit conversion >, ([(1, 0)–(10, 1)], (1, 0.3628), (2, 0.3922), (3, 0.4216), (4, 0.451), (5, 0.4804))
Domestic oil transport volume	L	Wt	$DV_T = c_T - Loss_T$
Domestic oil transport capacity	A	Wt/Year	$DC_T = \lambda_{ship} \cdot D$
Strategic oil reserves	A	Wt/Year	$RV_{str} = L_{res} \cdot 90 \cdot NI$
Domestic oil reserves	L	Wt	$RV = RV_{\mathrm{str}} + RV_{\mathrm{exp}} \cdot \kappa$
Domestic oil production	L	Wt	DV_{prod} = INTEG (+ΔV, *initial productivity*)
Changes in domestic oil production	A	Wt/Year	$\Delta \mathrm{V_d} = \Delta P_d \cdot DV_{\mathrm{pro}}$
Oil productivity fluctuation ratio	A	Wt/Year	$\lambda_{pro} = 0.5279 \cdot C_{tech} + 0.4721 \cdot I_{eq}$
Domestic oil supply	A	Wt	$\frac{\mathrm{d}DV}{dt} = \tau_{\mathrm{d}}(\frac{\mathrm{d}DV_{\mathrm{pro}}}{dt} + \frac{dRV}{dt} + \frac{\mathrm{d}DV_t}{dt})$
International oil transport volume	L	Wt	IV_{t} = INTEG (+ΔV_{t}, *initial transport value*)
Changes in international oil transport volume	A	Wt/Year	$\Delta V_{\mathrm{t}} = \frac{\mathrm{d}IC_T}{\mathrm{d}t} \cdot IV_{\mathrm{t}}$
International oil imports	L	Wt	IV = INTEG (+ΔIV, *initial import value*)
Changes in international oil imports	A	Wt/Year	$\Delta IV = \mu \cdot \lambda$
The rate of change in oil imports	A	Dmnl	$\tau_m = 0.1699\ I_{\mathrm{RMB}} + 0.2302\ I_{br} + 0.1381\ var_p + 0.2106\ \lambda_{\mathrm{ed}} d_{\mathrm{con}} + 0.1807\ S_{\mathrm{pol}} + 0.119\ I_{bp}$
Changes in international oil transport capacity	A	Wt/Year	$\Delta IC_t = 0.488\ C_{\mathrm{open}} + 0.512\ S_{\mathrm{line}}$
Unit conversion	C	fraction/Year	1
The overall oil supply	A	Wt	$V = DV_{\mathrm{s}} + IV_m$
Risk level	A	Dmnl	$r = w \cdot r_d + (1-w) \cdot r_i, w \in [0,1]$

* *L*, *R*, *A*, *T* respectively denote stock variables (level variables), flow variables, auxiliary variables, and table functions.

Appendix C. The General Assessment of Bilateral Relations

The scoring system works through a simple mechanism. Denoting a bilateral relation score between two countries, such as b, b_i is the score after experiencing a diplomatic event i, quantified with an event influence score e_i. As a new diplomatic event could also cause a change in bilateral relations, we have the following formula:

$$b_{i+1} = \begin{cases} \frac{c-b_i}{c} e_{i+1} \\ \frac{c+b_i}{c} e_{i+1} \end{cases} \text{,s.t. } b_i \in [-c, c],\ e_i \in [-\varepsilon, \varepsilon]$$

In our work, $c = 9$, $\varepsilon = 6$. When an event has a positive promoting effect on the relationship $(e_i \geq 0)$, the bilateral relations will become closer. If continuous positive events occur, the positive promoting effect of the event gradually decreases. When $e_i < 0$, the same goes the other way. In the tensest situation of bilateral relations, the negative promoting effect of a negative event tends toward 0. That is to say, negative events cannot make the bilateral relations score between the two countries less than $-c$.

Appendix D.

Table A3. The observation and forecast value of different oil volume.

Year	2012			2013			2014			2015		
Stock Variable	Observation	Forecast	$\bar{r}$	Observation	Forecast	$\bar{r}$	Observation	Forecast	$\bar{r}$	Observation	Forecast	$\bar{r}$
Domestic oil transport volume	12,652.42	12,652.40	0.44	12,731.76	12,403.47	0.45	12,806.97	12,154.54	0.47	12,552.95	11,905.60	0.49
Domestic oil production	20,747.80	20,747.80		20,991.90	20,998.34		21,142.90	21,153.38		21,455.60	21,474.49	
International oil transport volume	27,109.12	26,865.60		28,212.40	28,098.51		30,835.77	30,939.48		33,549.13	33,233.48	
International oil imports	26,865.63	26,865.60		28,050.40	28,040.31		30,775.75	30,841.67		32,968.51	33,757.46	
Year	**2016**			**2017**			**2018**			**2019**		
Domestic oil transport volume	12,478.22	11,656.67	0.51	11,747.38	11,407.74	0.53	11,507.51	11,158.80	0.55	11,761.06	10,909.87	0.48
Domestic oil production	19,968.50	19,946.79		19,150.60	19,108.22		18,392.40	18,331.72		19,101.40	19,057.04	
International oil transport volume	38,103.78	38,311.90		41,996.65	42,214.02		46,190.13	46,888.25		58,102.20	59,737.18	
International oil imports	37,809.72	38,681.38		41,510.31	42,927.28		45,927.13	47,532.59		58,021.20	60,702.88	
Year	**2020**			**2021**								
Domestic oil transport volume	10,979.99	10,660.94	0.54	10,563.84	10,412.01	0.59						
Domestic oil production	19,500.00	19,465.21		19,900.00	19,875.03							
International oil transport volume	54,201.00	55,468.45		51,292.00	52,090.69							
International oil imports	54,037.00	56,323.82		50,874.90	53,075.98						5	

$\bar{r}$ is the mean estimate of risk values provided by experts. The unit of observation data is wt.

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