Article

Risk Assessment and Monitoring of Green Logistics for Fresh Produce Based on a Support Vector Machine

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Abstract: The sustainability and profitability of fresh produce supply chains are contingent upon several risk factors. This work, therefore, examines several risk indicators that affect the quality and safety of fresh produce in transit, including technological, biological, sustainability, environmental, and emergency risks. Then, we developed a risk assessment and monitoring model that employs a machine learning algorithm, a support vector machine, based on historical monitoring data. The proposed methodology was then applied to simulation and numerical analysis to assess the risks incurred in the strawberry cold chain. After training, the algorithm predicted the risks incurred during transportation with an average accuracy of 90.4%. Therefore, the developed methodology can effectively and accurately perform a risk assessment. Furthermore, the risk assessment model can be applied to other fresh produce due to comprehensive risk indicators. Decision-makers in fresh produce logistics companies can use the developed methodology to identify and mitigate risks incurred, thus improving food safety, reducing product loss, maximizing profits, and realizing sustainable development.

Keywords: risk assessment; fresh produce; green logistics; support vector machine

1. Introduction

The development of fresh food e-commerce has provided comfort and convenience for consumers' daily lives and has modified cold chain management drastically [1]. However, as foodborne diseases can have a wide influence and reach epidemic speeds of transmission [2], monitoring and managing risks associated with the logistics of fresh produce must be addressed to ensure food safety [3,4]. As fresh products are characterized by their short shelf life and perishability, the continued development of fresh food e-commerce also brings new opportunities and challenges to global sustainable development. To reduce produce losses incurred during transport and storage, certain logistic and technological requirements must be met, such as refrigeration or an otherwise controlled atmosphere [5]. This has led to a rise in related costs. Logistics costs in China account for approximately 14–15% of GDP, of which fresh products account for 25–40% [6]. At 7–8% of GDP, logistics costs in developed countries are lower, but there is still room for improvement [7].

The modern logistics industry in developing countries started late and lagged behind developed countries in many aspects, such as the policy, facilities, technology, and management, etc. This led to the fresh produce loss and waste in the transport link of developing countries. Thus, it is necessary to assess the fresh food logistics risks in these countries.

Considering developing countries, the transportation of harvested fresh produce from farms to retailers or consumers is often poorly managed, such as incomplete preservation facilities and less specialized workers, increasing product losses and leading to higher market prices [8]. Most product

loss during this phase is due to food spoilage and deterioration, which can cause serious health problems. According to the Food and Agricultural Organization of the United Nations (FAO), approximately 14% of the global food produced in 2019 was lost after being harvested and before reaching the retail level [9]. FAO has thus included “reducing food loss and waste” as a sustainable development goal by 2030 [10]. Furthermore, FAO estimated that losses of fresh produce may be as high as 21.6%, representing the highest among all food types. These losses occur mainly in the harvesting, packaging, storage, transportation, and other supply chain links. Reducing these losses can thus contribute to achieving sustainable development goals and to reforming and improving transport, packaging, and storage technologies.

Previous researchers have focused their efforts on scheduling optimization when examining fresh produce logistics [11–16], as well as many studies have focused on supply chain risk identification and management [17–24], and several researchers have investigated fresh produce logistics risk. Therefore, fresh produce logistics still have bad classification and identification management, which may cause food loss in many supply chain links, including transport, storage, loading, unloading, handling, and packaging [23]. A comprehensive risk assessment system analyzing the logistics of fresh produce from an economic and ecological standpoint has not been established.

Furthermore, two main gaps exist in the research available on the risks incurred during the transit of fresh produce. Firstly, a few researchers have investigated logistic risks and most people have performed supply chain risk identification from a macro perspective. Secondly, existing risk classification lacks a unified standard: risks incurred during transport cannot be effectively identified. As a wide variety of factors affect the logistic risks incurred during the transportation of fresh produce, the presence of a unified risk classification standard would assist decision-makers in the identification, evaluation, and mitigation of transport risks.

Risk identification and evaluation during transportation aim to identify potential risks and take appropriate measures to avoid or minimize food losses. This work, therefore, aims to develop a green logistics risk assessment system for the transportation of fresh produce. Five risk factors are considered: technological, biological, sustainability, environment, and emergency.

The support vector machine as an artificial intelligence learning method is used to assess and predict risks on credit scoring, healthcare, and network security assessment [25,26]. As it has been demonstrated to be more accurate than traditional methods in developing big data and cloud computing, a support vector machine (SVM) algorithm was used to evaluate the green logistics risk.

The remainder of this paper is organized as follows. The state-of-the-art of green logistics of fresh produce and currently used methods for keeping produce fresh are outlined in Section 2. In Section 3, potential risks in the green logistics of fresh produce are identified and classified, and an assessment system was established. The proposed risk assessment method was then applied to simulation and numerical analysis on fresh produce using historical monitoring data in Section 4. For the strawberry cold chain, the implementation and training results of the SVM algorithm are then discussed in Section 5. Finally, conclusions and future research directions are presented in Section 6.

2. Literature Review

In this section, research developments in the green logistics and preservation of fresh produce are presented to provide a theoretical basis for the identification and evaluation of fresh produce logistic risks.

2.1. Green Logistics of Fresh Produce

As fresh products are perishable, their transit time must be strictly controlled. Many scholars have aimed to optimize the scheduling of fresh produce logistics. Cai et al. [12] investigated the effects of freshness-keeping efforts on the supply chain of fresh products and characterized optimal producers' wholesale price and distributors' order quantity in decentralized and centralized systems. Blackburn et al. [13] examined supply chain design strategies for perishable products by considering a

product's marginal value of time. Bogataj et al. [14] studied the effects of time, distance, and temperature in a cold supply chain. Based on fresh produce characteristics, carbon-trading behavior, and external environmental factors (e.g., emergency events, weather), scholars have established transportation scheduling models and proposed optimal scheduling and pricing strategies [15,16].

The transportation of fresh produce demands cold chain logistics with high requirements. Bad fresh-keeping management and technology causes produce loss, generating waste in transit, and creating challenges to realize sustainable development goals [27]. Ingraio et al. [18] addressed the environmental sustainability of food packing technology by applying life circle assessment, which is a tool that can be used to evaluate the potential environmental impacts of a product, material, process, or activity. Within the context of differing sustainability concepts and approaches, Perezmesa et al. [19] analyzed supply chain management strategies of large retail distribution chains in Europe. Kumar et al. [21] formulated an integrated interpretive structural modeling–analytic network process decision framework to identify and model key challenges to sustainability in perishable food supply chains. To reduce waste and improve sustainability, Gokarn [23] and Kaipia et al. [24] studied the influence of supply, demand, price uncertainties, and information sharing in fresh produce supply chains.

Several researchers have aimed to reduce the probability of uncertain events and fresh produce losses by risk identification and classification [28–30]. Nakandala et al. [4] analyzed risk factors of the fresh food supply chain from an internal and external perspective, and then built a hybrid risk assessment model to minimize the negative impact of the risk. Rangel et al. [22] used existing data to classify supply chain risks as plan, source, make, delivery, and return, etc. After exploring risk propagation mechanisms, Deng et al. [31] proposed risk management strategies for yogurt supply chains to improve sustainability using the Tropos Goal-Risk framework. Using a combined life cycle inventory and regional life cycle impact assessment method, Burek et al. [32] examined the impact of distribution centers on food distribution and sustainability. They also showed multifacility state-level environmental impacts of the largest DC network in the United States. Prakash et al. [33] presented a methodology to analyze the risks present and determine the most effective risk mitigation strategies using interpretive structural modeling.

2.2. Keeping Produce Fresh

As fresh produce is perishable, temperature management is important in all logistics activities to guarantee the quality and safety of fresh products [14]. Ruan and Shi [1] used scenario analysis and interval number approaches to monitor and assess fruit freshness based on the internet of things (IoT). There are several studies that focus on the influence of stacking patterns on food freshness. Chen et al. [34] found that the fruit stacking method can affect the temperature field inside the cargo compartment, which in turn affects the cooling speed. Song et al. [35] constructed multilayer food temperature models considering the spatial temperature distribution in the food, and found that stacking patterns affect the quality of eggs and milk.

Packing humidity and atmospheric composition are also important parameters affecting the quality of fresh produce during transportation and preservation. By changing the gas concentrations and relative humidity within the package, air-wet packaging was demonstrated to prolong the shelf life of fresh products and maintain their quality by Jalal et al. [36]. Expanding upon this study, they then analyzed the transpiration and respiration behavior of fresh produce, moisture absorption by the packaging tray, and gas and water vapor permeation through perforated packaging films to predict changes in the relative humidity of packaging headspace and moisture condensation [37]. By controlling the temperature, humidity, and concentration of oxygen and carbon dioxide during transportation or storage, the use of air conditioning storage can inhibit the respiration of fresh produce and extend their shelf-life [38,39].

As the storage temperature rises, the respiration of fresh foods increases. Additionally, precooling produce after harvest is an important step before storage and circulation: the applied precooling

temperature and time affect the quality and safety of the produce. Aung et al. [40] defined an optimal target temperature for multicommodity refrigerated storage, such as 0 to +1 °C for most vegetables and some fruit, and +10 °C to +15 °C for potatoes and bananas. Defraeye et al. [41] evaluated the performance of a cold supply chain by considering process parameters, such as fruit cooling rate, quality parameters, shelf life, pest disinfestation efficacy, and their spatial uniformity throughout the cargo load. Fresh produce is susceptible to static load, vibration, extrusion, and impact during transport, which result in immediate damage caused by plastic or brittle failure and delayed damage caused by viscoelastic deformation [42]. By measuring the vibration and consequential mechanical damage to bananas stacked at different stack heights and positions in a multi-trailer road train during a 3000 km interstate road transport, Fernando et al. [43] demonstrated that mechanical damage induced by vibration causes quality deterioration and wastage of fresh produce in postharvest supply chains. For more details regarding transportation modeling approaches in bulk, packages, and stacks, readers are directed to the review by Verboven et al. [44] addressing the impact of packaging material and size on the transportation risks of fresh food.

Researchers have also aimed to understand how climate change impact the transportation of fresh produce. Jaxsens et al. [45] proposed a methodology to analyze the complexity of climate change and the challenges of globalization on the fresh food supply chain. Accorsi et al. [46] formulated a mixed-integer linear programming model incorporating the increased risk of extreme weather conditions (e.g., snowstorm, typhoon) to plan the production, storage, and distribution of perishable products.

Overall, it has been demonstrated that adopting advanced technology (e.g., advanced precooling facility, air-wet packaging, intelligent temperature control equipment, and modified atmosphere packaging, etc.) or management measures (e.g., scenario analysis based on IoT) can reduce produce (and, therefore, monetary) losses in each link of the supply chain and help to realize the sustainable development of the fresh food supply chain.

2.3. Support Vector Machine

Depending on the characteristic of this research, we know that unsupervised learning and reinforced learning are not suitable for this problem. Supervised learning was applied to evaluate the fresh food logistics in this study. It has different algorithm mechanisms such as regression analysis, support vector machine, random forests, neural networks, and many more [47]. In this research, compared with the support vector machine, other algorithms usually do not have a good performance because they require a large amount of data. Additionally, support vector machines are better at processing high-dimensional data [47].

SVM is a supervised learning algorithm that is commonly used for classification and regression challenges. It has a simple structure, high adaptability, global optimization method, short training time, and good generalization performance [25,26]. Many researchers have employed SVM in pattern recognition, data mining, probability density estimation, and risk prediction [48].

As SVM algorithms can be used for data prediction and classification, many scholars have employed them in risk assessment [49]. Wang G et al. [26] used a support vector machine as a base learner enterprise credit risk assessment and verified the algorithm by an experiment. Harris T [50] constructed credit-scoring models based on the support vector machine using broad and narrow default definitions. Li F et al. [51] compared the support vector machine (SVM) and artificial neural network (ANN) in vulnerability assessment: the results show that the training out-puts of SVM are better fitted with the desired outputs than that of ANN. Lau, C. K et al. [52] proposed a fire risk assessment with a scoring system based on the support vector machine.

2.4. Research Focus and Contribution

We describe the difference between the current related studies and this paper in Table 1 [53]. It can be noticed from this table that many researchers constructed a mathematical model to investigate the

factors that influence fresh food logistics, such as freshness-keeping efforts, time, distance, temperature, disaster, and environmental [12,14–16].

Table 1. Comparison of current studies with the research.

Article	Methodologies	Research
Cai et al. [12] Bogataj et al. [14] Diabat A et al. [15] Mohammed A et al. [16]	Mathematic model	The effects of freshness-keeping efforts The effects of time, distance, and temperature Considering the disruption of disaster scenarios Investigating environmental impact
Ingrao et al. [18] Perezmesa et al. [19]	Life Circle Assessment Survey and Analysis	The effects of packing technology in environmental sustainability The response of suppliers to sustainable supply chain management
Kumar et al. [21]	Interpretive Structural Modelling–Analytic Network Process Decision Framework	Identify and model key challenges to sustainability in perishable food supply chains
Gokarn [23]	Structural Equation Modelling	The influence of supply, demand, and price uncertainties on the sustainability of cold chain.
Kaipia et al. [24]	Empirical study	Information sharing
Nakandala et al. [4]	Fuzzy Logic and Hierarchical Holographic Modelling	Internal risk and external risk
Deng et al. [31]	Tropos Goal-Risk Framework	Demand risk, staff risk, equipment risk, inventory risk, method risk, logistics risk, organizational risk, information risk, and environmental risk
Prakash et al. [29]	Interpretative Structural Modelling	Environmental risk, supply risk, demand risk, and process risk
Ruan and Shi [1]	Scenario Analysis and Interval Number Approaches	Monitor and assess fruit freshness based on the internet of things
Present study	Support Vector Machine	Technological risk, biological risk, sustainability risk, environmental risk, and emergency risk

Several scholars studied how to improve the sustainability of fresh food supply chains from different aspects, such as packing technology, information sharing, uncertainty demand, and price uncertainties [18,19,21]. Nevertheless, effectively identifying and managing logistic risks in the fresh produce supply is difficult due to the lack of targeted measures.

In addition, many scholars have explored supply chain risk management from the macro perspective [4,29,31], but no one analyzed the risks in fresh produce transport links from the micro perspective. The construction of the evaluation system from the micro point of view can enable managers to obtain real-time monitoring data and evaluation results in the transport.

Yet, there are a few works that have researched fresh food supply chains based on data collected from transport links [1]. It is, therefore, necessary to analyze logistic risks and build an early warning system to increase efficiency and ensure the freshness of food using a machine learning method. Based on historical data about transportation and fresh-keeping, this paper proposes a risk assessment model for fresh produce with the help of the support vector machine.

3. Proposed Risk Assessment Criteria System for Green Logistics of Fresh Produce

From the related studies of fresh produce logistics and fresh-keeping, we know that many factors will affect the quality and quantity of fresh food. Aiming for a systematic, simple, and feasible method, a risk assessment criteria system of green logistics of fresh produce was constructed to address five main risk aspects, as summarized in Figure 1.

Here, technological risk refers to the risk of food preservation facilities during logistics failing to ensure freshness of food, which is considered to be the most common and severe risk to the quality and safety of fresh food [17]. Biological risk indicates how sensitive a fresh product is to risk factors. For example, apples can be kept for about 10 days in summer, whereas strawberries can only be kept for one day at room temperature. Sustainability risk refers to the damage and loss of fresh food caused by the fresh-keeping technology and material used in packing [19]. Environmental risk represents the impact of uncertainty in the natural and social environment, such as changes in the weather or traffic congestion. Emergency risk is caused by insufficient management ability of logistics enterprises, including transportation optimization ability, staff training ability, and emergency

management ability [21]. Indicators are divided into two categories according to whether they can be measured directly.

Figure 1. Fresh produce green logistic risk assessment criteria system.

3.1. Direct Measurement Index of Proposed System

To analyze the transport fresh-keeping risk, the efficiency of fresh-keeping and logistics technology in transit is first considered using several measurable indicators known to impact the quality and safety of fresh produce:

- **Temperature (A1):** The suitable storage temperature can extend the shelf life of fresh produce and ensure that fresh food will be safe to eat. Logistics companies need to try to maintain properly refrigerated or frozen temperature to comply with food safety regulations in the transport link, e.g., 0 to +4 °C is the safe refrigerator temperature range for the strawberry [14,34,35].

- **Relative humidity (A2):** The relative humidity represents the ratio of the current absolute humidity to the highest absolute humidity at that temperature and is measured in real-time. High relative humidity levels (85–95%) are usually recommended for transporting most fresh food to prevent moisture loss [36,37].
- **Temperature uniformity (A3):** This measures the potential variation in temperature between different points in the boxcar. The temperatures are collected using six sensors from multiple sites in the boxcar to measure the temperature uniformity. (Temperature uniformity (Maximum temperature–Minimum temperature)/ Average temperature). Improving temperature uniformity (i.e., decreasing temperature variation inside the boxcar) is thus required to keep food fresh [54].
- **Refrigerated truck body pressure (A4):** An inappropriate pressure inside the truck body could have a negative influence on product freshness.
- **Storage density (A5):** Storage density is defined as the percentage of available storage space to the total warehouse space (Storage density = Total storage space in cubic feet/Total warehouse area in cubic feet). Extra space will be left when stacking to ensure that fresh products can carry out respiration, thus ensuring the freshness of produce [34].
- **Vibration frequency (A6) and Vibration acceleration (A7):** Vibration frequency, which is measured in hertz (Hz) units, is the rate at which vibrations and oscillations occur. This vibration acceleration may happen when encountering the bumpy roads, erratic driving, and so on. These indicators are used to measure the extent to which the goods vibrate, which may damage their integrity [42,43].
- **Precooling time (A8):** Precooling is a very important step in the postharvest stage of the fresh produce industry. Precooling means quickly removing the heat from harvested fruits and vegetables to reduce the loss in the quality of product once it has been picked. Likewise, efficient precooling equipment increases the shelf-life of fresh produce [55].
- **Transport time (A9):** The transport time represents the time needed to transport goods from the farm to a grocery store or a customer; a shorter transport time may ensure that the fresh produce quality better. For example, the plane takes less time to transport fresh products to consumers, but it also requires high transportation costs. On the contrary, road transportation costs are lower, but the freshness of fruits is sometimes not guaranteed due to the long transportation time [14].

Product characteristics also pose risk factors and can thus affect the freshness of fresh products. The following indicators are selected as the biological risks of the fruits or vegetables in certain seasons and locations.

- **Moisture content (B2):** This refers to the amount of water present in produce when it is loaded into the truck. The fruit with high water content will not rot easily, which can ensure the safety of transportation. This indicator can be measured by chemical experiments [41].
- **Safety time (B3):** This is also called shelf-life, which refers to the time from harvest to deterioration. In order to transport and store fruits and vegetables properly, it is useful to know approximately how long the fresh produce will last. Plan your transportation, preservation, sterilization, and other facilities accordingly so that fresh foods are at the peak of freshness when consumers plan to buy them [41].
- **Postharvest interval (B5):** The postharvest interval represents the time from harvest to transport, and mainly includes the time required for precooling, processing, and storage.

Logistics enterprises can achieve fresh-keeping by adjusting the gas concentration in the package using packing technology, such as modified atmosphere packaging (MAP). The technology substitutes the atmospheric air inside a package with a protective gas mix.

- **Gas composition (C5), (C6):** The gas composition (carbon dioxide and oxygen concentration) in the boxcar is used as an indicator. High carbon dioxide and low oxygen concentrations can inhibit produce respiration and is commonly used as a preservation practice (e.g., modified atmosphere packaging) [38,39].

3.2. Indirect Measurement Index of Proposed System

A hierarchical form was adopted to monitor the risks that cannot be measured with the help of measurement devices. For the indicators such as equipment efficiency, staff skill, and management level of logistics enterprises, etc. A five-level scale was adopted to measure these indicators, where level 1 indicates that the enterprise has efficient equipment and skilled staff, whereas level 4 indicates low equipment efficiency and unfamiliar staff operation.

Many methods can be used to measure staff performance, such as the rating scale method, critical incident method, and individual ranking method, etc. For the staff operation skill, logistics managers need to measure this indicator based on the operation data of logistics activities, the records from exception reports, and work schedules, etc. [56]. Furthermore, for transportation management, fresh-keeping planning, and emergency planning, managers can use the critical incident method to measure the performance [57]. Based on the characteristic of fresh produce, the manager can also measure the effectiveness of some equipment using the method of overall equipment effectiveness in the transport stage [58].

- **Loading and unloading safety (A10):** This factor is mainly dependent upon the training of the stevedore and the stability of the loading and unloading equipment. Standard operation technology can greatly reduce the loss of fresh products in the process of loading and unloading.
- **Equipment stability (A11):** The stability of equipment refers to the ability to maintain normal operation of the transportation equipment, refrigeration system, sanitation equipment, air conditioning system, and monitoring equipment. Damage to the fresh-keeping equipment in transit makes the fresh-keeping measures ineffective: long-term failure causes the produce to rot.
- **The sterilization efficiency and waste disposal plant (A12):** The capacity to inhibit bacterial reproduction and dispose of waste, respectively, thus guaranteeing the freshness of the produce. Efficient sanitary equipment can ensure the sustainability of preservation measures in fruit and vegetable logistics [59,60].

Specific to the characteristics of fresh produce, the influence of these factors should be considered in the evaluation model. The biological risk indicators are described as follows.

- **Perishability (B1):** We use perishability to measure whether the goods themselves are perishable; for example, strawberries have a shorter shelf life than apples [41].
- **Mechanical damage and integrity (B4):** These factors are used to indicate the integrity of the fresh food when loaded into the truck. A logistics company can use a nondestructive method to measure this indicator. Damaged fruit has a strong respiratory intensity and exposes wounds to pathogenic microorganisms, which lead to deterioration in quality [43].

We chose four indicators to measure sustainable risks related to packaging and fresh-keeping of the fresh produce.

- **Safety of packaging materials (C1):** This indicator is used to indicate whether the packaging materials affect the safety of fresh produce. If the packaging material contains substances that may harmful to consumers, it will be rated level 4 [37,44].
- **Packaging reliability and strength (C2):** The ability of the package to complete the specified function under the specified conditions and within the specified time. This indicator can be given based on the rate of damage previously caused by the packaging mode [61].

- **Packaging sustainability (C3):** This factor refers to the sustainability of the raw materials of the package. It can be measured with the help of the related international standards.
- **Preservatives (C4):** The safety of preservatives used in packaging, such as chemical or bio-antiseptic, vacuum packaging, or modified atmosphere packaging, is also assessed. Such as adding unsafe preservatives will be rated as level 4, whereas using gas fresh-keeping technology will be rated as level 1.

The environmental risks in the transportation of fresh produce were analyzed, which also have a negative impact on the smooth implementation of the plan.

- **Climate stability (D1):** This factor is used to indicate the possibility of encountering abnormal weather, such as rainstorms, ice, or snow, when transporting fresh goods [62].
- **Traffic stability (D2):** This indicates the frequency of traffic jams and accidents on the transportation route, which then increase the transportation time [62].
- **Road grade (D3):** The road grade represents the road traffic conditions during transportation, and is used as an indicator because frequent congestion and poor road conditions can prolong the transportation time.

Emergency management involves the systematic handling of emergencies to prevent, control, and mitigate them. The emergency risk indicators are described as follows.

- **Personnel emergency handling capacity (E1):** This indicates the ability of the transporter to handle any encountered emergency during transportation. An excellent driver can quickly deal with emergencies and minimize losses. Enterprises combine the theoretical examination and practical performance to determine the level of this indicator [19,63].
- **Scheduling optimization and transportation management capabilities (E2):** This refers to the ability to determine the optimal scheduling plan and solve unexpected traffic problems [19,63].
- **The equipment maintenance capability (E3):** This indicates the ability of transport personnel to repair equipment when the equipment fails, and an excellent operator can quickly repair the equipment and minimize the negative impact on fruit freshness [62].
- **Emergency plan management (E4):** This represents the ability to plan for possible emergencies; adequate plan management can reduce the transportation risk. The main objective of emergency planning is to reduce injuries, protect the community, and maintain business continuity.

For the convenience of further research by scholars, the reference of the all above indicators is summarized in Table 2.

Table 2. The indicator and reference.

First-Class	Second-Class	Explanation	Reference
Technological risk (A)	Temperature	The actual temperature of food	Bogataj, M. et al. [14] Song H. et al. [35]
	Relative humidity	Actual humidity of food	Jalal A. et al. [36] Jalali, A. et al. [37]
	Temperature uniformity	Measure the uniformity of temperature	
	Refrigerated truck body pressure	Pressure in the boxcar	
	Storage density	The space between the goods	
	Vibration frequencies	Measure the effect of vibration on food	Fernando, I. et al. [43] Berardinelli, A. et al. [42]
	Vibration acceleration		
	Precooling time	The time after harvesting to be cooled to the fresh-keeping temperature	
	Transport time	The time of the transport link	Bogataj, M. et al. [14]
	Loading and Unloading Safety	Handling the proficiency of workers	
	Stability of equipment	The old or new degree of equipment	
	Sterilization Efficiency and Waste Disposal Plant	Cleaning and sterilization of equipment	Gu, G. et al. [59] Bouwknegt, M. et al. [60]

Table 2. Cont.

First-Class	Second-Class	Explanation	Reference
Biological risk (B)	Perishability	Whether the specified fruit or vegetable is perishable	Defraeye, T. et al. [41]
	Moisture content	The moisture content of the specified fruit or vegetable	
	Safety time	Freshness keeping time	
	Mechanical damage and Integrity	Completeness of the specified fruit or vegetable before transportation	Fernando, I. et al. [43]
	Postharvest intervals	Time from harvest to transport	
Sustainability risk (C)	Safety of packaging materials	Whether the packing is safe	Wu, Y. et al. [64] Jalali, A. et al. [36] Verboven, P. et al. [44]
	Packaging reliability and strength	Whether the packing is strong	Fadiji, T. et al. [61]
	Packaging sustainability		
	Preservatives	Safety of anticorrosion measure	Ketsa, S. et al. [38] Chong, K.L. et al. [39]
	Carbon dioxide concentration	The concentration of the gas in the package	
	Oxygen concentration		
Environmental risk (D)	Climate stability	Possibility of extreme weather	Ali, S.M. et al. [62]
	Traffic stability	Possibility of traffic jams	
	Road grades	The capacity of a road	
Emergency risk (E)	Personnel emergency handling capacity	Capacity to tackle an emergency	Tramarico, C.L. [63]
	Scheduling optimization, transportation management capabilities	The capability of transportation route planning and management	
	Equipment maintenance capability	The maintenance level of transport workers	Ali, S.M. et al. [62]
	Emergency plan management	The capacity of early warning	

4. Risk Assessment Using an SVM

SVM is a supervised machine learning method that was proposed by Vapnik [65] in the mid-1990s and is based on the VC dimension theory and structural risk minimization (SRM). Traditional empirical risk minimization (ERM) does not have a good performance when training a small sample because this principle can only minimize empirical risk. However, SRM can minimize both empirical risk and confidence risk; it was constructed by Vapnik [65]. It can reduce the VC dimension of learning machines when ensuring classification accuracy, so that the expected risk of learning machines in the whole sample set can be controlled [47]. Then, SRM was used as the principle of SVM to ensure that it had a better performance than other machine learning algorithms in this study [66]. Furthermore, SVMs can model nonlinear decision boundaries, and there are many kernels to be used. They are also fairly robust against overfitting, especially in high-dimensional space [47].

The risk assessment model based on SVM has good generalization ability and robustness, which is more effective than the traditional assessment model. Common applications of the SVM algorithm are risk assessment, handwriting and images recognition, and healthcare evaluation, etc. Furthermore, traditional SVM is mostly used for binary classification problems, and the one-versus-one method was adopted in this paper to render it suitable for multiclassification problems [67,68]. Overall, in this study, we chose SVM to solve the small-sample and high-dimension problem.

4.1. Employed SVM Algorithm

SVMs establish a hyperplane as the decision surface to maximize the isolation edge between the positive and negative classes. Assuming the training set $(x^{(i)}, y^{(i)}) (i = 1, 2, \dots, n; x^{(i)} \in R^n; y^{(i)} \in \{-1, 1\})$ is linearly separated by a hyperplane, SVM works by mapping input data (x) into a high-dimensional feature space $(\phi(x))$; the optimal classification hyperplane is $f(x) = w \cdot \phi(x) + b = 0$, where w is normal to the hyperplane and b is the perpendicular distance from the hyperplane to the origin.

The distance between each sample point and the optimal classification hyperplane is represented by $1/\|w\|$. The maximum solution can be changed into a convex quadratic optimization statement, as [69]:

$$\begin{aligned} \min \quad & \frac{\|w\|^2}{2} + C \sum_{i=1}^n \xi_i \\ \text{s.t.} \quad & y^{(i)} \left[(w \cdot \phi(x^{(i)})) + b \right] \geq 1 - \xi_i \end{aligned} \quad (1)$$

where C is the penalty parameter, ξ is the relaxation variable, $x^{(i)}$ is a data example, and $y^{(i)}$ is the class.

To solve individual noise points, the SVM algorithm employed allows certain error classification to occur under given accuracy ε . The penalty parameter $C \geq 0$ and relaxation variable $\varepsilon \geq 0$ were introduced to ensure fault tolerance of the model [70].

Employing a kernel function $K = K(x^{(i)}, x^{(j)})$ realizes the function form of transformation operation of inner product in space, which not only solves the linear inseparability of low-dimensional space but also avoids the complexity of high-dimensional space. The dual problems after inner product transformation via the kernel function are [71]:

$$\begin{aligned} \min L(\alpha) = \quad & \sum_{i,j=1}^n \frac{1}{2} \alpha_i \alpha_j y^{(i)} y^{(j)} K(x^{(i)}, x^{(j)}) - \sum_{i=1}^n \alpha_i \\ \text{s.t.} \quad & \sum_{i=1}^n \alpha_i y^{(i)} = 0 \end{aligned} \quad (2)$$

where $0 \leq \alpha_i \leq C$, and $i = 1, 2, \dots, n$.

Two methods can be employed in multiclass classification problems. The first involves transforming the problem into a combination of multiple binary classification problems, using the one-versus-rest, one-versus-one, directed acyclic graph, and error-correcting codes [68]. The other involves modifying the decision function. Due to the difficulty of the second method and its narrow application, the first method was used here. Furthermore, we selected the one-versus-one method as the multiclass classifier. If k is the number of classes, then $k(k-1)/2$ classifiers are constructed and each one trains data from two classes. [72,73].

4.2. Developed Risk Assessment Model of Fresh Produce Transportation

Training samples were then constructed using the index system and the evaluation model was obtained using the MATLAB [73] to train the decision function. Using the historical data as the training sample can reduce the influence of human factors on the model construction, which can reduce errors and improve the objectivity of the evaluation method.

4.2.1. Risk Levels

The risks posed to the fresh produce in transit were divided into four severity levels (1–4, representing very low, low, high, and very high, respectively), as summarized in Table 3 [4].

Table 3. Risk assessment matrix.

Risk Level	Severity of Consequence	Enterprise Response Measures
1	Very low	Unnecessary
2	Low	Check the fresh-keeping plan
3	High	Upgrade equipment
4	Very High	Replace equipment and fresh-keeping plan

4.2.2. Data Acquisition

The development of the internet of things (IoT) and big data has allowed logistics companies to collect and store data in fresh produce transportation easily. For example, enterprises can use

temperature and humidity sensors to collect real-time data inside the carriage [64]. They can also invest in nondestructive monitoring equipment for fruits and vegetables to collect damage data. The gas concentration can be obtained in real-time through the detection device.

Furthermore, all the time data (e.g., precooling time, transport time, and postharvest intervals) can be calculated automatically from monitoring data stored in the database. With the help of global positioning systems (GPS) and database technology, data such as road conditions can be automatically matched [1].

Finally, for the qualitative indicators, we adopted the hierarchical method for quantitative treatment. In the early stage of data collection, the level should be determined through detection and investigation. As the amount of data increases, artificial intelligence technology can be used to learn and train a risk assessment model [25].

4.2.3. Standardized Processing

Standardized treatment of training samples can effectively adjust the range of indicators, avoid improper data selection, and reduce the prediction error. The following formula was adopted for standardized treatment, where Equation (3) was used for positive and negative dimensions, respectively.

$$\begin{cases} x_{ij}^* = \frac{x_{ij} - x_{j\min}}{x_{j\max} - x_{j\min}} & (3a) \\ x_{ij}^* = \frac{x_{j\max} - x_{ij}}{x_{j\max} - x_{j\min}} & (3b) \end{cases} \quad (3)$$

where x_{ij} is the original data and x_{ij}^* is the j th index of training sample i after standardized treatment.

Then, about 85 percent of standardized data sets were randomly chosen as the cross-validation sample. The remaining data sets were used as test data to verify the validity of the model [69].

4.2.4. Kernel Function and Cross-Validation

After the training samples were determined, the gaussian radial basis kernel function (RBF) was selected to train the evaluation model. Common kernel functions of support vector machine mainly include linear kernel function, polynomial kernel function, radial basis kernel function, and sigmoid kernel function. RBF kernel function was selected due to its high classification efficiency and strong applicability [70].

The employed RBF kernel expression is represented as:

$$K(x^{(i)}, x^{(j)}) = e^{-\gamma \|x^{(i)} - x^{(j)}\|^2} \quad (4)$$

where γ is the kernel parameter.

The value of function parameters directly affects model classification. The grid method was used to optimize the penalty parameter C and kernel parameter γ , and the optimization parameters were verified with cross-validation.

In this analysis, we selected 5-fold as the cross-validation procedure and followed the traditional grid used in MATLAB [69,70]. The parameter interval that reached the highest classification efficiency was determined with the stride length, and then, the parameter was determined with the small step length. These performances are presented in the following section.

5. Simulation and Numerical Analysis

The numerical analysis focuses on logistics enterprises transporting fresh produce, such as S.F. Express of China, CR-England Logistics of America, and N&K Spedition of Europe, etc. To enhance their competitiveness and risk exposure, these cold chains need to be introduced to a series of risk assessment methods on food safety and quality. Strawberries have a shorter shelf life and stricter freshness preservation requirements than other fruits. Moreover, strawberries are more sensitive

to various risk factors, such as high temperature requirements; 0 to +4 °C is the optimal storage temperature [64].

We created a company to emulate the situations of a strawberry transportation firm which may not be aware of the potential risk threats such as preservation technology and unexpected disruptions of transport [4]. The increasing demand for fresh food brought opportunities and challenges to the fresh logistics company. Owing to the lack of advanced cold chain equipment, skilled employee, and experienced managers, the freshness of strawberries transported by the company cannot meet the requirements of consumers.

To deal with this problem, firstly, the company must invest in new technologies, such as 5G, big data, cloud computing, and the IoT, etc. Meanwhile, the introduction of equipment and professional staff is also necessary, such as advanced fresh-keeping equipment and skilled staff who can operate new equipment, as well as managers who are proficient in fresh food supply chain management. At the same time, there are still some problems to be solved, such as unstable equipment operation, uncertainty traffic accidents, bad weather, and incomplete emergency plans, etc.

We built a fresh food logistics risk assessment model, which aims to provide a theoretical basis and management method for managers to monitor food quality during transportation. Meanwhile, consumers can also obtain detailed data about fresh food when they buy it, to improve consumer satisfaction. The proposed methodology was then applied to a strawberry supply chain as a simulation and numerical analysis to evaluate the risks incurred during transportation.

Although strawberries are preserved optimally from 0 to +4 °C, many enterprises have not yet adopted cold chain technologies and still transport strawberries and other fruits at room temperature; thus, the temperature range was set from 0 to +22 °C. The precooling time is determined by the advanced degree of equipment, but advanced machines lead to high costs. Logistics enterprises have different optimal decisions to purchase precooling equipment depending on the size and economy of the business, so the precooling time varied from 0.2 to 2.55 h relying on the efficiency of equipment [55].

As a fruit with a high moisture content, the relative humidity of strawberries is between 80 and 95%, although it may be reduced due to irregular harvesting. Here, the moisture content was set between 86 and 96% to facilitate risk analysis [64]. The temperature uniformity of the transporting van body also has a significant effect on the quality of fruits and vegetables: a lower vibration frequency and acceleration indicate a more stable vehicle and thus less damage to the produce. The vibration frequency and acceleration of the truck during the transportation ranged from 14 to 25 Hz and 2.94 to 14.7 m/s², respectively [74]. Resistant to carbon dioxide, strawberries can be kept fresh in an environment with a concentration of up to 20% carbon dioxide. As such, high carbon dioxide and low oxygen levels were adopted during air conditioning: 2–15% and 5–20%, respectively.

Transport exists in different links in logistics, such as from farm to retailer or warehouse (e.g., CR-England Logistics of America and N&K Spedition of Europe) and from retailer to consumer (Hema: Alibaba's new fresh produce retail). Transportation time is affected by the distance and mode of transportation, and can thus vary greatly with different transportation schemes; here, due to the high perishability of strawberries, transportation was assumed within two days because trucking takes a long time, whereas air transport takes only a few hours.

Furthermore, we observed all the properties of strawberries as the basis and set original training samples. Each factor in strawberry transportation was given according to its reasonable range, and each group of data contained 30 indicators, which were used to represent the conditions of a single strawberry shipment.

In theory, more training samples allows for a more realistic model but leads to longer calculation times. After comprehensive consideration, training samples of the support vector machine were established with a sample size of 310. Because the amount of data is very high and it cannot be displayed, we only list part of the data, as shown in Table 4 (For more details please refer to Supplementary Materials).

Table 4. The original sample data.

	Index	Dimension	Range	1	2	3	...	349	350
Technological risk (A)	Temperature	Positive	[0,22]	0.11	17.21	5.22	...	10.64	7.00
	Relative humidity	Negative	[0.8,0.95]	0.91	0.85	0.91	...	0.91	0.87
	Temperature uniformity	Positive	[0.4,3.2]	1.05	1.38	1.56	...	2.00	0.98
	Refrigerated truck body pressure		[1.28,2.72]	1.69	2.15	1.67	...	2.13	1.74
	Storage density		[0.68,0.98]	0.80	0.83	0.82	...	0.75	0.86
	Vibration Frequencies		[14,25]	17.49	20.77	17.39	...	16.45	19.21
	Vibration acceleration		[2.94,14.7]	8.09	14.12	13.34	...	5.30	4.70
	Precooling time		[0.2,2.55]	1.72	1.07	1.66	...	1.62	1.81
	Transport time		[0,49]	23.91	4.54	8.50	...	24.95	8.18
	Loading and Unloading Safety		[1,5]	1	1	2	...	5	1
	Stability of equipment		[1,5]	2	1	1	...	4	2
	Sterilization Efficiency and Waste Disposal Plant		[1,5]	5	4	2	...	2	2
Biological risk (B)	Perishability	Negative	[1,5]	5	5	4	...	2	2
	Moisture content		[0.86,0.96]	0.92	0.91	0.91	...	0.88	0.88
	Safety time		[2,17]	4.73	8.93	5.93	...	7.85	4.28
	Mechanical damage and Integrity		[1,5]	3	4	4	...	2	5
	Postharvest intervals		[1,121]	83.60	65.27	73.21	...	37.31	77.35
Sustainability risk (C)	Safety of packaging materials	Positive	[1,5]	5	2	5	...	1	3
	Packaging reliability and strength		[1,5]	5	1	5	...	4	2
	Packaging sustainability		[1,5]	1	4	4	...	4	5
	Preservatives		[1,5]	2	1	4	...	1	5
	Carbon dioxide concentration	Negative	[0.05,0.25]	0.16	0.14	0.11	...	0.10	0.15
Environmental risk (D)	Oxygen concentration	Positive	[0.02,0.15]	0.07	0.03	0.10	...	0.09	0.09
	Climate stability		[1,5]	3	2	2	...	4	2
	Traffic stability		[1,5]	4	3	1	...	1	4
	Road grades		[1,5]	2	1	5	...	2	1
Emergency risk (E)	Personnel emergency handling capacity	Positive	[1,5]	5	1	2	...	1	1
	Scheduling optimization, transportation management capabilities		[1,5]	4	3	4	...	1	3
	Equipment maintenance capability		[1,5]	5	5	3	...	2	3
	Emergency plan management		[1,5]	3	2	1	...	3	3
Risk level				3	2	3	...	2	1

The original sample data sets in Table 4 contain indicator data and the given risk level. We calculated the standardized data from the original data using Equation (3). In order to prove the scientific and the effectiveness of the method, of the 350 data sets, 310 sets were randomly selected to train the risk evaluation model using the SVM. The trained model was used to predict the risk level of the remaining 40 data sets. The prediction risk level of the 40 remaining validation datasets was then compared with the given risk level. Then, we obtained the model-predicted risk accuracy. The accuracy represents the effectiveness of the trained evaluation model in predicting the logistics risk level.

The LIBSVM toolbox of MATLAB R2008 (a) was used to simulate the same set of training data many times. The results, summarized in Table 5, demonstrated the prediction accuracy is between 85% and 97.5%; thus, the developed model accurately predicted the risks incurred during the transportation of fresh products.

Table 5. The prediction accuracy of logistic risks incurred as calculated by the trained SVM-based model and sample data.

Simulation Number	1	2	3	4	5	6
Prediction Accuracy	90%	90%	97.5%	85%	90%	90%

To show the prediction results of the evaluation model more intuitively, take the first simulation for example: the model-predicted risk accuracy was 90%. We used the trained model to predict the risk level of the remaining validation data sets and then compared the prediction and the given risk level as shown in Figure 2. Except for sample number 5, 15, 29, and 40, we found that the prediction risk level of the remaining validation datasets was consistent with the given risk level. The prediction risk level of the above 4 sample datasets was inconsistent with the given risk level. However, the gap between these levels was small (only one level), indicating that managers can still adjust the fresh-keeping measure and management schemes timely according to the assessment risk level. The developed model thus helps the logistics company to identify risks effectively and implement measures on time, which can minimize the loss of agricultural products, reduce food waste, and support sustainable development.

Figure 2. Comparison of the prediction and the given risk level.

Here, only 310 data sets were used for training. In practical applications, logistic enterprises can use the IoT, big data, and cloud computing technologies to collect vast data sets for model training. Increasing the data sets can ensure that the training data are widely different from each other and include a variety of different transportation scenarios, which can be used for training and will allow decision-makers to obtain a more accurate risk assessment model.

Although the transportation of strawberries was considered in this case study, the risk indicators considered included characteristics relevant to the transportation of most fresh foods. Unlike previous models developed, the developed risk assessment model uses a large number of risk indicators, most of which can be obtained timely by monitoring equipment. When evaluating the logistic risks of other fresh produce, the relevant historical data can be substituted into the developed SVM model to allow for training and the development of a new produce-specific model. Biological risk indicators need to be adjusted according to the new product. Other indicators are still given based on a specific logistics company.

The developed methodology employing an SVM and a kernel function is thus robust, accurate, reproducible, and can effectively process small high-dimensional data. From the results, three main suggestions to fresh produce logistics enterprises can be drawn.

First, logistic enterprises must invest in new technologies, such as big data, cloud computing, and the IoT (including many sensors), to efficiently collect, store, and process a large amount of data (e.g., temperature, relative humidity, and gas concentration) in real-time. The large amounts of historical

data can be used as a training sample of the assessment model. Limited initial historical data may result in relatively low accuracy by using the machine learning algorithm. However, compared with other machine learning algorithms, SVM performs better for small samples and high-dimensional data.

Then, the current logistics risk level can be obtained by inputting the real-time data detected in the transportation process into the risk assessment model. With the increase in transportation data and the supplement of data diversity, large amounts of historical data can improve the accuracy of the developed risk assessment model.

Additionally, the risk assessment model contains a large number of risk indicators; this can help decision-makers accurately assess risk levels, and thus implement targeted risk mitigation measures, saving time and money. Finally, the developed risk assessment methodology can assist managers in adjusting fresh-keeping plans, upgrading preservation equipment, and deciding where experienced employees are most necessary, which can help to reduce food loss and related costs.

There are also some suggestions for the decision-makers of long-established enterprises. Different from new enterprises, they have a complete infrastructure, but they may be old and inefficient. The company collects data based on the existing equipment as much as possible to assess the risk level using this model. Based on the risk level, managers, experts, and scholars in the field should discuss what needs be repaired, replaced, and improved. At the same time, the company also needs to invest in more advanced and professional fields like the new enterprise, such as big data, cloud computing, and the IoT. Then, the risk is monitored and assessed in real-time based on the data collected in transit, which ensures the problems in transit can be found and solved in time.

6. Conclusions

The strict requirements necessary for the effective transportation management and technology of fresh produce have led to the emergence and development of cold chain logistics, which has increased the requirements for preservation equipment and management skills. The use of intelligent fresh-keeping and transportation facilities has also improved the working efficiency of logistics managers. However, with the development of e-commerce, higher requirements have been put forward for the timeliness and quality of fresh produce transportation. Urgent problems in the aspects of fresh-keeping, monitoring, and risk management must be addressed, such as unsuitable transportation and fresh-keeping equipment, failure to timely collect data, and imperfect emergency management.

We established a risk assessment model of fresh produce in transit from five aspects: technological, biological, sustainability, environment, and emergency. Data acquisition and analysis technology (such as IoT and big data) enables managers to assess risk levels incurred during the transportation of fresh produce. To realize sustainable development and reduce the loss of fresh produce, this work first identified and classified the risks.

An SVM was then used to develop a risk evaluation model, which can monitor risk levels and provide early warnings to logistics managers. The developed model was then applied to a strawberry supply chain as simulation and numerical analysis. Of the obtained 350 data sets, 310 were used to train the model, and the remaining 40 were used for model verification. The trained model monitored and evaluated the logistic risk levels with an accuracy rate of 85–97.5% through big data, cloud computing, and the IoT. Because our risk assessment system includes 30 indicators from 5 aspects, the developed methodology applies to the risk evaluation of other fresh produce, as well.

Due to the lack of an available evaluation method on the logistic risks of agricultural products, identifying and qualifying these risks would be beneficial to decision-makers of the enterprise. The developed methodology would allow enterprises involved with fresh produce logistics to effectively identify, monitor, and mitigate risk levels in real-time. Low-risk transportation and preservation measures can help logistic enterprises reduce product loss in transit while providing consumers with access to safe, high-quality produce. Timely identification and mitigation of risks can reduce costs and maintain the stability of the fresh produce market. There is also an urgent need for policymakers

to invest in infrastructure development and provide financial assistance to enterprises that purchase green and sustainable fresh-keeping facilities.

This study also has academic implications. With the development of 5G, big data, IoT, and other technologies, it becomes easier to acquire and process data. Researchers should help logistics enterprises make good use of relevant technologies and historical data, which can improve logistics efficiency and ensure the quality and quantity of fresh products.

Overall, this work proposes a robust method to assess the transportation risks of fresh produce. Extended research can be carried out based on two aspects, which are exactly what this research did not involve. First, future research can establish corresponding risk evaluation models for meat products and seafood products. Second, we can continue to study other links of logistics, such as storage and production, and build evaluation models based on the same principles to ensure that managers can monitor risks in every link of logistics at any time.

Supplementary Materials: The following are available online at <http://www.mdpi.com/2071-1050/12/18/7569/s1>, Table S1: The sample data.

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