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Research on the whole chain low-carbon transformation Path of Yunnan fresh cut Rose under the guidance of AI-driven ESG -- From the perspective of LCA and intelligent collaborative governance

Ni Li[1] *and Xijia He*[2,*]

[1] Guangdong-Hongkong-Macao Greater Bay Area College of Intelligent Cold-Chain Industries, Guangzhou College of Technology and Business, Guangzhou, 510850, Guangdong, China
[2] School of Information and Management, Guangxi Medical University, Nanning 530021, Guangxi ,China

SUMMARY: *Yunnan, as a major global production base for cut roses, faces the challenge of high carbon emissions in its industry, including greenhouse gas emissions and resource consumption in planting, harvesting, processing, transportation, and sales. This study quantifies the carbon footprint across the entire supply chain using the LCA method, investigating carbon emissions and their main sources during the planting and transportation stages. AI technology is introduced to optimize planting forecasts using machine learning algorithms, blockchain enables transparent supply chain tracking, and an IoT-supported intelligent collaborative governance framework promotes collaboration among multiple stakeholders (farmers, businesses, and government) to achieve carbon reduction targets. The transformation path includes: (1) AI-assisted precision agriculture to reduce fertilizer input; (2) promoting renewable energy substitution under the ESG framework to enhance social responsibility and governance efficiency; and (3) establishing a low-carbon certification system to enhance market competitiveness. This study emphasizes the synergistic effect of AI and intelligent governance, providing theoretical and practical guidance for the sustainable development of Yunnan's cut rose industry.*

KEYWORDS: *AI-driven optimization; Life Cycle Assessment (LCA); Low-carbon supply chain; ESG-oriented governance*

1 Introduction

Intelligent collaborative governance, as an innovative model combining technology and management, is an important means to achieve low-carbon transformation. This model emphasizes multi-party participation, including farmers, enterprises, the government, and third-party regulatory agencies, through information sharing, intelligent monitoring, and collaborative decision-making, to achieve the balance between carbon reduction targets and production efficiency. In the fresh-cut rose industry of Yunnan, intelligent collaborative governance can utilize IoT devices to collect real-time production data, monitor and optimize each link through a centralized data platform, and guide farmers and enterprises to adjust operation plans through a decision support system, achieving low-carbon and efficient production management. This model not only solves the problems of information isolation and

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*hxj@gxmu.edu.cn
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insufficient supervision, but also enhances the overall carbon reduction capacity and governance efficiency of the industry through data-driven methods.

The design of the transformation path should take into account environmental, economic and social benefits. In practice, AI-assisted precision agriculture can significantly reduce carbon emissions during the planting stage by optimizing fertilization, irrigation and greenhouse management; in terms of energy substitution, introducing renewable energy sources such as solar and wind power to replace traditional fossil energy not only reduces carbon emissions but also meets ESG social responsibility requirements; the establishment of a low-carbon certification system can strengthen the market's recognition of low-carbon products and enhance the market competitiveness of enterprises and farmers. This integrated low-carbon transformation model combining technology and management provides a systematic sustainable development solution for the fresh-cut rose industry in Yunnan.

In conclusion, the low-carbon transformation of the fresh-cut rose industry in Yunnan requires the support of three technologies: LCA quantitative analysis, AI prediction optimization, and intelligent collaborative governance. Through the ESG framework, strategy design can be guided to achieve carbon reduction throughout the chain and sustainable development goals. This research will focus on these technical means to construct a systematic low-carbon transformation path, providing operational technical solutions and practical guidance for the industry, and promoting the high-quality development of the fresh-cut rose industry in the international market.As an important fresh cut rose production base in the world, Yunnan has a large industrial scale and complete industrial chain. However, for a long time, there are problems such as high carbon emissions, large resource consumption and significant environmental pressure in industrial development. The use of large amounts of fertilizers and pesticides, the energy consumption of greenhouses, and the centralized management of water resources all contribute to increasing greenhouse gas emissions. In the transportation and logistics link, fresh cut roses have strict requirements for fresh preservation environment, and cold chain transportation has become necessary, but the accompanying energy consumption and carbon emission problems have gradually become prominent. Packaging materials, cold chain storage and transport across regions also generate significant direct and indirect emissions during processing and marketing. These problems not only increase the carbon footprint of the industry, but also restrict the sustainable development ability of Yunnan's fresh cut rose industry in the domestic and foreign markets. Therefore, how to effectively reduce the carbon emissions of the whole chain under the premise of ensuring output and quality has become an important topic in the current industrial transformation and upgrading.

In recent years, with the global attention to sustainable development and low carbon economy, the concept of environment, society and governance (ESG) has gradually become an important indicator to measure the comprehensive value of enterprise and industry development. ESG framework not only focuses on environmental protection and resource conservation, but also emphasizes social responsibility and the improvement of governance mechanisms. In the field of agriculture, ESG concept provides new management ideas and technology application directions for traditional industries, especially in the fresh cut rose industry, where its operability and practical value are gradually emerging. Through the ESG evaluation system, the carbon emission, resource consumption, social responsibility and governance efficiency of each link of the industry can be quantitatively analyzed, so as to guide enterprises and farmers to formulate low-carbon development strategies and realize the dual goals of economic benefits and environmental protection.

In terms of technical means, the rapid development of artificial intelligence (AI) technology provides new solutions for the low-carbon transformation of agriculture. AI can realize the accurate management and optimization of planting, transportation and processing links through methods such as big data analysis, machine learning and deep learning. For example, in the planting stage, AI can use environmental monitoring data and historical production data to build crop growth models and optimize fertilization, irrigation, and greenhouse control programs to reduce fertilizer and energy use. In the transportation link, the AI algorithm can optimize the cold chain logistics path to reduce unnecessary energy consumption and carbon emissions. In the processing and sales links, through the combination of AI and blockchain technology, the transparent management of the supply chain can be realized, and the carbon emission data of products can be tracked in real time to ensure that all links meet low carbon standards. The application of this technical means not only improves the management efficiency, but also provides a reliable guarantee for the realization of carbon reduction in the whole chain.

The whole Life Cycle Analysis (LCA) method plays a central role in the research of industrial low-carbon transformation. By quantifying the carbon emissions in the whole life cycle of a product from raw material acquisition, planting, processing, transportation to sales, LCA can identify the carbon emissions contribution of each link and key emission reduction nodes. In the fresh-cut rose industry of Yunnan, LCA analysis is helpful to identify the high-emission operations in the planting stage, the energy consumption bottlenecks in the transportation link, and the carbon intensive points in the processing and sales link, which provides a scientific basis for the design of low-carbon strategies. Combining AI prediction and intelligent collaborative governance, LCA can not only quantify the current carbon emissions, but also simulate the effects of different emission reduction strategies, providing data support for decision-making.

As an innovative model combining technology and management, intelligent collaborative governance is an important means to realize low-carbon transformation. This model emphasizes the participation of multiple parties, including farmers, enterprises, governments and third-party regulators, and achieves the balance between carbon emission reduction targets and production efficiency through information sharing, intelligent monitoring and collaborative decision-making. In the fresh cut rose industry in Yunnan, intelligent collaborative governance can use Internet of things devices to collect real-time production data, monitor and optimize each link through a centralized data platform, and guide farmers and enterprises to adjust their operation plans through a decision support system to achieve low-carbon and efficient production management. This model not only solves the problem of information island and insufficient regulation, but also improves the overall carbon emission reduction ability and governance efficiency of the industry through data-driven.

The design of transition path should take into account the environmental, economic and social benefits. In practice, AI-assisted precision agriculture can significantly reduce carbon emissions at the planting stage by optimizing fertilization, irrigation, and greenhouse management. In terms of energy substitution, the introduction of renewable energy such as solar energy and wind energy to replace traditional fossil energy not only reduces carbon emissions, but also meets the requirements of ESG social responsibility. The establishment of low-carbon certification system can strengthen the market recognition of low-carbon products and enhance the market competitiveness of enterprises and farmers. This whole chain low-carbon transformation mode combining technology and management provides a systematic sustainable development plan for Yunnan's fresh cut rose industry.

In summary, the low-carbon transformation of Yunnan's fresh cut rose industry needs to rely on the three major technical supports of LCA quantitative analysis, AI prediction optimization and intelligent collaborative governance, and guide the strategy design through the ESG framework to achieve the goal of carbon emission reduction and sustainable development of the whole chain. This study will focus on these technical means to build a systematic low-carbon transformation path, provide operational technical solutions and practical guidance for the industry, and promote Yunnan's fresh cut rose industry to achieve high-quality development in the international market.

2 Whole-chain carbon emission quantification and LCA modeling

2.1 Life Cycle Analysis (LCA) method

2.1.1 Functional unit setting and system boundary delineation

The setting of functional units is the basis of Life cycle Analysis (LCA) when quantifying the whole-chain carbon emissions of Yunnan fresh-cut rose industry. In this paper, each production unit of fresh cut rose bouquet is considered as a functional unit to ensure that the emissions of each link can be directly quantified and to facilitate horizontal comparison. The system boundary covers the whole chain process from planting, harvesting, processing, transportation to sales, including greenhouse planting environment, fertilizer and water input, harvesting artificial and mechanical energy consumption, energy consumption required for packaging and processing, cold chain transportation and final retail link energy consumption and emissions. This study places special emphasis on comprehensive coverage of carbon emissions and resource consumption, not only counting direct emissions, but also considering indirect sources of emissions, such as electricity consumption and GHG emissions in logistics and transportation. By clarifying the boundaries between functional units and systems, it can provide a reliable analysis basis for subsequent data acquisition, carbon emission calculation and low-carbon strategy design, and provide a quantitative basis for the priority assessment of emission reduction measures in each link.

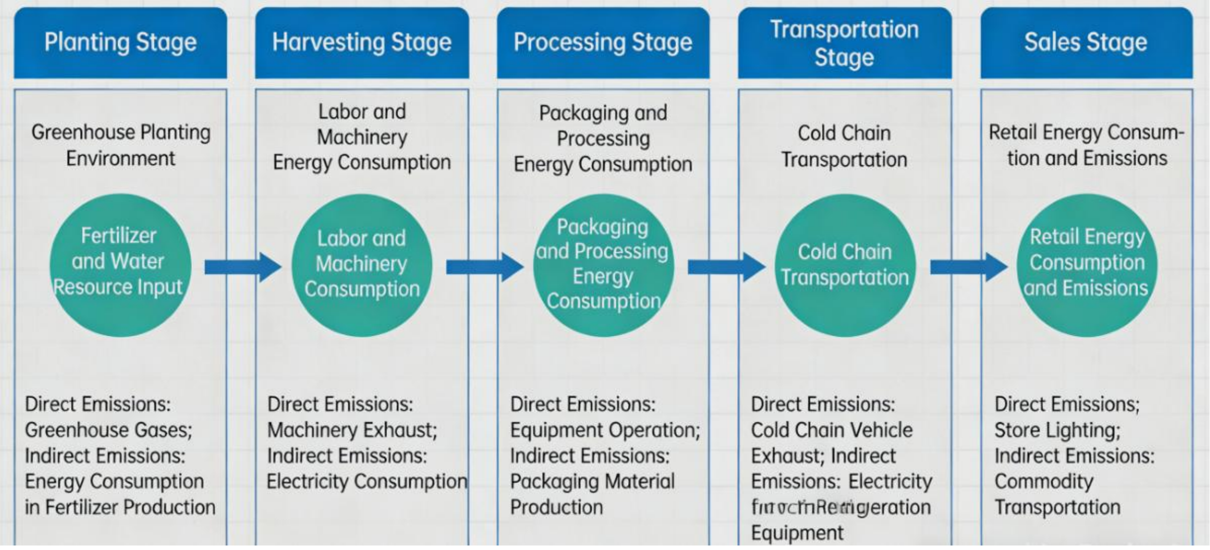

Figure 1: Schematic representation of the system boundary

2.1.2 Identification of key carbon emission links

In the whole chain of fresh cut rose industry in Yunnan, there are significant differences in the carbon emission contributions of each link. The planting stage is mainly composed of fertilizer application, pesticide input and greenhouse energy consumption, which directly affects the carbon footprint of unit bouquet. The carbon emission from harvesting comes from the energy consumption of labor and machinery, as well as the fuel consumption from transportation to processing. The processing link mainly includes the use of packaging materials, power consumption and waste disposal and discharge; The carbon emission of transportation is concentrated in the fuel consumption and energy consumption of vehicles in the process of cold chain logistics. Carbon emissions from sales come from retail storage and terminal transportation. In order to quantify the contribution of each link to the total carbon emissions, the following formula is used to calculate the carbon emissions of each link:

$$\mathrm{CF_i} = \sum_{j} \mathrm{E_{ij}} \times \mathrm{GWP_j}$$

Among them, CF_i represents the total carbon emission of the ith link, E_{ij} represents the amount of the JTH resource or energy consumed by the link, and GWP_j is the Global Warming Potential corresponding to the resource or energy. Through this formula, the main carbon emission links can be identified, and the quantitative basis for subsequent emission reduction strategies can be provided to achieve targeted low-carbon optimization.

2.1.3 Carbon emission data acquisition and preprocessing method

In order to ensure the accuracy of carbon emission quantification of the whole chain, this study systematically collects and preprocesses the data of each link of Yunnan fresh cut rose industry. The data sources include greenhouse environment data monitored by IoT sensors, irrigation and fertilization records, fuel consumption of transportation vehicles, and electricity usage at processing stages. Firstly, the raw data are standardized to unify the energy consumption and resource usage of different units into carbon equivalents to form a comparable dataset. Subsequently, data integrity and reliability were ensured by imputation of missing values and elimination of outliers. Finally, the carbon emission intensity per unit product of each link was calculated by integrating the data of each link, which provided a data basis for the identification of key emission links and low-carbon optimization. The standardization process is expressed by the following formula:

$$\mathrm{X_{std}} = \frac{\mathrm{X} - \mathrm{X_{min}}}{\mathrm{X_{max}} - \mathrm{X_{min}}}$$

Here, X_{std} is the normalized value, X is the original measurement value, X_{min} and X_{max} are the minimum and maximum values of the index in the data set, respectively. Through this formula, data from different sources and different dimensions can be unified to the same scale, which is convenient for subsequent statistical analysis and model calculation.

2.2 Data processing and analysis

2.2.1 Standardization of IoT sensors and meteorological data

In the carbon emission quantification of full-chain fresh cut rose in Yunnan, there are many kinds of data collected by IoT sensors and weather stations with different dimensions. In order to ensure data comparability, it is necessary to standardize the original data. The standardization process includes unifying indicators such as temperature, humidity, light intensity, irrigation amount and fertilization rate into a dimensionless numerical range, eliminating unit differences and dimensional effects, so that data from different sources can be directly used in carbon emission calculation and AI prediction models. This method can reduce the interference of different data scales on subsequent statistical analysis and modeling, and facilitate data visualization and outlier detection. The normalization formula is as follows:

$$X' = \frac{X - \mu}{\sigma}$$

Here, X' is the normalized value, X is the original measurement value, μ is the mean value of the data, and σ is the standard deviation. Through this formula, the original data can be converted into a standardized value with zero mean and unit variance, which provides a consistent data basis for the modeling and prediction of carbon emissions of the whole chain.

2.2.2 Data cleaning, missing data handling, and outlier detection

In the full-chain carbon emission analysis of Yunnan fresh-cut rose, the collected IoT sensors and meteorological data may have missing values, noise and outliers, which affect the calculation of carbon emission and the prediction accuracy of AI model. Therefore, the data must be systematically cleaned and preprocessed. Missing values are usually handled by means of mean imputation or nearest neighbor interpolation to replace the missing data with reasonable estimates. Outlier detection is based on statistical methods such as standard deviation or boxplot methods to identify outliers and remove or adjust for them. This process ensures data integrity and reliability while avoiding extreme values that bias subsequent model training. The specific outlier determination formula is as follows:

$$X_i \text{ is an outlier if } |X_i - \bar{X}| > k \cdot \sigma$$

where, X_i is the $_i$th observation value, $\bar{X}$ is the mean value of the variable, σ is the standard deviation, k is usually set to 3, corresponding to the principle of 3 times the standard deviation. Through this formula, outliers can be systematically identified and processed, the stability and availability of the whole chain data can be guaranteed, and a reliable basis for carbon emission quantification and subsequent AI prediction can be provided.

2.2.3 Calculation of emission coefficient and data integration

In the whole-chain carbon Emission quantification, in order to unify the carbon emission data of each link, the cleaned and standardized data need to be further converted into Emission Coefficient for inter-link comparison and total carbon footprint calculation. The emission factor calculation is based on the consumption of energy or resources in each link and its corresponding Global warming potential (GWP) to obtain the carbon emissions per unit of product. In addition, considering the integration requirements of multi-source data, this study integrates the emission data of planting, harvesting, processing, transportation and sales through the method of weighted average or total sum, forming a unified whole-chain carbon emission data set to provide input for the AI optimization model. The emission coefficient is calculated as follows:

$$EC_i = \frac{CF_i}{Q_i}$$

Here, EC_i is the unit product emission coefficient of the ith link, CF_i is the total carbon emission of the link, and Q_i is the number of products or functional unit output of the link. Through this formula, the carbon emission intensity of different links can be quantified, and the comprehensive analysis and visual display of the whole chain emission can be supported.

3 AI drives low-carbon prediction and optimization

3.1 Carbon emission prediction at planting stage

3.1.1 Input variable selection

In the carbon emission prediction of the entire chain of fresh-cut roses in Yunnan, the selection of input variables directly affects the accuracy and interpretability of the AI prediction model. For the planting stage, this paper comprehensively considers three types of factors - environment, crop management, and soil conditions - as feature inputs. Environmental factors include temperature, humidity, light intensity, and rainfall, which are collected in real time by IoT sensors and meteorological stations. Crop management factors cover fertilizer application volume, pesticide input volume, irrigation volume, and greenhouse heating energy consumption, which are obtained through agricultural management records and intelligent control systems. Soil condition factors include soil type, pH value, organic matter content, and nutrient status, which are obtained through on-site sampling and laboratory testing. To ensure data consistency and comparability, all input variables are standardized and missing values are filled after collection. Through careful selection and processing of input variables, the model can accurately reflect the carbon emission characteristics of the planting process, providing a high-quality data foundation for the design of subsequent prediction models and serving as a reference for optimizing carbon reduction strategies.

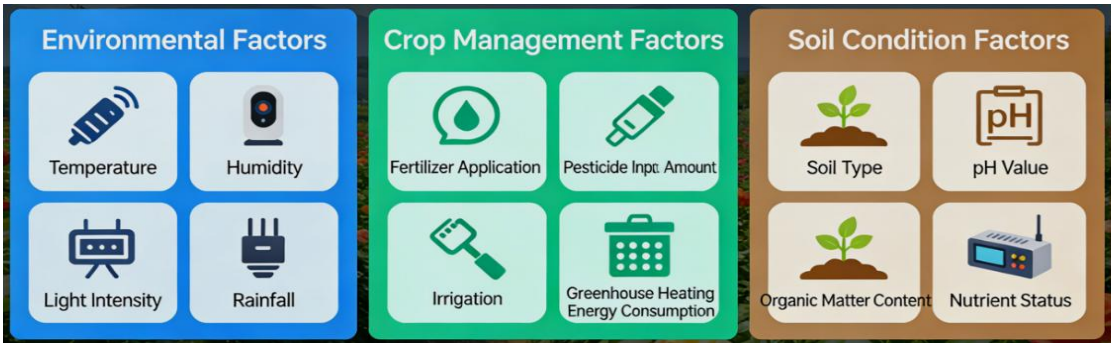

Figure 2: Input Variables in the Planting Stage

3.1.2 Prediction Model Design

For the multi-dimensional characteristics input of carbon emissions during the planting stage, this paper adopts a prediction model combining machine learning and deep learning methods. Firstly, based on the data characteristics, random forest (Random Forest) and gradient boosting decision tree (GBDT) are selected for baseline prediction, leveraging their ability to handle nonlinear relationships and high-dimensional features to achieve rapid preliminary modeling. Secondly, considering the characteristics of time series data, long short-term memory network (LSTM) is introduced, which can capture the dynamic effects of factors such as environment, fertilization, and irrigation on carbon emissions. The model inputs include temperature, humidity, light intensity, soil nutrients, fertilizer application amount, and irrigation amount, and the output is the predicted value of carbon emissions per functional unit. The prediction function formula can be expressed as:

$$\widehat{\mathrm{CF}}_{\mathrm{plant}} = \mathrm{f}(\mathrm{X}_{\mathrm{env}}, \mathrm{X}_{\mathrm{soil}}, \mathrm{X}_{\mathrm{management}})$$

Among them, $\widehat{\mathrm{CF}}_{\mathrm{plant}}$ represents the predicted carbon emissions, X_{env} is the environmental variable, X_{soil} is the soil characteristics, and $X_{management}$ is the crop management data. The model structure diagram can show the relationship between data input, feature extraction layer, hidden layer, and output layer, as well as the parallel or combined mode of random forest, GBDT and LSTM models, thereby clearly demonstrating the model design concept and prediction logic, and providing a basis for subsequent training and accuracy evaluation.

3.1.3 Model Training and Prediction Accuracy Evaluation

In the carbon emission prediction during the planting stage, the model training uses historical data sets for supervised learning, randomly dividing the training set and test set to ensure the model's generalization ability. During the training process, by optimizing the loss function and adjusting model parameters, the predicted results are made to be as close as possible to the actual observed carbon emissions. To quantify the prediction accuracy, commonly used indicators include root mean square error (RMSE) and mean absolute error (MAE), which can be used to compare the performance of different models. The root mean square error is used to reflect the square average of the deviation between the predicted values and the actual values, while the mean absolute error provides the linear average of the prediction deviation. The combination of the two can comprehensively evaluate the model accuracy. The specific formulas are as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}}(\mathrm{y_i} - \hat{\mathrm{y}}_{\mathrm{i}})^2}, \quad \mathrm{MAE} = \frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}}|\mathrm{y_i} - \hat{\mathrm{y}}_{\mathrm{i}}|$$

where y_i is the ith observation, $\hat{y}_i$ is the predicted value of the model, and n is the number of samples. After the training is completed, a line chart and a residual distribution chart can be generated to visualize the model performance, facilitate the analysis of error sources and model improvement directions, and provide high-quality input data for transportation and supply chain optimization.

3.2 Transportation and supply chain optimization

3.2.1 Path planning algorithm design

In the transportation link of fresh cut rose in Yunnan, path planning is the core link to reduce transportation carbon emissions. Since fresh-cut roses have high requirements for cold chain transportation, multi-dimensional constraints such as transportation distance, time, vehicle load and temperature control conditions need to be considered. This study constructs an optimization model for the transportation network. Firstly, the transportation nodes, storage locations and distribution terminals were formed into a complete transportation graph structure, with edges representing paths and weights representing transportation costs or carbon emissions. Then, the combination of heuristic algorithm and intelligent optimization algorithm was used for path selection. The heuristic algorithm is used to quickly generate the feasible path candidate set to ensure that the transportation time and temperature control constraints meet the requirements. Intelligent optimization algorithms, such as genetic algorithm, ant colony algorithm or reinforcement learning, find the global optimal solution among the candidate paths to minimize the total transportation carbon emissions. In addition, the dynamic changes of vehicle scheduling and cold chain energy consumption should be considered in the path planning process to realize the collaborative optimization of transportation planning and carbon emission reduction targets. Finally, by comparing the path schemes before and after optimization, the effectiveness of the algorithm in reducing transportation carbon emissions and ensuring the quality of fresh cut rose was verified.

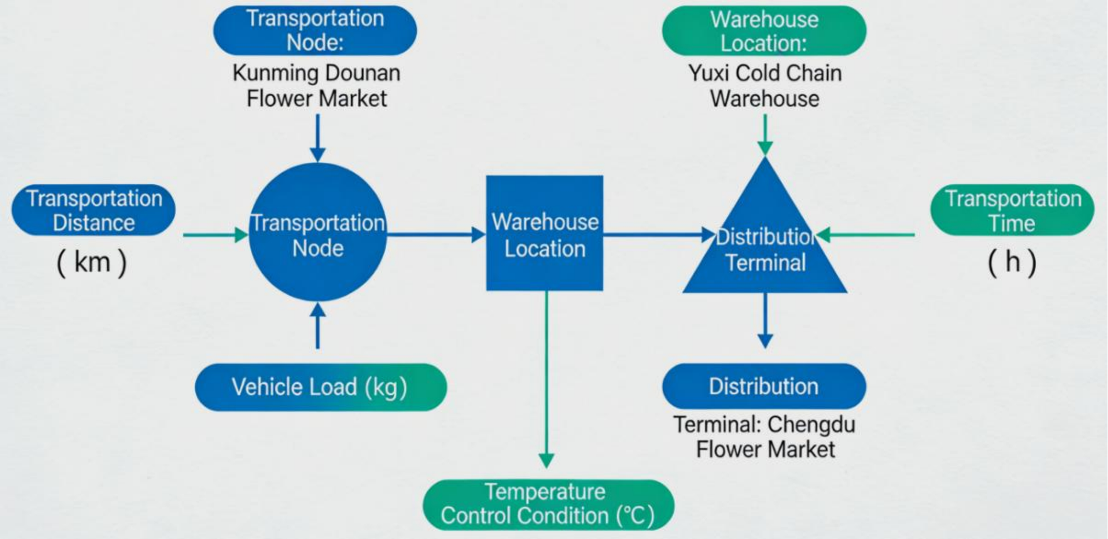

Figure 3: Transportation network path planning

3.2.2 Objective function design of carbon emission minimization

In the transportation link, in order to achieve the carbon emission reduction target of the whole chain, this study establishes a carbon emission minimization objective function, and combines transportation path planning with vehicle scheduling optimization. Based on the transportation distance, vehicle load, cold chain energy consumption and fuel consumption, the objective function calculates the carbon emission contribution of each transportation path and each vehicle, so as to select the optimal solution under the premise of meeting the transportation time and temperature control requirements. Through this objective function, the total carbon emission in the transportation network can be quantified as an optimized index, which provides a clear optimization goal for the path planning algorithm. The objective function is formulated as follows:

$$\min C\,F_{\text{transport}} = \sum_{i,j} E_{ij} \times GWP_j$$

Here, $CF_{\text{transport}}$ is the total transport carbon emissions, E_{ij} is the consumption of the JTH type of energy or fuel used in the ith path, and GWP_j is the global warming potential corresponding to the energy or fuel. The formula not only quantifies the carbon emissions of each route, but also provides accurate evaluation criteria for intelligent optimization algorithms. It can be combined with genetic algorithm, reinforcement learning and other optimization methods to minimize transportation carbon emissions.

3.2.3 Transportation optimization simulation and result analysis

In order to verify the effect of transportation route optimization, this study carried out a simulation test on the transportation network of Yunnan fresh cut rose. In the simulation process, the path scheme before optimization was compared with the optimal path after optimization, considering the transportation distance, vehicle load, cold chain energy consumption and fuel consumption. The carbon emission calculation uses the previously designed transportation carbon emission objective function to quantitatively evaluate each route and vehicle. Through the analysis of the simulation results, it is found that the optimized path can significantly reduce the total carbon emissions while maintaining the transportation time and temperature control requirements. In order to quantify the effect of carbon emission reduction, the formula of carbon emission reduction rate is introduced:

$$\Delta \mathrm{CF} = \mathrm{CF}_{\mathrm{baseline}} - \mathrm{CF}_{\mathrm{optimized}}$$

Here, ΔCF represents the carbon emission reduction, $\mathrm{CF}_{\mathrm{baseline}}$ is the total transportation carbon emission before optimization, and $\mathrm{CF}_{\mathrm{optimized}}$ is the total transportation carbon emission after optimization. By calculating the carbon emission reduction rate, the path optimization effect can be intuitively evaluated, and the decision-making basis for the subsequent supply chain low-carbon strategy can be provided. At the same time, the "carbon emission comparison map of transportation path before and after optimization" and "optimal path heat map" can be generated to intuitively display the optimization effect and carbon emission distribution characteristics, which provides reference for low-carbon management in transportation links.

3.3 AI in concert with blockchain

3.3.1 Transparent tracing mechanism of supply chain

In the whole chain low-carbon management of Yunnan fresh cut rose, the transparent tracking of supply chain is an important link to ensure the verifiability and reliability of carbon emission data. In this paper, blockchain technology is used to construct a distributed ledger, and the carbon emission and energy consumption records of planting, harvesting, processing, transportation and sales are put on the chain, so as to realize data non-tampering and full traceability. Each supply chain node can upload data in real time, including greenhouse energy consumption, fertilizer application, cold chain transportation energy consumption and packaging usage, etc., ensuring that each record corresponds to a functional unit. At the same time, the blockchain system supports multi-party access rights management, so that farmers, enterprises and regulatory authorities can share and supervise data under the premise of ensuring data security. The mechanism not only enhances the transparency of the supply chain, but also provides data support for the implementation of carbon emission reduction policies, and provides a reliable basis for intelligent collaborative governance and low-carbon optimization. Combined with the AI prediction model, the supply chain tracking mechanism can perform real-time carbon emission analysis while uploading data, assist decision makers to optimize production and transportation plans, and achieve the goal of low carbon management of the whole chain.

Figure 4: Blockchain supply chain tracing

3.3.2 Smart contract carbon emission monitoring

In the whole chain low-carbon management, in order to ensure the execution and timely response of carbon emission standards, this paper introduces the smart contract mechanism into the blockchain supply chain system. The smart contract can preset the carbon emission threshold. When the carbon emission data uploaded by any link exceeds the threshold, the system automatically triggers an early warning notice or executes emission reduction measures. This mechanism can realize the automation and real-time of carbon emission monitoring, reduce human intervention, and improve data reliability. Through automatic verification and execution of rules, smart contracts compare carbon emissions of planting, processing, transportation and other links with predetermined targets, and generate operation suggestions or adjustment strategies. The carbon emission trigger determination formula is as follows:

$$\mathrm{Trigger} = \begin{cases} 1, & \text{if } \mathrm{CF_i} > \mathrm{CF_{threshold}} \\ 0, & \text{if } \mathrm{CF_i} \leq \mathrm{CF_{threshold}} \end{cases}$$

Among them, $\mathrm{CF_i}$ is the carbon emission of the ith link, $\mathrm{CF_{threshold}}$ is the preset threshold, Trigger=1 means to Trigger the smart contract execution operation, Trigger=0 means not to trigger. Through this formula, the smart contract can monitor the carbon emissions of each link in real time, and combine with the AI optimization model to realize dynamic regulation and low-carbon control.

3.3.3 Data validation and visual analysis

In the whole chain low-carbon management, in order to ensure the reliability of AI prediction models and blockchain supply chain data, it is necessary to verify and visually analyze uploaded carbon emission data. Data validation includes comparison with measured IoT sensor data, historical emission data, and field sampling results to quantify data bias and identify abnormal records. In order to measure the matching degree between the predicted value and the actual observed value, the Data Consistency Index (DCI) is introduced, which can calculate the error degree of each link and evaluate the overall. The DCI formula is as follows.

$$\mathrm{DCI_i} = 1 - \frac{\left|\mathrm{CF_i^{observed}} - \mathrm{CF_i^{reported}}\right|}{\mathrm{CF_i^{observed}}}$$

Among them, $\mathrm{CF_i^{observed}}$ is the measured carbon emission value of the ith link, $\mathrm{CF_i^{reported}}$ is the uploaded or predicted carbon emission value, and the closer $\mathrm{DCI_i}$ is to 1, the higher data consistency is. Through this index, the accuracy of each link data can be intuitively judged.

4 Smart collaborative governance and ESG low-carbon transformation

4.1 Multi-party collaboration model design

4.1.1 Collaboration mechanism among farmers, enterprises and government

In the low-carbon transformation of the whole chain of fresh cut rose in Yunnan, multi-party cooperation is the key to achieve carbon emission reduction goals and resource optimization. Farmers, enterprises and government play their own roles in the collaborative mechanism. Farmers are responsible for planting management, fertilization, irrigation and greenhouse energy consumption control. The enterprise is responsible for the carbon emission monitoring of processing, packaging and transportation, and coordinates the cold chain logistics and supply chain optimization. The government is responsible for setting low-carbon policy standards, monitoring the implementation of carbon emissions, and guiding all parties to implement low-carbon operations through incentives or subsidies. Through the establishment of information sharing platform, the mechanism integrates the data of each subject, realizes real-time information exchange and decision-making cooperation. Multi-party collaboration can not only improve the controllability of carbon emissions in the whole chain, but also optimize production scheduling, reduce energy waste and carbon emissions, and enhance the participation and responsibility of each subject in the low-carbon strategy. Through practical application, a closed-loop collaboration model of farmers' active emission reduction, enterprises' optimized operation, and government's scientific supervision can be formed, which provides institutional and technical support for ESG low-carbon transformation.

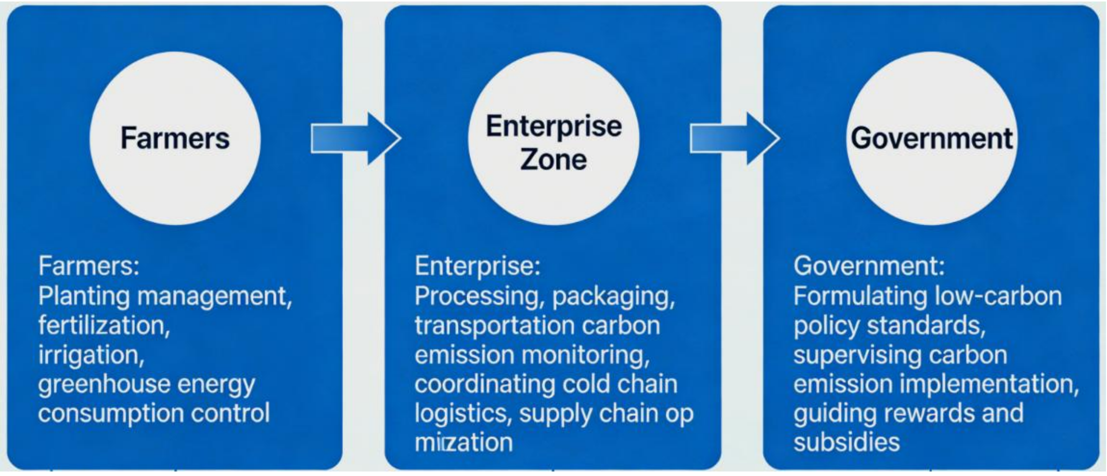

Figure 5: Mechanism of farmer-enterprise-government collaboration

4.1.2 Measurement methods of collaborative governance

In order to quantify the collaborative effect of farmers, enterprises and the government in low-carbon collaborative governance, this study introduced the Coupled Coordination Score (CCS) index to evaluate the degree of collaboration of multi-party carbon emission reduction targets. This index comprehensively considers the emission reduction contribution and weight allocation of each subject, which can intuitively reflect the collaboration efficiency and the overall governance level. In the calculation process, the actual contribution of carbon emission reduction of each subject is compared with its expected contribution, and the weighted average is performed combined with the weight, so as to obtain the collaborative governance degree of the whole chain. The formula is as follows:

$$\mathrm{CCS} = \frac{\sum_{i=1}^{n} S_i \cdot W_i}{\sum_{i=1}^{n} W_i}$$

where S_i is the carbon emission reduction contribution score of the ith agent, W_i is the weight of the agent in collaborative governance, and n is the number of participating agents. The closer CCS is to 1, the more efficient cooperation of each agent is, and the less than 1 indicates that there is room for improvement of cooperation. Through this index, the collaborative governance effect under different policies or technical interventions can be evaluated, and a quantitative basis can be provided for optimizing the low-carbon transition strategy.

4.1.3 Optimization of multi-agent carbon emission reduction strategy

In the low-carbon transformation of the whole chain of fresh cut rose in Yunnan, the multi-agent carbon emission reduction strategy needs to take into account the resource constraints and emission reduction capabilities of farmers, enterprises and the government. In order to minimize the carbon emission of the whole chain, this study constructs a multi-objective optimization model, and integrates the emission reduction contribution, weight and cost factors of each subject into a unified optimization framework. The optimization objective is to maximize the abatement benefit of the whole chain, while ensuring that the production and economic benefits of each subject are not significantly affected. The specific optimization formula is as follows:

$$\max Z = \sum_{i=1}^{n} W_i \cdot R_i$$

where Z is the overall carbon emission reduction benefit, R_i is the carbon emission reduction amount of the ith subject, W_i is the weight of the subject, and n is the number of participating subjects. The formula integrates the contributions of each subject by weighting, so that the optimization results give consideration to both fairness and efficiency. Combined with constraints, such as energy consumption limits, production capacity, and carbon emission reduction caps, the optimal policy can be solved by genetic algorithms, reinforcement learning, or linear programming methods.

4.2 IoT intelligent monitoring and feedback

4.2.1 Carbon emission regulation of real-time fertilization, irrigation and transportation

In the low-carbon transformation of the whole chain of fresh cut rose in Yunnan, the IoT intelligent monitoring system can realize the real-time adjustment of carbon emissions in planting and transportation. By placing sensors in the greenhouse to collect environmental data such as temperature, humidity, light, soil moisture and nutrient content in real time, and monitor the amount of fertilization and irrigation at the same time, the system can automatically adjust the fertilization and irrigation strategy according to the AI prediction model to ensure that carbon emissions are minimized and crop growth conditions are best. In the transportation link, IoT devices monitor the temperature control status, fuel consumption and transportation routes of cold chain vehicles, and adjust the transportation plan through real-time data feedback to avoid redundant trips and energy waste. The whole regulation process is centrally managed through the data platform to realize the dynamic control of carbon emissions in each link. Real-time regulation not only ensures production efficiency and product quality, but also significantly reduces greenhouse gas emissions, providing technical support for multi-agent collaborative governance and ESG low-carbon transformation.

4.2.2 Automatic decision-making mechanisms and feedback loops

In the IoT intelligent monitoring system, an automatic decision-making mechanism and a feedback loop are established to achieve the low carbon goal of planting and transportation. According to the real-time collection of greenhouse environmental data, fertilizer rate, irrigation rate and fuel consumption information of transportation vehicles, combined with the carbon emission data output by the AI prediction model, the system automatically generates operation suggestions. The feedback loop pushes the recommendation results to the farmers and enterprises to realize the dynamic adjustment of fertilization, irrigation and transportation plans. For example, when the greenhouse soil moisture is too high or the amount of fertilizer exceeds a preset threshold, the system automatically prompts to reduce irrigation or adjust the fertilization scheme. In the process of transportation, if the carbon emission of cold chain vehicles exceeds the target range, the system will re-plan the route or adjust the vehicle load. The mechanism ensures that the operation of each link is synchronized with the low-carbon strategy, and improves the data response speed and management efficiency. Through the integration of automatic decision-making and feedback loop, the closed-loop control of carbon emissions can be realized, which provides technical support for multi-agent collaborative governance and ESG low-carbon transformation.

4.2.3 Data visualization and alerting mechanism

In the IoT intelligent monitoring system, in order to ensure the efficiency of low-carbon management of the whole chain of Yunnan fresh cut rose, a data visualization and alarm mechanism is established. The system displays the real-time collected carbon emission data of environment, fertilization, irrigation and transportation through the visualization platform, so that managers can intuitively understand the carbon emission status and resource usage of each link. At the same time, the system sets an alarm threshold, and when the carbon emissions, energy consumption or temperature and humidity index of a link exceed the set range, an early warning notice is automatically triggered, so that regulation measures can be taken immediately. The alarm triggering mechanism can be expressed as follows.

$$\mathrm{Alert_i} = \begin{cases} 1, & \text{if } \mathrm{CF_i} > \mathrm{CF_{limit}} \\ 0, & \text{if } \mathrm{CF_i} \leq \mathrm{CF_{limit}} \end{cases}$$

where, CF_i is the real-time carbon emission of the ith link, CF_{limit} is the preset carbon emission limit of this link, and $Alert_i=1$ means to trigger an alarm. Combined with visual charts, such as the carbon emission heat map of the whole chain and the time series trend chart, the carbon emission dynamics and abnormal conditions of each link can be clearly displayed, which provides a real-time decision-making basis for intelligent collaborative governance.

4.3 ESG-oriented low-carbon strategy

4.3.1 AI precision agriculture reduces fertilizer input

In the low-carbon transformation of fresh cut rose industry in Yunnan, AI precision agriculture technology can effectively optimize the amount of fertilizer application and reduce carbon emissions in planting. By collecting data of greenhouse environment, soil nutrients and crop growth status through IoT sensors, and combining with historical fertilization records, the AI model can predict the actual demand of crops for nutrients such as nitrogen, phosphorus and potassium, so as to dynamically adjust the fertilization rate. This method not only reduces greenhouse gas emissions caused by excessive fertilization, but also improves fertilizer utilization and crop growth efficiency. The specific formula for chemical fertilizer emission reduction is as follows:

$$\mathrm{F_{opt}} = \mathrm{F_{base}} \times (1 - \alpha \cdot \mathrm{R_{pred}})$$

Here, F_{opt} is the optimized fertilization rate, F_{base} is the traditional fertilization rate, α is the reduction coefficient ($0<\alpha<1$), and R_{pred} is the proportion of crop nutrient requirements predicted by AI. Through this formula, the system can adjust the fertilization strategy according to real-time prediction to achieve the balance between low-carbon planting and yield.

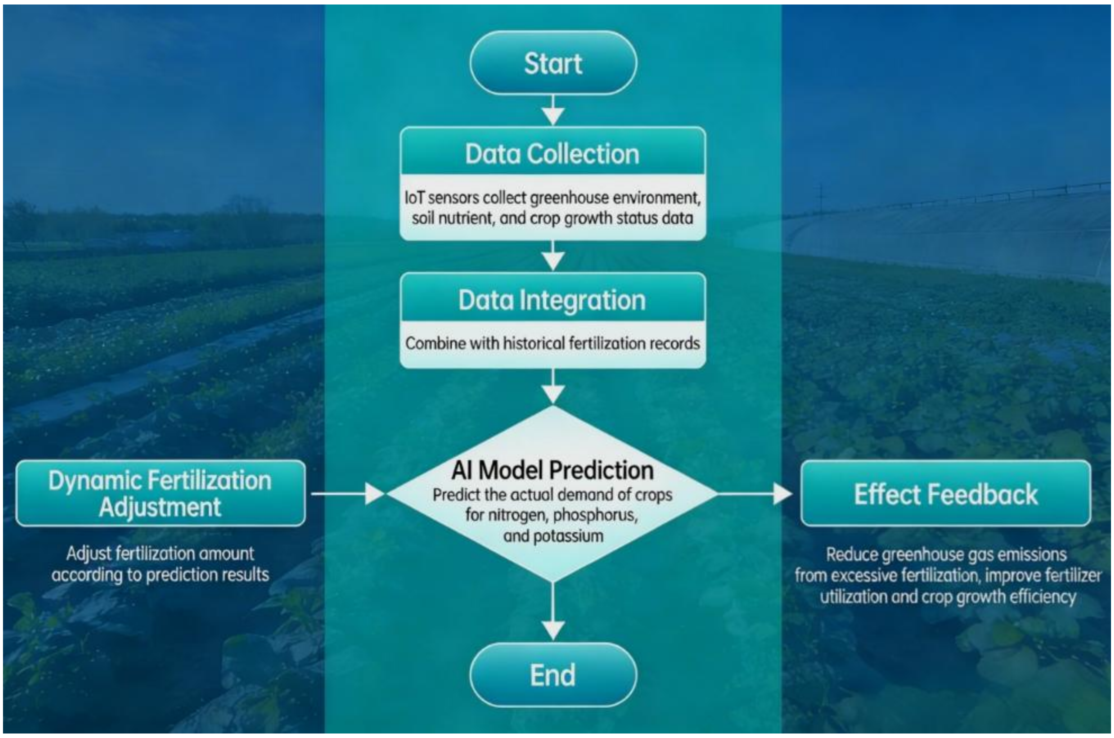

Figure 6: AI precision fertilization optimization process

4.3.2 Renewable energy substitution and carbon emission reduction benefits

In the low-carbon transformation of Yunnan's fresh cut rose industry, the replacement of traditional fossil energy by renewable energy is an important measure to reduce carbon emissions of the whole chain. Clean energy sources such as solar and wind can be introduced into greenhouse heating, power supply and transportation to reduce carbon emission intensity. Carbon abatement benefits are quantified by comparing the carbon emissions before and after substitution. The specific calculation formula is as follows:

$$\Delta \mathrm{CF}_{\mathrm{energy}} = \mathrm{CF}_{\mathrm{conv}} - \mathrm{CF}_{\mathrm{renew}}$$

where $\Delta\mathrm{CF}_{\mathrm{energy}}$ is the carbon emissions saved, $\mathrm{CF}_{\mathrm{conv}}$ is the carbon emissions from using traditional fossil energy, and $\mathrm{CF}_{\mathrm{renew}}$ is the carbon emissions from replacing renewable energy. Through this formula, the contribution of different alternatives to carbon emission reduction can be accurately evaluated and a quantitative basis can be provided for energy substitution decisions. At the same time, it can show the carbon emission reduction effect of different links (greenhouse heating, electricity consumption, transport fuel), intuitively reflect the effectiveness of low-carbon strategies, and provide technical support for ESG low-carbon transformation.

4.3.3 Low-carbon certification system design and market application

In order to promote the low-carbon development of Yunnan fresh cut rose industry, the establishment of a low-carbon certification system can quantify the carbon emissions of each link and give market recognition. The system will be planting, processing, transportation and sales of carbon emissions standardized assessment, according to carbon emission intensity and emission reduction effect grading certification, so as to form a tradeable or market publicity of low carbon product label. At the same time, combined with ESG principles, the certification system not only evaluates environmental performance, but also considers corporate social responsibility and governance efficiency. Through carbon emission monitoring, AI prediction and intelligent collaborative governance data, enterprises can obtain the carbon footprint of each batch of fresh-cut roses, and link it with the market price or subsidy policy to realize low-carbon incentives. The implementation of the system helps to enhance the competitiveness of the product market, promote the optimization of the supply chain, and provide reliable low-carbon information for consumers.

Table 1: Low carbon certification grading standards and market applications

Carbon emission level	Carbon emission range per functional unit (kg CO_2e/ bundle)	Authentication conditions	Market Application Example
A	≤ 1.0	Minimize the carbon emissions of the whole chain and optimize the energy use	High-end market, green label promotion
B	1.0 – 2.0	Carbon emissions are lower than the industry average	Regular market sales, low carbon publicity
C	2.0 – 3.0	Carbon emissions are controllable and meet the basic low carbon requirements	Standard Marketing and sales
D	> 3.0	Carbon emissions are higher than the industry average	Only internal management reference, limit marketing publicity

5 Empirical verification and performance evaluation

5.1 Measured and simulated data

5.1.1 Data collection of major fresh-cut rose bases in Yunnan

In order to verify the effectiveness of AI-driven low-carbon transformation strategy, this study carried out field measurement and data collection in the main fresh-cut rose production base in Yunnan. The collection content covers planting, harvesting, processing and transportation, including greenhouse environmental parameters (temperature, humidity, light), fertilization rate, irrigation rate, energy consumption, transportation route and vehicle fuel use. Through IoT sensors, weather stations and enterprise management records, the data with high spatial and temporal resolution are obtained, and the data are standardized and outliers are removed. The collected data are used to train AI prediction models, simulate transportation optimization schemes, and evaluate the effects of low-carbon strategies, which provide a reliable basis for the quantification of carbon emissions of the whole chain and intelligent collaborative governance. The collected data can be visually displayed through a table, which facilitates the analysis of the differences in carbon emission characteristics and management levels of different bases.

Table 2: The measured data of the South main fresh cut rose base

Name of base	Temperature (℃)	Humidity (%)	Illumination (lux)	Fertilizer application rate (kg/acre)	Irrigation (m^3/ mu)	Electricity Consumption (kWh)	Fuel consumption (L)
Base A	22.5	65	12000	30	8	150	25
Base B	23.1	70	11000	28	7.5	140	22
Base C	21.8	68	11500	32	8.2	155	26
Base D	22.9	66	11800	29	7.8	148	24

5.1.2 Simulation platform and IoT system configuration

In order to evaluate the application effect of AI-driven low-carbon transformation strategy in the whole chain of fresh cut rose in Yunnan, this study built a simulation platform and IoT system. The simulation platform simulates carbon emissions and energy consumption of greenhouse planting, harvesting, processing and transportation, and combines AI prediction models to test different low-carbon strategies. The IoT system includes temperature and humidity sensors, light sensors, soil moisture and nutrient monitoring devices, energy consumption monitoring modules, and transportation vehicle positioning and fuel monitoring devices. Through real-time data acquisition and transmission to the centralized data platform, the dynamic monitoring and analysis of carbon emissions of the whole chain can be realized. The data of the simulation platform and IoT system configuration can be displayed in a table to intuitively reflect various sensor types, monitoring indicators and sampling frequencies, which provides support for experimental design, model training and strategy optimization.

Table 3: Simulation platform and IoT system configuration

System modules	Type of device	Indicators of monitoring	Sampling frequency	Purpose of Data
Greenhouse environment monitoring	Temperature and humidity sensor	Temperature (℃), Humidity (%)	Every 5 minutes	Planting environment monitoring, AI model input
Light monitoring	Light sensor	Light intensity (lux)	Every 10 minutes	Photosynthesis and carbon emission calculation of crops
Soil monitoring	Soil moisture/nutrient sensors	Water (m^3/ mu), NPK content (%)	Per hour	Precision fertilization and irrigation strategy optimization
Energy consumption monitoring	Electricity meter, energy meter	Electricity (kWh), fuel (L)	Every 15 minutes	Carbon Emissions Calculation and Energy Optimization
Transportation control	GPS+ fuel sensor	Vehicle location, fuel consumption (L)	Real time	Route optimization, transportation carbon emission monitoring

5.1.3 Data preprocessing and model input design

On the basis of raw data collected by simulation platforms and IoT systems, data preprocessing is required to ensure the accuracy of AI model training and simulation analysis. Preprocessing includes data cleaning, missing value imputation, outlier removal, and standardization processing to unify data from different sources and dimensions to a comparable scale. Indicators such as greenhouse environmental data, fertilization and irrigation amount, soil nutrients and transportation energy consumption were normalized or standardized to form high-quality feature vectors. Then, according to the model requirements, the data is divided into training set, validation set and test set to ensure that the model can capture the law of carbon emission of the whole chain and take into account the generalization ability. The final processed data is used as a functional unit to construct the input matrix of the AI model, and the input parameter set for transportation optimization and low-carbon strategy evaluation is generated, which provides a comprehensive and reliable data basis for model training and simulation.

5.2 Design of model performance indicators

5.2.1 Prediction accuracy index

In order to evaluate the performance of the AI prediction model in the carbon emissions of the whole chain of Yunnan fresh-cut roses, this paper uses a variety of prediction accuracy indicators, including root mean square error (RMSE), Mean absolute error (MAE) and coefficient of determination (R^2). RMSE is used to measure the squared average deviation of the predicted value from the actual observed value, MAE is used to reflect the absolute mean of the predicted deviation, and r-squared is used to assess the ability of the model to explain the variance of the data. Through these indicators, the prediction accuracy of the model in planting, transportation and processing can be comprehensively evaluated, and used for performance comparison and optimization selection between different models. The data can visually display the prediction effects of different models in each link through the form of tables, which provides a quantitative basis for model optimization and low-carbon strategy adjustment.

Table 4: Prediction model accuracy indicators

Model types	RMSE of planting link	Planting link MAE	The planting link R squared	RMSE of transportation link	Transportation link MAE	The transportation link R squared
Random forest	0.45	0.32	0.87	0.50	0.35	0.85
GBDT	0.42	0.30	0.89	0.48	0.33	0.86
LSTM	0.38	0.28	0.91	0.44	0.31	0.88

5.2.2 Evaluation of collaborative governance efficiency

In order to evaluate the collaborative effect of farmers, enterprises and the government in the low-carbon transformation of the whole chain of fresh cut rose in Yunnan, this paper designed a collaborative governance efficiency index. This index comprehensively considers the contribution of each agent in terms of carbon reduction, resource use and information sharing, and obtains the overall collaboration level by weighted calculation. The higher the index, the more efficient the multi-agent collaboration in production, transportation and implementation of low-carbon strategies, which can be used to compare the governance effects in different bases or under different policy conditions. The evaluation results of collaborative governance efficiency can be displayed in a table, which not only reflects the overall level of collaboration, but also visually displays the contribution differences of each subject, providing a basis for optimizing low-carbon collaborative strategies.

Table 5: Evaluation of collaborative governance efficiency

Base/Experimental group	Contribution of farmers (%)	Enterprise Contribution (%)	Government contribution (%)	Collaborative governance efficiency CCS
Base A	35	40	25	0.88
Base B	30	45	25	0.85
Base C	33	42	25	0.87
Base D	36	38	26	0.86

5.2.3 Visual analysis of indicators

In order to visually show the effect of low-carbon transformation of the whole chain of fresh cut rose in Yunnan, this study visually analyzed the prediction accuracy indicators and collaborative governance efficiency indicators. By quantifying the carbon emission prediction error (RMSE, MAE) and collaborative governance efficiency (CCS) of each link in a unified way, heat charts and line charts can be generated to visually present the performance of different bases or experimental groups. At the same time, the Composite Performance Index (CPI) index is introduced to combine the prediction accuracy and collaborative governance efficiency for the overall effect evaluation, and its calculation formula is as follows:

$$\mathrm{CPI} = \frac{\sum_{i=1}^{n} W_i \cdot \mathrm{KPI}_i}{\sum_{i=1}^{n} W_i}$$

where KPI_i is the ith performance index (such as RMSE, MAE, CCS), W_i is the weight of each index, and n is the number of indicators. Higher CPI values indicate better overall performance.

5.3 Comparative experiment and result analysis

5.3.1 Comparison between traditional methods and AI+LCA+ collaborative governance methods

In order to evaluate the effect of AI-driven low-carbon transformation programs, this study compares the traditional management approach with the AI+LCA+ smart collaborative governance approach. The experimental data cover the carbon emissions of planting, transportation and processing. The comparison results show that the carbon emissions of the traditional method are higher in all links, especially in the links of greenhouse fertilization, irrigation and cold chain transportation, and the proportion of its emissions in the total carbon emissions is significantly higher than that of the optimization scheme. The AI+LCA+ collaborative governance method effectively reduces the carbon emissions of the whole chain and improves the collaboration efficiency through accurate prediction, path optimization and multi-agent collaborative management.

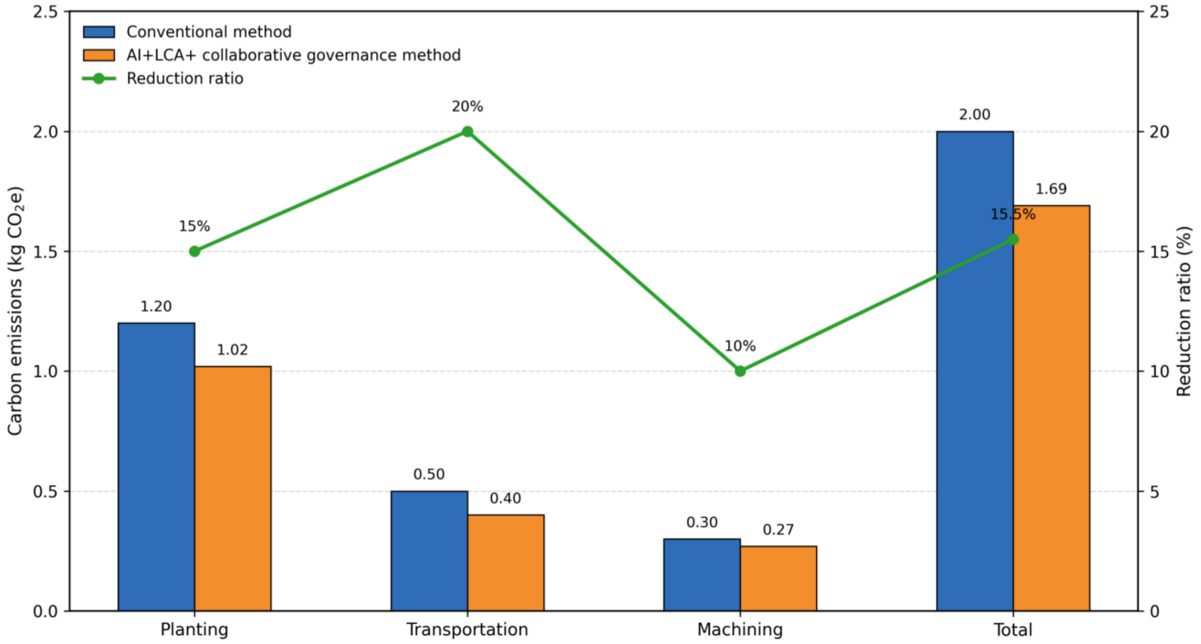

Figure 7: Comparison of carbon emissions between traditional method and AI+LCA+ collaborative governance method

It can be observed from the bar chart that the optimization method reduces carbon emissions in the planting link by about 15%, the transportation link by about 20%, and the processing link by about 10%, indicating that AI prediction and collaborative governance have a significant effect on carbon emission reduction of the whole chain. The overall decline trend of carbon emissions intuitively reflects the effectiveness of the intelligent low-carbon strategy, which provides data support and decision-making basis for further promotion.

5.3.2 Analysis of carbon emission reduction effect of each link

In order to intuitively show the carbon emission reduction effect of each link, this study compares and analyzes the carbon emissions of planting, transportation and processing links under the traditional method and the AI+LCA+ collaborative governance method. The line chart can clearly show the emission reduction trend and optimization range of each link. The data show that the AI+LCA+ collaborative governance method reduces carbon emissions by about 0.18 kg CO_2e/ bundle in the planting link, about 0.10 kg CO_2e/ bundle in the transportation link, and about 0.03 kg CO_2e/ bundle in the processing link, indicating that the optimization method has a more significant effect in the high emission link.

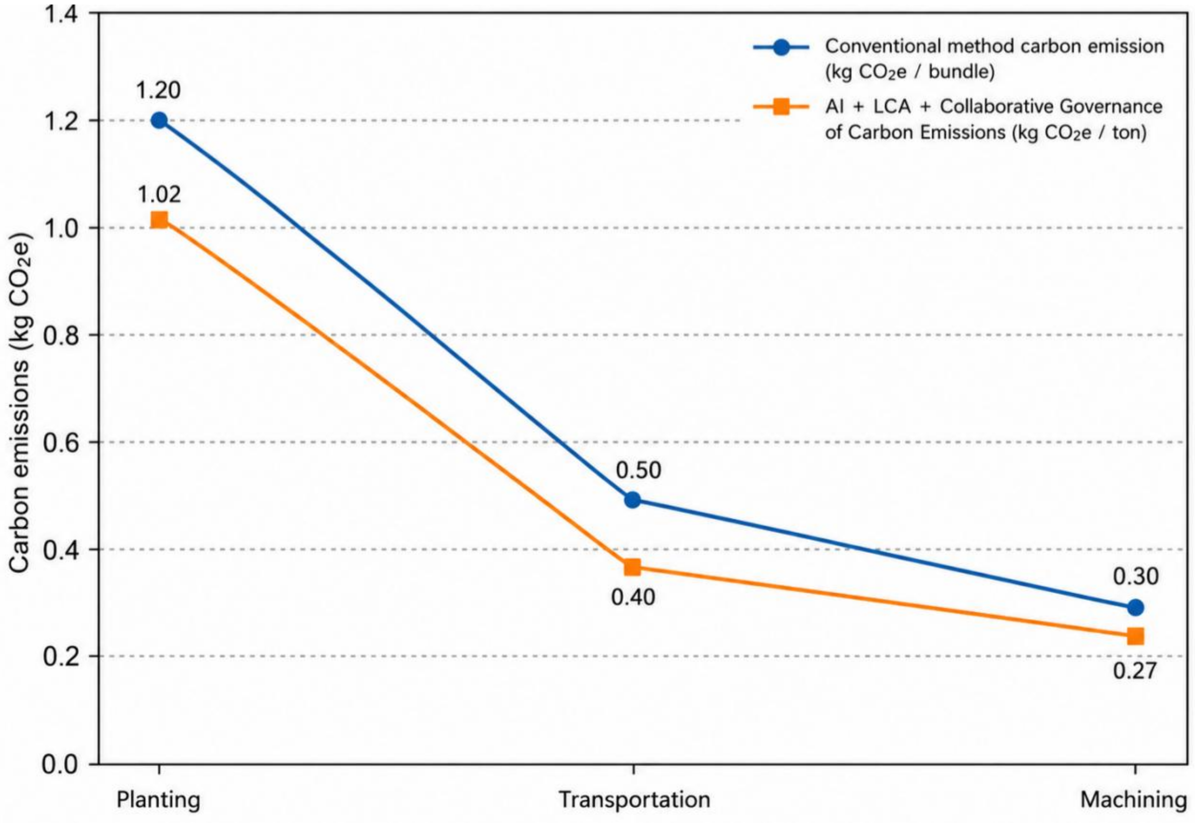

Figure 8: Carbon emission reduction effect of each link

From the line chart, it can be seen that the optimization method has the largest emission reduction in planting and transportation, mainly benefiting from AI precision fertilization irrigation, path optimization, and multi-agent collaborative governance. The emission reduction range of the processing link is relatively small, but the overall carbon emission of the whole chain decreases significantly, which verifies the effectiveness of AI+LCA+ collaborative governance in low-carbon transformation, and provides a basis for further promotion and strategy optimization.

5.3.3 Sensitivity analysis and robustness verification

In order to evaluate the stability and adaptability of AI+LCA+ collaborative governance scheme in the low-carbon transformation of the whole chain of fresh cut rose in Yunnan, this study carried out sensitivity analysis and robustness verification. The sensitivity analysis mainly focused on the key input variables, including greenhouse temperature, soil nutrients, fertilizer application rate, irrigation amount and transportation route, etc., by adjusting the range of ±10% to 20% of each variable, the impact of the change of carbon emissions of the whole chain on the model prediction and optimization results was observed. The results showed that the carbon emission of planting link was most sensitive to the changes of fertilizer application rate and soil nutrients, while the transportation link was sensitive to the changes of route and vehicle load, indicating that the optimization strategy should focus on the highly sensitive link. The robustness verification is performed by introducing different noise levels and abnormal data scenarios to test the performance of the AI prediction model and collaborative governance scheme under non-ideal conditions. The experimental results show that the optimization method can still maintain the overall downward trend of carbon emissions under the input disturbance, and the model prediction error increases slightly, but the impact on the whole chain emission reduction effect is limited, which proves that the strategy has strong robustness.

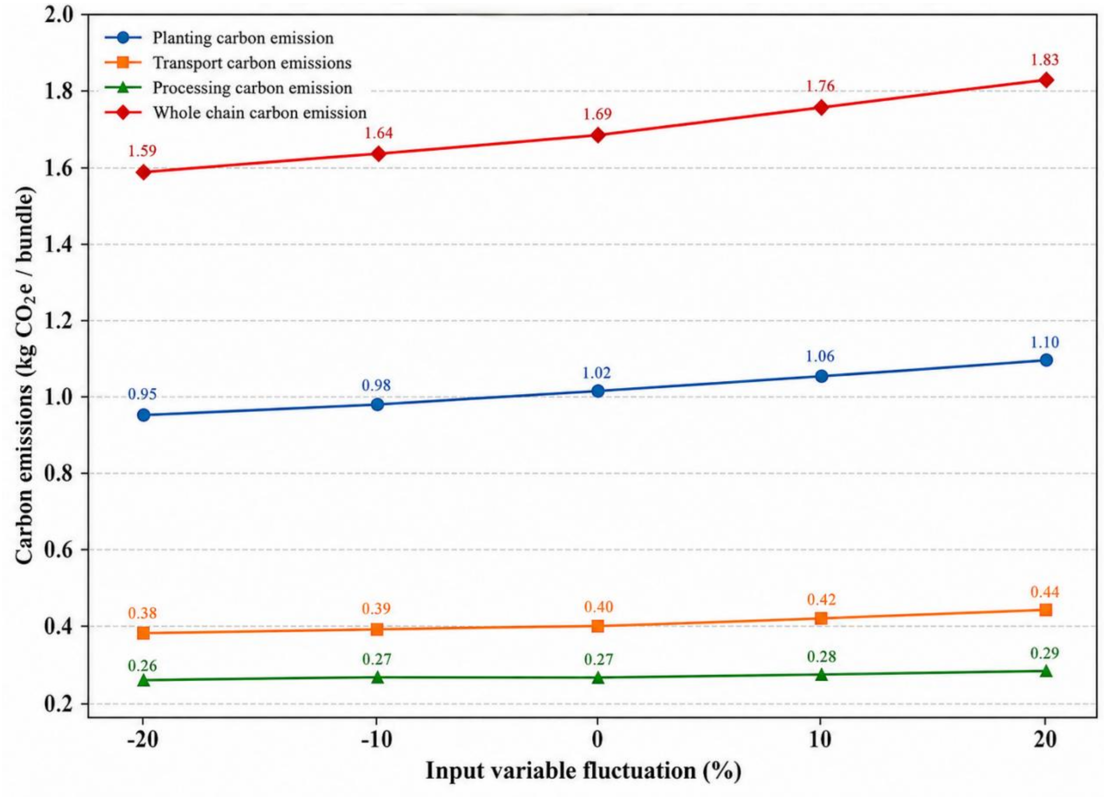

Figure 9: Sensitivity analysis and robustness verification

The line chart shows that the fertilization rate and soil nutrients in the planting link have the greatest impact on the change of carbon emissions, the transportation link is significantly affected by the change of path and load, and the processing link is relatively stable. Even when the input variables fluctuate and are abnormal, the AI+LCA+ collaborative governance scheme can still maintain the overall emission reduction effect, which verifies the stability and adaptability of the strategy and provides a reliable basis for the actual promotion. The line chart intuitively presents the sensitivity differences of each link and the overall robustness, which provides a scientific basis for further optimizing the low-carbon strategy.

6 Conclusions

Based on AI, LCA and intelligent collaborative governance methods, this study systematically studied the low-carbon transformation path of the whole chain of fresh cut rose in Yunnan. Firstly, through the whole chain life cycle analysis (LCA), the carbon emissions of planting, harvesting, processing, transportation and sales were quantified, and the key links of carbon emissions and reduction potential were clarified, which provided a data basis for optimization strategies. The measured data and simulation platform show that the fertilization and irrigation operation and greenhouse energy consumption in the planting link are the main sources of carbon emissions, and the cold chain logistics and route selection in the transportation link also have a significant impact on the carbon footprint of the whole chain. Through the standardization, cleaning and preprocessing of data, high-quality model input is constructed, which provides reliable support for AI prediction and optimization.

Secondly, the introduction of AI prediction model can effectively identify the dynamic change law of carbon emissions. In the planting stage, the greenhouse environment, soil and management measures are predicted by random forest, GBDT and LSTM models to achieve accurate estimation of carbon emissions, and the prediction accuracy of the model is verified by RMSE, MAE and R-² indicators. In the transportation link, the path planning algorithm combined with the carbon emission minimization objective function to optimize the transportation route. The simulation results show that the carbon emission of the whole chain is significantly reduced. At the same time, the application of smart contract and blockchain technology in the transparency and real-time monitoring of supply chain ensures the non-tampering and traceability of carbon emission data, and improves the reliability of decision-making through data verification and visual analysis.

Furthermore, the intelligent collaborative governance and ESG oriented strategy realize the closed-loop control of low-carbon management of the whole chain. The multi-agent collaboration model clarified the responsibility division among farmers, enterprises and government in carbon emission reduction, quantified the collaboration efficiency through Collaborative governance metrics (CCS), and proposed the emission reduction strategy allocation scheme based on the multi-agent optimization model. AI precision agriculture technology optimizes fertilization and irrigation to reduce greenhouse emissions; Renewable energy alternatives reduce the carbon footprint of energy consumption; The low-carbon certification system provides the market with quantitative and tradable low-carbon information, and improves the competitiveness and sustainable development level of the industry. Through sensitivity analysis and robustness verification, it is proved that the proposed method can still maintain significant emission reduction effect in the case of input variable disturbance and anomaly, which shows the stability and adaptability of the strategy.

In summary, AI+LCA+ intelligent collaborative governance provides a systematic and operational technical path for the low-carbon transformation of the whole chain of Yunnan fresh cut rose. The research not only quantifies the carbon emissions of each link and verifies the effectiveness of the optimization strategy, but also puts forward an intelligent low-carbon management scheme that can be applied in actual production and market promotion. In the future, this method can be extended to the whole chain low-carbon management of other high-value agricultural products, providing reference and technical support for the green development of agricultural industry and the implementation of ESG strategy.

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About the Author

Ni Li was born in Chuxiong, Yunnan. P.R. China, in 1995. She received the doctor's degree from Faculty of Logistics and Digital Supply Chain at Naresuan University in Thailand, in 2025. She has currently working at the Guangdong-Hongkong-Macao Greater Bay Area College of Intelligent Cold-Chain Industries, Guangzhou College of Technology and Business in Guangdong, China. Her research include agricultural cold chain, Low-Carbon Sustainable Development, digital transformation and supply chain management. Her experience also included the cross-border trade and logistics in term of operation. Email: lini@gzgs.edu.cn

Xijia He was born in Maoming, Guangdong. P.R. China, in 1983. He obtained a doctor's degree from Naresuan University in Thailand. He has currently working at the School of

Information and Management, Guangxi Medical University. His main research direction is Applications of Big Data Science in Supply Chain Management for Healthcare, Agricultural Products and Other Fields. Email: hxj@gxmu.edu.cn

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