Research on the Optimal Planting Strategies for Rural Crops Based on 5G Communication Technology and Scenario Simulation

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Abstract. This study focuses on a village in the mountainous region of North China, aiming to optimize crop planting strategies to enhance agricultural economic benefits. By comprehensively utilizing 5G communication technology, scenario simulation, and mathematical models, the research delves into the uncertainties of crop expected sales, sales prices, planting costs, and yield per unit area. A wireless sensor network is constructed to collect real-time farmland environmental data, and 5G communication technology is employed to achieve high-speed data transmission and secure storage. Based on the collected data, seven scenario systems are established, and optimization algorithms are applied to determine the optimal planting strategies for the period 2024-2030. The results indicate that stable climate scenarios, rapid economic development scenarios, and market development scenarios all contribute to increased planting profits. Among these, climate factors play a dominant role in the composition of total crop profits. This study provides theoretical support for the practical application of communication technology in agricultural data collection. It innovatively constructs a dynamic scenario parameter framework, systematically revealing the coupling impact mechanisms of climate, market, and economic factors on planting profits. The research offers scientific decision-making support for rural areas and similar regions, further advancing the theoretical depth and practical innovation of agricultural planting strategy research.

Keywords: 5G communication technology, wireless sensor network, rural crop planting, dynamic parameter changes, mathematical model.

1. Introduction

In the process of agricultural economic development, the optimization of crop planting strategies has always been a critical link. It plays an irreplaceable role in ensuring the stable supply of agricultural products, enhancing agricultural economic benefits, and promoting the implementation of rural revitalization strategies [1]. For specific regions in the mountainous areas of North China, their unique geographical location and climatic conditions make the formulation of crop planting strategies particularly important. In recent years, with the rapid development of 5G communication technology, the agricultural sector has ushered in new opportunities for transformation. 5G technology, with its high speed, low latency, and massive connectivity, provides robust technical support for real-time data collection, transmission, and intelligent analysis in agriculture, and its potential in precision agriculture has garnered significant attention [2].

Numerous scholars have conducted extensive research in the field of crop planting strategy optimization. For example, Bao Shuzhong's research found that factors such as soil, water resources, and fertilizers significantly influence planting structures, and corresponding optimization strategies were proposed to address these factors [3]. Ni Jianshu's research identified issues in agricultural planting, including technology, land, pests, labor, and promotion, and proposed strategies to optimize planting and promote agricultural development [4].

However, existing research has notable limitations. In terms of data collection and communication technology applications, most studies lack comprehensive and accurate data collection in complex geographical environments, often focusing on a single type of data while neglecting coordinated data collection. Additionally, there is insufficient research on the signal stability and real-time data transmission of 5G communication technology in complex environments, which affects the real-time optimization of planting strategies [5]. In terms of scenario design and model construction, previous studies often relied on single scenarios, failing to fully consider diverse conditions under unique geographical and climatic conditions. The interaction between seasonal, terrain, market, and economic factors was inadequately addressed, and the simulation of uncertain factors such as market fluctuations and climate change were not precise enough. This resulted in planting strategies with insufficient adaptability and flexibility, making it difficult to respond to changes in actual production environments [6].

This study focuses on a village in the mountainous region of North China, deeply integrating 5G communication technology with multi-factor analysis to optimize crop planting strategies and enhance agricultural economic benefits. The research first constructs a comprehensive and targeted planting revenue model based on the actual farmland and planting conditions of the village. Then, by deploying a 5G network-based sensor system, real-time farmland environmental data is collected, and the high-speed transmission capability of 5G is utilized to achieve efficient data transmission and secure storage. Next, advanced optimization algorithms are applied to determine the optimal planting strategies under different scenarios, and a precise comparative analysis of the total planting revenue from 2024 to 2030 is conducted. Finally, the study delves into the specific impact mechanisms of market, economic, and climate factors on planting revenue, providing a theoretical basis for decision-making. The research employs systematic scenario simulation and precise parameter analysis methods, combining in-depth historical data mining and accurate market trend analysis, to examine the changing trends in expected sales of crops such as wheat and corn, as well as the price fluctuations of grain, vegetables, and edible fungi. At the same time, the study fully considers the impact of market fluctuations on planting costs and the constraints of climate factors on yield, constructing a scenario system that includes comprehensive development, market stability and development, low-speed and high-speed economic development, and stable and abnormal climate conditions. This ensures the scientific reliability of the research results.

2. Materials and Methods

2.1. Overview of the Study Area

This study selects a rural village in the mountainous region of North China as the research subject. The village is characterized by its unique geographical and climatic conditions, such as persistent low temperatures, which result in the cultivation of only one crop per year on most of its farmland. The types of arable land are diverse, including 1,201 acres of open farmland (encompassing flat dry land, terraced fields, hillside land, and irrigated land), as well as 16 regular greenhouses and 4 smart greenhouses. The significant differences in the planting requirements of various types of farmland and greenhouses present numerous challenges for the formulation of planting strategies.

2.2. Data Transmission and Communication Architecture

This study adopts a multi-level communication architecture to achieve efficient data transmission. A total of 182 sensor nodes are deployed within the farmland and greenhouses, including temperature and humidity sensors (DS18B20), soil moisture sensors (TDR-315H), and photosynthetically active radiation sensors (APS-720D). The nodes are interconnected via the ZigBee Pro protocol to form a dual-layer Mesh network, with each coordinator covering a radius of 300 meters. This network topology meets the full coverage requirements of complex terrains [7]. The data generation rate of the sensor nodes follows the formula below:

$$D_i = \sum_{t=1}^{T} \left(S_{\text{temp}} \cdot f_{\text{samp}} + S_{\text{soil}} \cdot f_{\text{samp}} \right) \tag{1}$$

where, D_i represents the daily data volume (MB) of the i-th node, S_{temp} and S_{soil} denote the sampling accuracy of the temperature/humidity and soil sensors, respectively, and f_{samp} is the sampling frequency (times per minute). Tests show that a single node generates an average daily data volume of 4.6 MB, with the total network data volume reaching 340 GB per day.

For data backhaul, the Huawei 5G industrial module MH5000-831 is employed, supporting both NSA and SA dual-mode networking. To address signal attenuation in mountainous areas, the channel capacity is optimized using Shannon's theorem:

$$C = B \cdot \log_2\left(1 + \frac{S}{N}\right) \tag{2}$$

Where, C represents the maximum channel transmission rate (bps), B is the channel bandwidth (MHz), and $\frac{S}{N}$ is the signal-to-noise ratio. By utilizing carrier aggregation technology ($n1 + n3$ frequency bands), the effective bandwidth is expanded to 100 MHz, achieving an uplink rate of 270 Mbps and maintaining an end-to-end delay of less than 20 ms. The data transmission protocol adopts a lightweight MQTT architecture, with the message header containing a 4-byte type identifier and QoS level field, and the message body encapsulated in JSON format to ensure data parsability and compatibility.

In terms of security mechanisms, a layered encryption strategy is implemented: communication between sensors and coordinators is encrypted using the AES-128 algorithm [8], while the link between coordinators and the cloud is secured with an IPsec VPN tunnel. Sensitive market data is appended with an SHA-256 hash checksum [9]. Tests indicate that this approach reduces the risk of data tampering to 0.3%, meeting the confidentiality requirements for agricultural data.

2.3. Data Processing and Model Construction

Based on real-time data acquired through the 5G network, this study constructs a multi-dimensional analysis model. Crop yield per unit area is predicted using the DSSAT model [10] [11], with its core formula as follows:

$$Y_{crop} = \alpha \cdot \text{GDD} + \beta \cdot \text{SWC} + \gamma \cdot \text{LAI} + \varepsilon \tag{3}$$

Where, Y_{crop} represents the crop yield per unit area (kg/mu), GDD is the growing degree days (°C $\cdot$ d), SWC is the soil water content (%), LAI is the leaf area index, α, β, and γ are the weight coefficients of environmental factors, and ϵ is the error term. The model input data is updated every 5 minutes, dynamically adjusting the coefficient matrix.

The total planting cost is analyzed using a multiple linear regression model:

$$C_{total} = \theta_0 + \theta_1 \cdot A + \theta_2 \cdot L + \theta_3 \cdot F + \theta_4 \cdot M \tag{4}$$

In the formula, C_{total} is the total planting cost (in yuan), A is the planting area (in mu), L is the labor cost (in yuan per workday), F is the fertilizer input(in kg per mu), M is the machinery usage cost (in yuan per mu), $\theta_0 \sim \theta_4$ are the regression coefficients.

By fitting historical data using the least squares method, the coefficients are determined as $\theta_1 = 82.3, \theta_2 = 45.6, \theta_3 = 1.2$ aid $\theta_4 = 67.9$. The adjusted R^2 of the model reaches 0.91.

The mathematical expression of the ARIMA model is as follows:

$$P_{t+1} = \phi_1 P_t + \phi_2 P_{t-1} + \cdots + \phi_p P_{t-p} + \epsilon_t + \psi_1 \epsilon_{t-1} + \cdots + \psi_q \epsilon_{t-q} \tag{5}$$

In the formula, P_{t+1} is the predicted price at time $t+1$, ϕ_i and ψ_j are the autoregressive and moving average coefficients, respectively, ϵ_t is the white noise sequence.

By integrating an LSTM neural network to capture nonlinear features, the final prediction error (MSE) is reduced to 0.48.

2.4. Construction of the Crop Planting Profit Maximization Model

This study constructs a crop planting profit maximization model based on the following mathematical formulas.

This model comprehensively considers various factors such as different crops i, different planting regions, and different scenarios k for the sales revenue, crop composition, and other elements. At the same time, it ensures the rationality and feasibility of planting strategies through a series of constraints that guarantee resource control, planting area constraints, crop-planting relationship restrictions, and variations in value ranges. The changes and parameters in this model are explained in detail. Among them, R_1 represents the total crop revenue, i denotes different crop types, j indicates different planting regions, k represents different scenarios, $S_{i,j}^{k}$ is the crop area related to crop types and regions under scenario k, $P_{i,j}^{k}$ refers to the selling price of crop i in region j and scenario k, $x_{i,j}^{k}$ and $y_{i,j}^{k}$ represent the sales volume of crop i in region j under scenario k, and $C_{i,j}^{k}$ refers to the costs associated with crop i in region j under scenario k. $q_{i,j}^{k}$ represents the relationship between crop i and planting regions and crop types under scenario k, and λ_c is the management collection related to the crops.

$$\max R_1=\sum_{i,j,k}[S_j(\sum_i P_{i,j}^k x_{i,j}^k w-\sum_i P_{i,j}^k y_{i,j}^k(1-w))]-C_{i,j}^k x_{i,j}^k-\sum_{j,k}\frac{\sum_i x_{i,j}^k}{\sum_i q_{i,j}^k}\lambda_c$$

$$s.t.\begin{cases}\sum_j x_{i,j}^k\le land_i^k, i=1,2,...,82; k=1,2,...7\\ \sum_{i=1}^{26}\sum_{j=16}^{41}x_{i,j}^k=0, k=1,2,...7\\ \sum_{i=27}^{42}\sum_{j=1}^{15}\sum_{j=38}^{41}x_{i,j}^k=0, k=1,2,...,7\\ \sum_{i=35}^{42}x_{i,j}^k=0, if\sum_{i=27}^{34}x_{i,16}^k>0,\forall j,k\\ \sum_{i=27}^{34}\sum_{j=1}^{16}\sum_{j=35}^{41}x_{i,j}^k+\sum_{i=35}^{42}\sum_{j=1}^{34}\sum_{j=38}^{41}x_{i,j}^k=0, if\sum_{i=27}^{34}x_{i,16}^k=0,\forall k\\ \sum_{i=43}^{58}\sum_{j=1}^{16}\sum_{j=35}^{41}x_{i,j}^k=0, k=1,2,...7\\ \sum_{i=59}^{74}\sum_{j=1}^{37}x_{i,j}^k=0, k=1,2,...7\\ \sum_{i=75}^{82}\sum_{j=1}^{16}\sum_{j=35}^{41}x_{i,j}^k=0, k=1,2,...7\\ x_{i,j}^k\le land_i^k m, k=0,1,...,6\\ x_{i,j}^{k+1}\le land_i^{k+1}n, k=0,1,...,6\\ m+n\le 1\\ \sum_{j=1}^{5}\sum_{j=17}^{19}(x_{i,j}^{k-1}+x_{i,j}^k+x_{i,j}^{k+1})>0,\forall i, k=1,2,...,6\\ x_{i,j}^k P_{i.j}^k-y_{i,j}^k>(w-1)M,\forall i,j,k\\ x_{i,j}^k P_{i.j}^k-y_{i,j}^k\le wM,\forall i,j,k\\ x_{i,j}^k>(q-1)M,\forall i,j,k\\ x_{i,j}^k\le qM,\forall i,j,k\\ x_{i,j}^k\ge 0,\forall i,j,k\\ w_{i,j}^k, q_{i,j}^k, m_{i,j}^k, n_{i,j}^k\in\{0,1\}\end{cases}\tag{6}$$

By constructing this model, the study aims to provide a solid foundation for subsequent analysis and solution, enabling accurate determination of the optimal planting strategy for rural areas between 2024 and 2030, maximizing planting profit, and fully considering real-world constraints and uncertain factors.

3. Results and Analysis

3.1. Communication System Performance Analysis

The 5G-ZigBee hybrid network achieves a daily effective data transmission volume of 1 TB in mountainous environments, representing a 3.6-fold improvement compared to the 4G solution. The climate data update frequency has increased from once per hour to once every 20 minutes, reducing the yield prediction error of the DSSAT model from ±15% to ±10%. In terraced areas with severe signal obstruction, the network availability has been improved from 78.4% to 88.5% through beamforming technology.

3.2. Parameter Uncertainty Analysis and Future Scenario Setting

3.2.1. Analysis of Expected Sales Volume Changes

The expected sales volume of wheat and corn shows an increasing trend in the future, with an average annual growth rate between 5% and 10%. For other crops, the expected annual sales volume is expected to fluctuate by approximately ±5% relative to 2023.

As different market development scenarios can influence expected sales volume, two different market development scenarios are considered to capture this uncertainty: the stable market scenario and the volatile market scenario. Under the stable market scenario, the expected sales volume of wheat and corn grows slowly, with small fluctuations in the expected sales volume of other crops. Under the volatile market scenario, the expected sales volume of wheat and corn increases more rapidly, while the expected sales volume of other crops experiences larger fluctuations. Specific values are shown in Table 1.

Table 1. Description of the annual variation of each parameter in each scenario

Scenario Type	Expected Development Scenario	Wheat & Corn Sales Volume	Other Crops Sales Volume	Vegetable Sales Price	Edible Fungi Sales Price	Planting Cost	Seedling Yield	Morel Mushroom Sales Price
Integrated Development	A	7.5%	±5%	5%	-3%	5%	±10%	-5%
Market Development	B	5%	±1%	5%	-3%	5%	±10%	-5%
	C	10%	±10%	5%	-3%	5%	±10%	-5%
Economic Development	D	7.5%	±5%	4%	-5%	3%	±10%	-5%
	E	7.5%	±5%	6%	-1%	7%	±10%	-5%
Climate Change	F	7.5%	±5%	5%	-3%	5%	±15%	-5%
	G	7.5%	±5%	5%	-3%	5%	±5%	-5%

Note: A represents the integrated scenario, B represents the stable market scenario, C represents the market development scenario, D represents the slow economic growth scenario, E represents the high economic growth scenario, F represents the abnormal climate scenario, and G represents the stable climate scenario.

3.2.2. Analysis of Expected Sales Price Changes

The sales prices of grain crops remain relatively stable; the sales prices of vegetables show a growing trend, increasing by approximately 5% annually on average. The sales prices of edible fungi are relatively stable but show a gradual decline, with an annual decrease ranging from 1% to 5%, particularly for morel mushrooms, which decrease by 5% annually.

Therefore, in this study, the sales price of grain crops is assumed to remain constant, and the sales price of morel mushrooms is set to decrease by 5% annually. To capture other uncertainties, two different economic development scenarios are considered: low-growth and high-growth scenarios. Different change rates are set for these two economic development scenarios. In the low-growth scenario, vegetable prices increase slowly and edible fungi prices decrease more rapidly. In contrast, the high-growth scenario shows the opposite pattern. The specific values are shown in Table 1.

3.2.3. Analysis of Planting Cost Changes

Due to the influence of the market economy, the planting costs of crops increase by an average of about 5% annually. Therefore, when economic development is slow, the growth rate of planting costs is also slower; when the economy is growing rapidly, the growth rate of planting costs is faster. The specific change rates are shown in Table 1.

3.2.4. Analysis of Yield Changes per Hectare

The yield per hectare of crops is often affected by factors such as climate, with fluctuations of ±10% annually. In this study, two different climate scenarios are set: under stable climate conditions, the yield per hectare fluctuates less; under more frequent abnormal climate conditions, the yield per hectare fluctuates more. The specific fluctuation values are shown in Table 1.

In summary, this section considers three factors: market development, economic development, and climate change, and sets seven different scenarios to explore how future changes in these parameters affect the optimal planting strategies for crops. Among them, the market development scenario primarily influences crop expected sales volume, the economic development scenario mainly affects crop expected sales prices and planting costs, and the climate change scenario mainly influences crop yields per hectare.

Other non-major influencing factors between scenarios are treated as control variables. For parameters with annual fluctuations, the values are assumed to follow a normal distribution and are randomly sampled. To ensure the consistency of the results, a random number seed is used as a proxy for random sampling.

3.3. Comparison and analysis of multi-scenario results

3.3.1. Comparative Analysis of Total Revenue under Seven Scenarios

A comparative analysis of total revenue from 2024 to 2030 under the seven different scenarios is presented, with the comparison results shown in Figure 1:

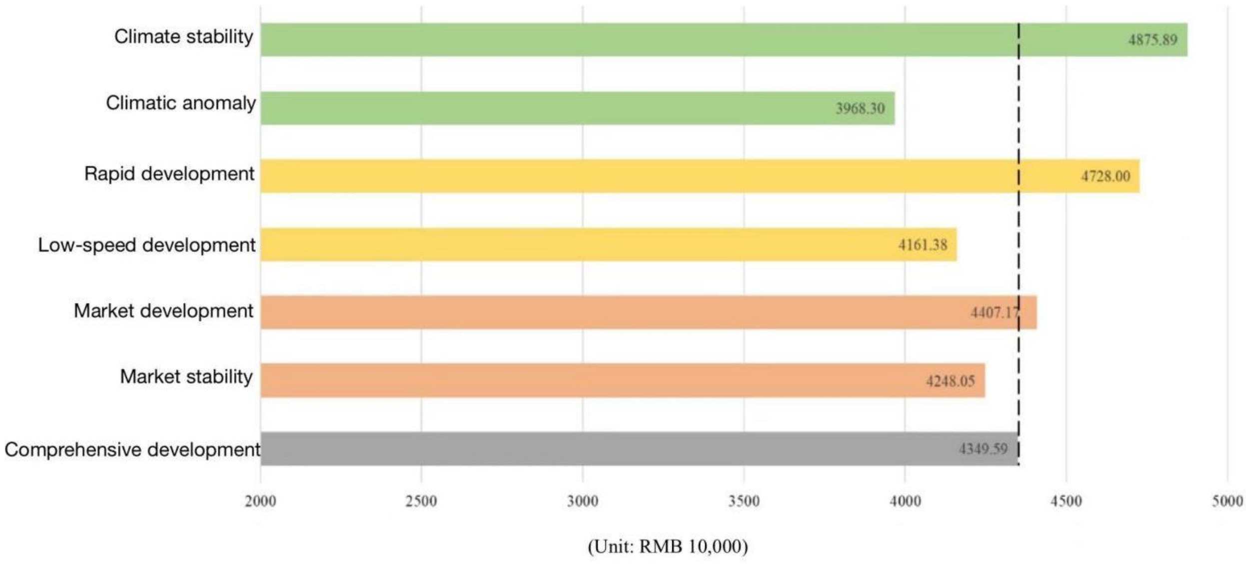

Figure 1. Comparative Analysis of Revenue Across Multiple Scenarios

As shown in Figure 1, using the integrated development scenario as a benchmark, total planting revenue increases under the climate stability scenario, the high economic growth scenario, and the market development scenario. In contrast, the other three scenarios lead to a decline in total revenue. Among them, the climate stability scenario shows the largest increase in revenue, reaching 5.263 million yuan; followed by the high economic growth scenario, with an increase of 3.7842 million yuan; and finally, the market development scenario, with an increase of 575,800 yuan. The patterns of profit loss and profit increase are similar, indicating that climate factors have the greatest impact on the total profit of crops, followed by the speed of economic development, while market development has the least impact. In the future, more consideration should be given to the potential impacts of climate change when making planting decisions.

3.3.2. Comparative Analysis under Market, Economic and Climate Scenarios

The following analysis compares the changes in sales revenue, planting costs, and total profit caused by variations in market development, economic growth, and climate change factors, using the integrated development scenario as a benchmark. First, a comparative analysis of the optimization results considering climate factors is presented, as shown in Figure 2:

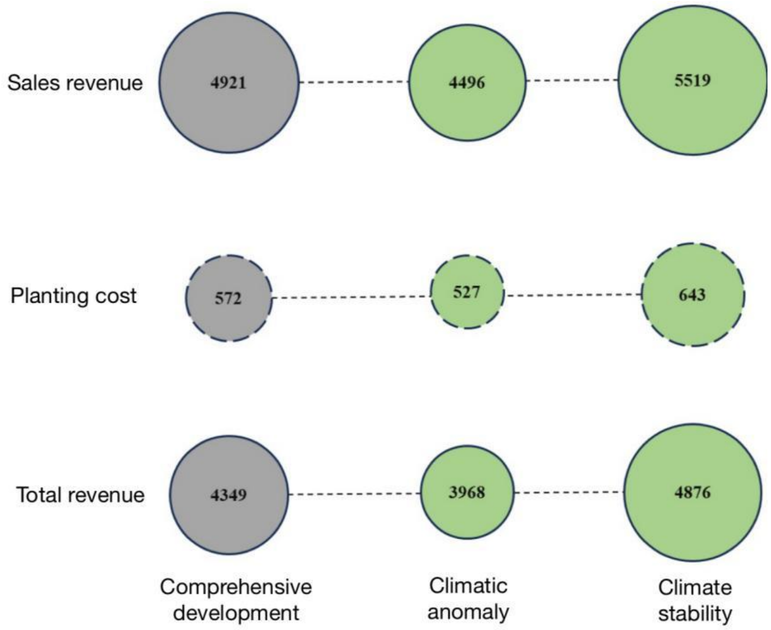

Figure 2. Comparative analysis considering the optimization results of climate factors

As shown in Figure 2, using the integrated development scenario as a benchmark, changes in climate factors primarily affect sales revenue, with minimal impact on planting costs. This can be interpreted as climate factors causing changes in yield, which in turn affect sales revenue, while having little direct effect on planting costs.

Next, a comparative analysis of the optimization results considering market factors is presented, as shown in Figure 3:

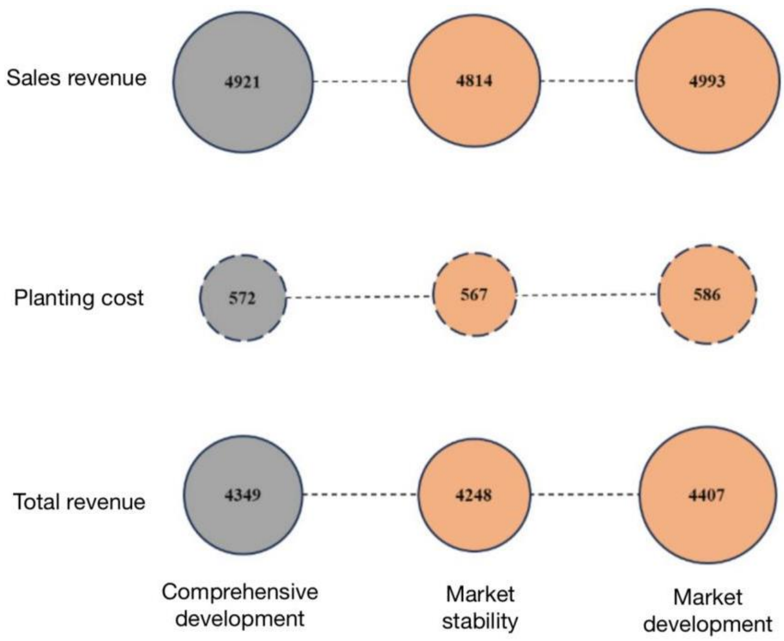

Figure 3. Comparative analysis of the optimization results considering market factors

As shown in Figure 3, using the integrated development scenario as a benchmark, changes in market factors primarily affect sales revenue, with minimal impact on planting costs. This can be interpreted as the pace of market development having a significant impact on expected sales volume, which in turn affects sales revenue, while having little direct effect on planting costs.

Next, a comparative analysis of the optimization results considering economic factors is presented, as shown in Figure 4:

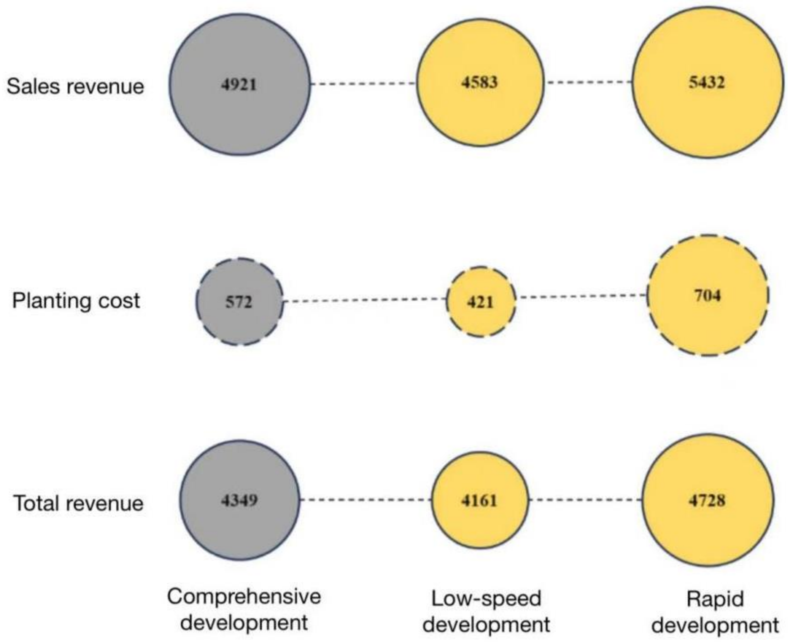

Figure 4. Comparative analysis of the optimization results considering economic factors

As shown in Figure 4, using the integrated development scenario as a benchmark, changes in economic factors have a significant impact on both sales' revenue and planting costs. This can be interpreted as the pace of economic development influencing monetary tightening or inflation, which in turn affects sales prices and planting costs.

In summary, climate factors have the greatest impact on the total profit of crops, followed by the speed of economic development, while market development has the least impact. This conclusion provides a theoretical foundation for future crop planting and serves as a reminder that more consideration should be given to the potential impacts of climate change when making planting decisions.

4. Conclusion

This study has achieved efficient data collection and transmission for mountainous agricultural data through 5G communication technology, providing a data foundation for optimizing dynamic planting strategies. The research results indicate that stable climate conditions, rapid economic development, and market expansion contribute to increased total planting revenue, with climate factors playing a key role in overall profitability.

The marginal contributions of this study are mainly reflected in the following aspects:

(1) A more comprehensive scenario system and parameter analysis framework were constructed, integrating communication technology to enable real-time data collection and processing, significantly enhancing the adaptability of planting strategies to complex real-world environments.

(2) Through multi-scenario comparative analysis, the impact of different factors on planting revenue was clearly revealed, providing more precise guidance for agricultural production decision-making.

However, this study also has certain limitations. In the process of setting some parameters, subjective factors were relatively strong. Future research could further increase the collection of actual agricultural production data from the village, utilize advanced technologies such as big data analysis and machine learning, and combine communication technology to obtain richer data resources. This would continuously optimize the model structure and parameter settings, improve the accuracy and practicality of research outcomes, and provide stronger intellectual support for rural agricultural development.

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