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Reinforcement Learning-Driven Resource Allocation Optimization and Sustainable Development Pathways for Digital Village Development in Guangdong Province

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SUMMARY: *Based on panel data from 21 prefecture level cities in Guangdong Province from 2018 to 2024, this article constructs the Digital Village Development Index (DVI) and Sustainable Development Performance Index (SDI), and introduces the Proximal Policy Optimization (PPO) model to explore the optimization of digital rural resource allocation and sustainable development path under budget constraints. The results show that the digital rural development index in Guangdong has increased from 0.310 to 0.565, but there is still a stable gradient between the Pearl River Delta and non Pearl River Delta, and the growth rate of digital governance is higher than that of digital infrastructure and digital industrialization. Compared with the average distribution, the PPO strategy increased the comprehensive return by 19.6%, DVI by 13.4%, SDI by 11.2%, and the convergence rate of regional differences reached 15.7%. Further analysis reveals that the Pearl River Delta is more suitable for efficiency improvement paths, while eastern, western, and northern Guangdong are more suitable for fair compensation paths. Ecological sensitive agricultural areas should strengthen green collaboration. The study provides a quantitative basis for the implementation of policies and dynamic optimization in the zoning of digital rural areas in Guangdong.*

KEYWORDS: *Digital rural development; Resource allocation optimization; Near end strategy optimization; Sustainable development path; Rural construction*

1 Introduction

Against the backdrop of comprehensively promoting rural revitalization and digital China construction, digital countryside is no longer just an extension of information infrastructure to rural space, but has gradually evolved into an important lever connecting agricultural production, rural governance, public services, and the reconstruction of farmers' lifestyles. For Guangdong, this issue is particularly urgent and realistic. On the one hand, Guangdong is one of the most active provinces in the development of digital economy, with relatively mature platform economy, digital finance, intelligent manufacturing, and digital governance systems, providing strong external support for the penetration of digital technology into counties and rural areas; On the other hand, there is a clear development gradient within Guangdong Province, and the Pearl River Delta region has significant advantages in network infrastructure, capital agglomeration, industrial synergy, and technology diffusion. However, many areas in eastern, western, and northern Guangdong still face practical constraints such as weak infrastructure, low level of digitalization of public services, incomplete rural

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e-commerce chain, and insufficient supply of digital capabilities. Previous studies have shown that the development of the digital economy can significantly promote the process of rural revitalization in Guangdong, but this promoting effect is not homogeneous and is influenced by regional foundations, institutional environments, and resource allocation methods. Furthermore, the construction of digital rural areas is not only related to the improvement of agricultural production efficiency and farmers' income, but also deeply embedded in the optimization process of rural governance structure. There are significant differences in its action path and combination mechanism under different governance conditions. From the experience nationwide, it has been proven that the development of rural digital economy can promote rural revitalization by improving information flow, expanding market accessibility, and enhancing factor allocation efficiency, but the degree of benefit varies among different regions. Meanwhile, the digital economy and rural revitalization are not naturally synchronized, and their degree of coupling and coordination is also constrained by factors such as industrial structure, public investment, and spatial connections. This means that the key issue in the construction of digital villages in Guangdong is no longer just "whether to advance", but "in which regions, in what ways, and where to allocate limited resources, in order to more effectively transform them into sustainable development performance".

Although existing research provides an important foundation for understanding the relationship between digital rural areas and rural revitalization, there are still several areas that need to be advanced if it is used to guide more operational policy allocation within Guangdong Province. Firstly, most existing research has focused on identifying the impact of digital rural construction or digital economic development on agricultural upgrading, green transformation, public services, and farmer welfare, but there has been little further translation of this issue into a decision-making problem of "how to allocate resources more effectively". In other words, existing literature is better at answering whether digitization is effective, but less likely to answer which investment combinations are more worthwhile to prioritize given limited budget. Secondly, existing analysis paths mainly rely on static regression, coupled coordination measurement, or decomposition of influencing factors. For digital rural construction with strong multi-stage, dynamic feedback, and path dependence characteristics, such frameworks are still insufficient in dealing with continuous decision-making problems. Previous studies have found that there is a significant temporal and spatial differentiation between digital rural areas and green and high-quality agricultural development. Their synergistic enhancement and non-linear expansion are jointly shaped by regional endowments and development stages; The construction of digital rural areas will also affect structural variables such as land scale management, indicating that its policy effects have medium - to long-term transmission characteristics, rather than being exhausted by a one-time impact [6]. Again, policy research on rural revitalization often remains at the level of average effects, lacking path classification and scenario design for internal differences within provinces, especially lacking systematic discussions on how to coordinate the three goals of "efficiency improvement, fair compensation, and green constraints". In fact, resource allocation itself is an important variable that affects the quality of rural revitalization. Agricultural technology innovation resources will correspond to different revitalization effects in different regions and investment methods. This finding has already reminded us that if we ignore the allocation strategy itself and only start from the average policy effect, it is difficult to provide high-quality decision-making basis for provinces like Guangdong with significant internal differences [7]. Therefore, it is necessary to further advance the research on digital rural areas from "effect identification" to "dynamic optimization", and from "overall evaluation" to "heterogeneity zoning and sustainable path design".

Based on the above understanding, this article takes the construction of digital villages in

Guangdong Province as the research object, attempting to establish a closer analytical framework between regional differences, dynamic decision-making, and sustainable development. This article proposes three interconnected research questions around this goal: firstly, what is the differentiation pattern of the development level of digital rural areas in Guangdong in terms of time and space dimensions, and whether there are stable gradient characteristics in infrastructure, governance capacity, industrial integration, and public services in different regions; Secondly, under budget constraints and multi-objective considerations, is the resource allocation strategy driven by reinforcement learning superior to uniform allocation, empirical allocation, or static optimization schemes, and can it better improve the performance of digital rural construction; Thirdly, in the face of significant differences in development stages, factor endowments, and governance needs between the Pearl River Delta and non Pearl River Delta regions, what sustainable development paths should different types of regions adopt in order to form a more reasonable balance between efficiency improvement, opportunity balance, and green performance. Previous studies have shown that digital rural construction can improve the supply of basic public services in rural areas. This indicates that the value of digital investment should not be measured solely by output growth, but should also be included in the dimensions of public service accessibility and governance inclusiveness; In addition, the development of digital rural areas will also enhance the dietary diversity of farmers, indicating that its impact has extended to family welfare and quality of life; At the same time, digital development also has positive significance for rural women's participation in village governance, indicating that its institutional meaning is not limited to technological substitution, but closely related to the reshaping of rural social structure [10]. Based on this, the marginal contribution of this article is mainly reflected in three aspects: firstly, starting from dimensions such as digital infrastructure, digital governance, digital industry applications, and public services, a comprehensive indicator system for the development and sustainable performance of Guangdong's digital countryside is constructed to enhance the measurability of the research object. The second is to formalize the problem of resource allocation into a dynamic decision-making process, introducing reinforcement learning frameworks to identify better investment strategies, thereby advancing the judgment of whether the digital countryside is effective to the level of how to allocate resources more effectively. Thirdly, based on the regional heterogeneity and scenario simulation results within Guangdong Province, a sustainable development path of zoning and classification is proposed to provide analytical support for the transition of digital rural construction from universal promotion to precise policy implementation. Overall, this article aims to integrate the three levels of evaluation, optimization, and path design in the study of digital rural areas, providing a more explanatory evidence framework for understanding the internal mechanisms and policy implementation logic of Guangdong's digital rural construction.

2 Methods

2.1 Study area, data sources, and indicator system

This article takes Guangdong Province as the research area. Guangdong is not only one of the most active provinces in China in terms of digital economy and information infrastructure construction, but also has significant intra provincial gradient differences [11]. Specifically, the Pearl River Delta region started earlier in terms of network coverage, industrial digitization, platform economy integration, and governance coordination, while many areas in eastern, western, and northern Guangdong still face constraints such as weak digital infrastructure, uneven supply of public services, and insufficient factor aggregation. Therefore, Guangdong is not only representative of observing the diffusion effect of digital rural areas, but also suitable for discussing the issue of differentiated allocation under resource constraints [13]. In theory, county-level samples are closer to the actual landing point of digital rural construction. However, considering the significant limitations in caliber uniformity, comparability, and availability of county-level continuous public data from 2018 to 2024, this article uses a balanced panel composed of 21 prefecture level cities in Guangdong Province as the benchmark sample, with a sample period set from 2018 to 2024. This processing can cover the continuous stages of "Digital Countryside - Hundred Counties, Thousand Towns, Ten Thousand Villages Project - Deepening Digital Governance", and also facilitate the annual state transition and resource allocation simulation of subsequent reinforcement learning models.

The data mainly comes from five types of public channels. The first category includes comprehensive statistical yearbooks and survey yearbooks, including Guangdong Statistical Yearbook, China County Statistical Yearbook, Guangdong Rural Statistical Yearbook, various city statistical yearbooks, and statistical bulletins, which are used to obtain basic indicators such as rural residents' income, agricultural output, employment, fiscal expenditure, postal and telecommunications, and urban-rural structure [14, 15]. The second type is government department public information, mainly including Guangdong Provincial Department of Agriculture and Rural Affairs, relevant departments of industry and information technology, communication management departments, government service data management departments, and public annual reports, announcements, and special reports from various cities, used to supplement indicators such as digital rural project construction, digital governance, 5G base stations, rural logistics, and training. The third type is thematic index data, which focuses on using the Peking University Digital Inclusive Finance Index to characterize the accessibility and depth of digital finance in the region. The fourth category is remote sensing and spatial data, which uses publicly available data such as VIIRS nighttime lights to characterize digital infrastructure density, economic activity, and service accessibility. The fifth category is industry supplementary information, such as public statistical information of rural e-commerce service stations, express network coverage, Internet broadband access, online government services, etc. For a small number of missing values, this article combines the trends of adjacent years for linear interpolation. For variables with significant dimensional differences, direction unification and standardization are first carried out before entering the comprehensive evaluation stage [17].

Based on the research objectives, this article constructs a three-layer indicator system of "resource input - digital rural development - sustainable performance". The first layer is the resource input layer, which mainly reflects the investment foundation and supporting conditions for digital rural construction, including indicators such as rural broadband access rate, 5G base station density, digital investment in agricultural finance, number of rural e-commerce service stations, number of digital skill training personnel, and availability of digital finance. Among them, broadband and 5G represent basic connectivity capabilities, financial investment and training reflect government and human capital support, and digital finance and e-commerce service stations reflect the convenience of digital elements penetrating rural scenes. The second layer is the digital rural development layer, which is used to depict the development status after investment transformation, including five dimensions: digital infrastructure, digital industrialization/agricultural e-commerce, digital governance, digital public services, and farmers' digital literacy. Unlike simply counting how many sites have been built, this layer emphasizes more on whether digital technology is truly embedded in agricultural production, rural governance, and livelihood services. The third layer is the sustainable performance layer, which focuses on whether digital rural construction can ultimately be transformed into high-quality development results. Specifically, indicators such as per capita disposable income of rural residents, agricultural labor productivity, accessibility of public services, degree of narrowing of urban-rural income gap, and unit agricultural output energy consumption or carbon intensity are selected, corresponding to economic gains, efficiency improvement, livelihood improvement, fair restoration, and green constraints [19]. In terms of index construction, this article uses the entropy method as the weight method to reduce the bias caused by subjective weighting. Firstly, the original indicators are non dimensionalized to obtain standardized indicators zkit and ymit. Subsequently, the Digital Rural Development Index and Sustainable Development Performance Index were constructed separately. The calculation of the Digital Rural Development Index is shown in formula (1).

$$DVI_{it} = \sum_{k=1}^{K} w_k z_{kit} \tag{1}$$

In formula (1), DVI_{it} represents the digital rural development level of region i in year t. w_k represents the weight of the index measured by the entropy method. This index is used to characterize the comprehensive status of digital rural construction in various regions and serves as a key state variable in subsequent resource allocation models. The calculation of the Sustainable Development Performance Index is shown in formula (2).

$$SDI_{it} = \sum_{m=1}^{M} v_m y_{mit} \tag{2}$$

In formula (2), SDI_{it} represents the sustainable performance level of region i in year t. v_m represents the corresponding weight. By simultaneously characterizing the development status and performance results, a clearer state recognition foundation and goal constraint framework can be provided for subsequent reinforcement learning driven resource allocation optimization.

2.2 Reinforcement learning-driven resource allocation optimization model

In order to identify a more optimal resource allocation method for Guangdong's digital rural construction under budget constraints, this paper formalizes the cross regional and cross year digital rural resource allocation process as a continuous dynamic decision-making problem. Unlike traditional static optimization or experience allocation, digital rural construction has obvious stages and feedback: current investment not only affects the improvement of digital infrastructure, industrial services, and governance capabilities in the current period, but also has a sustained impact on the development status of the next period through public service supply, farmers' digital capacity accumulation, and regional gap adjustment [20]. Therefore, this article adopts a reinforcement learning framework to depict the progressive process of "input state change performance feedback reconfiguration", and embeds it into the panel scenario of prefecture level cities in Guangdong Province.

In terms of state setting, this article represents the system state of region i in year t as a state vector composed of the level of digital rural development, sustainable performance, infrastructure conditions, public service levels, digital financial support, and regional disparities, i.e. $s_t = [DVI_{it}, SDI_{it}, Infra_{it}, Service_{it}, Finance_{it}, Gap_{it}]$. Among them, DVI_{it} and SDI_{it} respectively reflect the current development foundation and comprehensive performance of the region. $Infra_{it}$ represents digital infrastructure conditions, such as broadband and 5G support capabilities. $Service_{it}$ represents the supply status of digital public services. $Finance_{it}$ represents the availability of digital finance. Gap_{it} is used to identify the level of gap between the region and the provincial average or similar regions. This state definition can simultaneously capture the level of development, constraints, and relative position, thereby making resource allocation no longer limited to average investment, but closer to the actual context of differentiated governance.

In terms of action design, this article divides the annual disposable resource budget into five policy directions: digital infrastructure, e-commerce and industrial chain services, digital governance platforms, digital skills training, and green agriculture digital applications. The model determines the allocation ratio of various resources based on the current state in each period, thus forming a continuous decision variable. Considering that the actual policy budget usually manifests as proportional adjustment and structural redistribution, rather than discrete choices of several fixed levels, this article uses a continuous action space to describe resource allocation behavior. Compared to the simple "invest more or less" approach, this setting better reflects the differences in development stages, weaknesses, and policy priorities among different regions in Guangdong. On this basis, this article defines the optimal resource allocation strategy as the strategy function that maximizes the cross period cumulative return, and its objective function is shown in formula (3).

$$\pi^* = arg\max_{\pi} E\left[\sum_{t=0}^{T} \gamma^t r_t\right] \tag{3}$$

In formula (3), π^*represents the optimal resource allocation strategy, and π represents the policy function to be learned. $E[\cdot]$ represents the expected operator, used to represent the average cumulative return under random environments and state transitions. T represents the end point of the decision-making cycle. γ represents the discount factor, typically between 0 and 1, used to measure the relative importance of future returns to current returns. r_t represents stage return. This objective function emphasizes maximizing overall returns in multi period decision-making. Considering the practical limitations of local finance and project resources, this article further incorporates budget and allocation constraints, as shown in formula (4).

$$\sum_{j=1}^{J} x_{ijt} \le B_{it}, \qquad x_{ijt} \ge 0 \tag{4}$$

In formula (4), J represents the project category to which the resource allocation belongs. x_{ijt} represents the resource investment of region i in the j-th category of digital rural projects in year t. B_{it} represents the budget ceiling. $x_{ijt} \ge 0$ indicates that there is no negative allocation. In order to enable the model to simultaneously respond to the three policy objectives of efficiency, fairness, and green development, this paper designs the stage return function in a multi-objective weighted form, as shown in formula (5).

$$r_t = \alpha \Delta DVI_{it} + \beta \Delta SDI_{it} - \lambda_1 Inequality_{it} - \lambda_2 Carbon_{it} - \lambda_3 CostOverrun_{it} \tag{5}$$

In formula (5), α represents the reward weight for the incremental development of digital rural areas. β represents the reward weight for sustainable performance increment. ΔDVI_{it} and ΔSDI_{it} respectively represent the increment of the Digital Rural Development Index and Sustainable Performance Index, reflecting the efficiency benefits of resource allocation. $Inequality_{it}$ is used to characterize the degree of widening of regional or urban-rural disparities. $Carbon_{it}$ represents the carbon emissions or energy consumption pressure per unit of agricultural output. $CostOverrun_{it}$ is used to reflect the risk of budget overruns or resource mismatches. λ_1, λ_2 and λ_3 represent the weight coefficients of the gap penalty term, carbon constraint penalty term, and cost overrun penalty term, respectively. Through this reward design, the model can balance regional balance and green constraints while improving the quality of digital rural development. To more intuitively demonstrate the resource allocation logic driven by reinforcement learning, the structure of the resource allocation optimization model is shown in Figure 1.

In terms of algorithm implementation, considering that this article focuses more on continuous proportional allocation scenarios, Proximal Policy Optimization (PPO) is more suitable as the main model. PPO has good training stability in continuous action space and can avoid excessive oscillation in multiple rounds of strategy updates, which is more in line with the stable characteristics of annual adjustment of fiscal resources [21]. To verify the effectiveness of reinforcement learning strategies, this paper sets three baseline schemes, including equal allocation, expert rule allocation based on policy experience, and static linear programming/entropy priority configuration scheme. In summary, the schematic diagram of the reinforcement learning driven optimization model for digital rural resource allocation is shown in Figure 1.

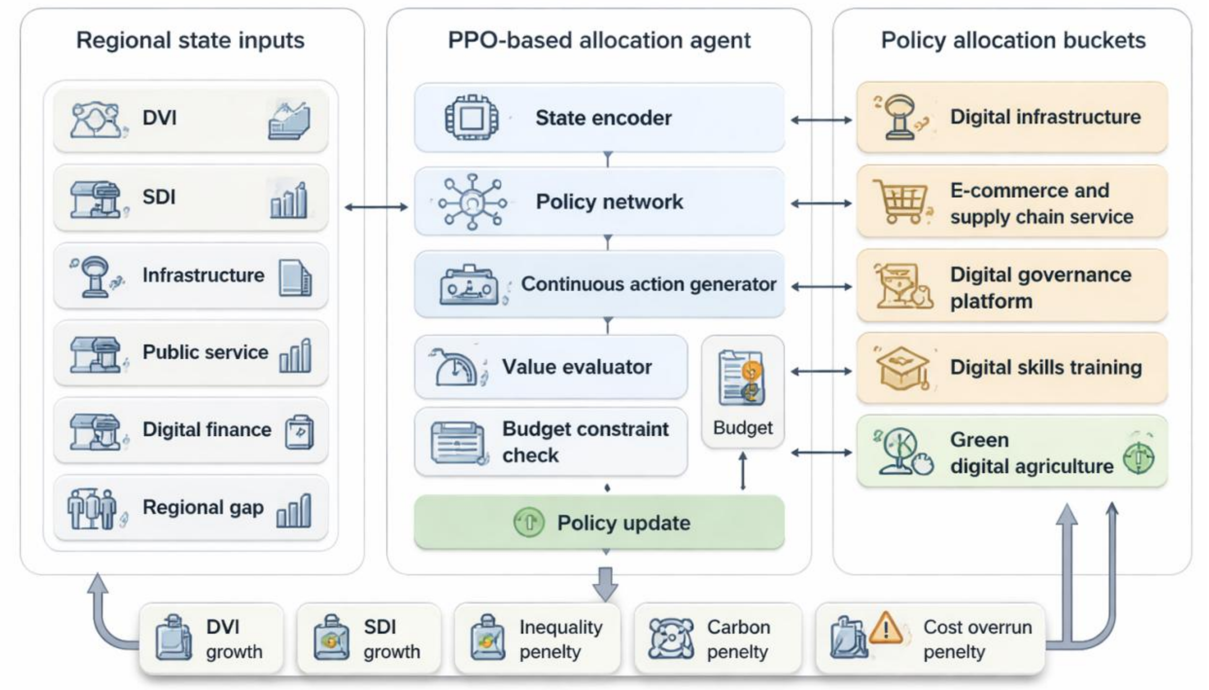


Figure 1: Structure diagram of reinforcement learning driven optimization model for digital rural resource allocation.

In Figure 1, the state of regional development, budget constraints, and policy allocation directions collectively constitute the decision-making environment. The agent generates continuous allocation actions based on state information and continuously updates its strategy in response to feedback regarding development gains, performance improvements, narrowing gaps, and green constraints, thereby forming an intertemporal iterative optimization process.

2.3 Empirical validation and sustainable pathway identification

To further test the explanatory power of reinforcement learning optimization configuration in real development performance and extract the differentiated promotion path of Guangdong's digital countryside based on this, this paper introduces an empirical identification step after simulating resource allocation. The purpose is to examine whether the optimized resource allocation intensity can significantly improve regional sustainable development performance, and whether this improvement shows stable differences under different development foundations and regional conditions. Considering the significant regional heterogeneity and time accumulation effects of digital rural construction, this paper adopts a two-way fixed effects model for estimation to control for regional characteristics that do not change over time and common annual shocks [23]. The model setting is shown in formula (6).

$$SDI_{it} = \theta_0 + \theta_1 AllocOpt_{it} + \theta_2 DVI_{it} + \theta_3 X_{it} + \mu_i + \tau_t + \varepsilon_{it} \tag{6}$$

In formula (6), θ_0 represents a constant term. $AllocOpt_{it}$ represents the resource allocation intensity or resource allocation efficiency index after reinforcement learning optimization. X_{it} represents the set of control variables. μ_i represents regional fixed effects. τ_t represents the time fixed effect. ε_{it} represents the random perturbation term. θ_1 represents the regression coefficient of $\mathrm{AllocOpt}_{\mathrm{it}}$, reflecting the marginal impact of optimized configuration on sustainable development performance. θ_2 represents the regression coefficient of $\mathrm{DVI}_{\mathrm{it}}$, which is used to control the impact of the overall development level of digital rural areas on performance. θ_3 represents the regression coefficient of X_{it}.

The setting of control variables mainly revolves around the regional development foundation, public investment capacity, and structural conditions, including per capita GDP, fiscal expenditure on agriculture, education level, highway density, urbanization rate, advanced industrial structure, and financial development level [24]. The reason for including these variables is that the performance of digital rural areas is not only affected by resource allocation itself, but also by the combined effects of economic development stage, transportation accessibility, human capital accumulation, and financial support capacity. By controlling for these factors, the model can more accurately identify the marginal effects of optimized allocation and reduce estimation errors caused by regional endowment differences. To enhance the robustness of the conclusion, this article can further use methods such as lagged term replacement, regional regression, and core variable replacement indicators for supplementary testing. After completing the empirical identification of optimized configuration, this article further transforms the estimation results into regional development paths. The empirical testing and sustainable development path identification framework are shown in Figure 2.

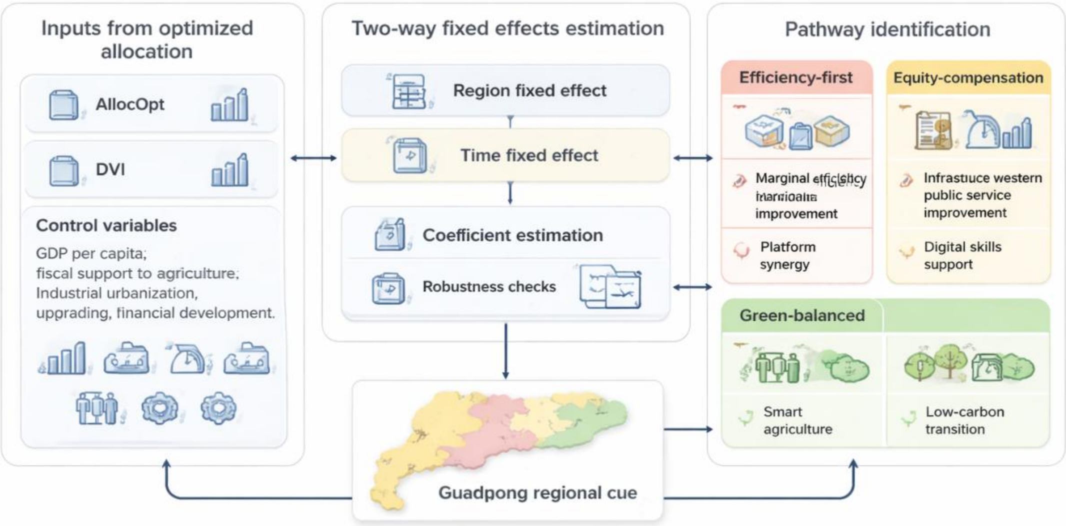


Figure 2: Empirical testing and framework for identifying sustainable development paths.

In Figure 2, the configuration strength indicator generated by reinforcement learning first enters the bidirectional fixed effects test to identify its direction and strength of impact on sustainable performance. Subsequently, based on the regional development foundation, public service shortcomings, and green constraints, the construction of digital villages in Guangdong was classified and identified, ultimately forming three types of promotion paths: efficiency improvement, compensation improvement, and green collaboration. After completing empirical identification, this article further classifies the sustainable development path of Guangdong's digital countryside based on regional development level, resource gap structure, and green constraints. The first type is the "Efficiency first" path, mainly corresponding to the Pearl River Delta region. These regions have a good digital foundation and strong industrial collaboration capabilities. The focus of subsequent allocation should be on improving marginal efficiency, optimizing platform collaboration, and expanding high value-added digital applications to increase resource utilization output rate [25]. The second type is the "Equity competition" path, mainly targeting some areas with weak foundations in eastern, western, and northern Guangdong. The policy focus should be on extending digital infrastructure, digitizing public services, improving grassroots governance platforms, and compensating for digital skills to narrow regional disparities and enhance basic development capabilities. The third type is the "Green balanced" path, which is mainly suitable for ecologically sensitive agricultural areas and areas with high pressure for green transformation. When promoting the construction of digital rural areas in such areas, more attention should be paid to the application of digital agricultural technology, energy conservation and emission reduction constraints, and ecological benefits coordination, directing resource investment towards green production, smart agriculture monitoring, and low-carbon public service system construction.

By combining the optimized configuration results with fixed effects estimation and regional classification identification, this article can further advance from the analysis level of "how to allocate resources more effectively" to the analysis level of "how to promote more appropriate allocation in different regions", thus providing empirical support for the zoning and continuous optimization of digital rural construction in Guangdong.

3 Results and Discussion

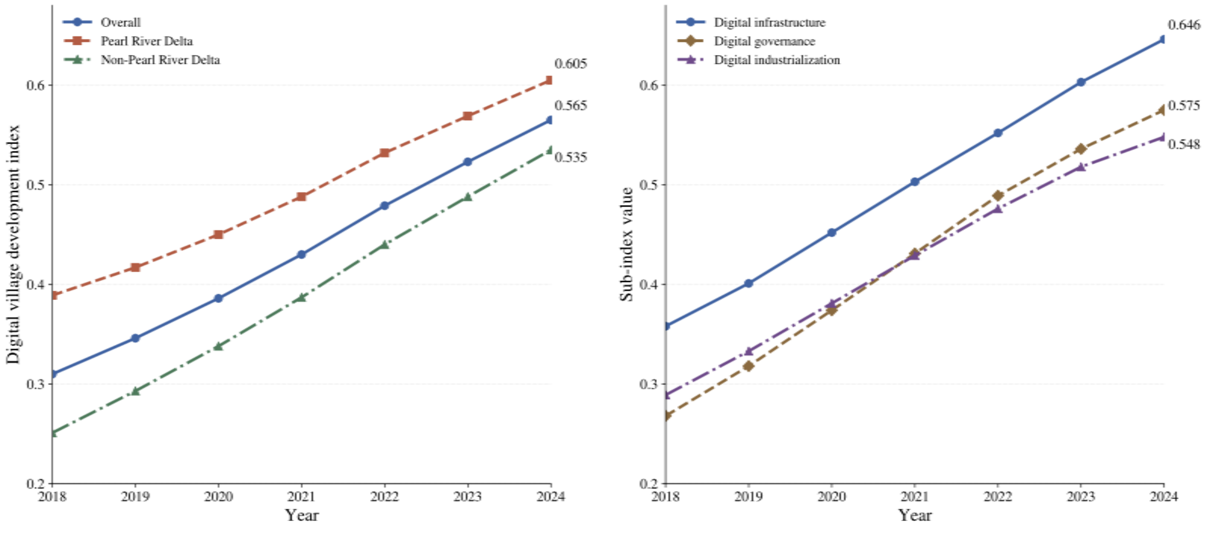
3.1 Spatiotemporal evolution of digital village development in Guangdong Province

The temporal statistical characteristics of Guangdong Digital Rural Development Index are shown in Table 1. Table 1 shows that from 2018 to 2024, the average digital rural development index in the province increased from 0.312 to 0.571, with a cumulative growth rate of 83.0%, indicating that the overall digital rural construction in Guangdong has entered a sustained upward phase during the sample period. The standard deviation (SD) during the same period decreased from 0.077 to 0.044, indicating a reduction in regional dispersion and a certain convergence of intra provincial disparities. By regional comparison, it can be seen that the Pearl River Delta region has always been higher than non Pearl River Delta regions, with an average increase from 0.389 to 0.605, and from 0.251 to 0.535 in non Pearl River Delta regions. The gap between the two types of regions has narrowed from 0.138 to 0.070. It can be seen that while the overall acceleration of digital rural construction in Guangdong is accompanied by a certain degree of peripheral catch-up, the leading pattern has not fundamentally changed.

Table 1: Time series statistical characteristics of Guangdong Digital Rural Development Index

Year	Provincial Mean	SD	Pearl River Delta Mean	Non-Pearl River Delta Mean	Moran's I
2018	0.310	0.077	0.389	0.251	0.352
2019	0.346	0.071	0.417	0.293	0.348
2020	0.386	0.064	0.450	0.338	0.335
2021	0.430	0.059	0.488	0.387	0.328
2022	0.479	0.054	0.532	0.440	0.324
2023	0.523	0.048	0.569	0.488	0.312
2024	0.565	0.044	0.605	0.535	0.277

The detailed changes in time evolution are shown in Figure 3. As shown in Figure 3 (a), the overall curve of the province continued to rise from 2018 to 2024, with a more significant increase after 2021, indicating that digital rural construction has entered an accelerated stage in the later stage of the sample. The Pearl River Delta curve has always been at its highest position, but the upward slope is greater in non Pearl River Delta regions, indicating the catch-up effect brought by the sinking of infrastructure and the expansion of digital public services. As shown in Figure 3 (b), all three core sub dimensions showed significant growth, with digital governance increasing from 0.268 to 0.575, an increase of 114.6%, making it the dimension with the fastest improvement. The digital industrialization increased from 0.289 to 0.548, with a growth rate of 89.6%. The digital infrastructure has increased from 0.358 to 0.646, an increase of 80.4%. This indicates that the incremental source of Guangdong's digital rural construction is no longer limited to hardware expansion, and the contribution of governance platform connectivity, online service coverage, and institutional embedding to the overall index improvement is more prominent.



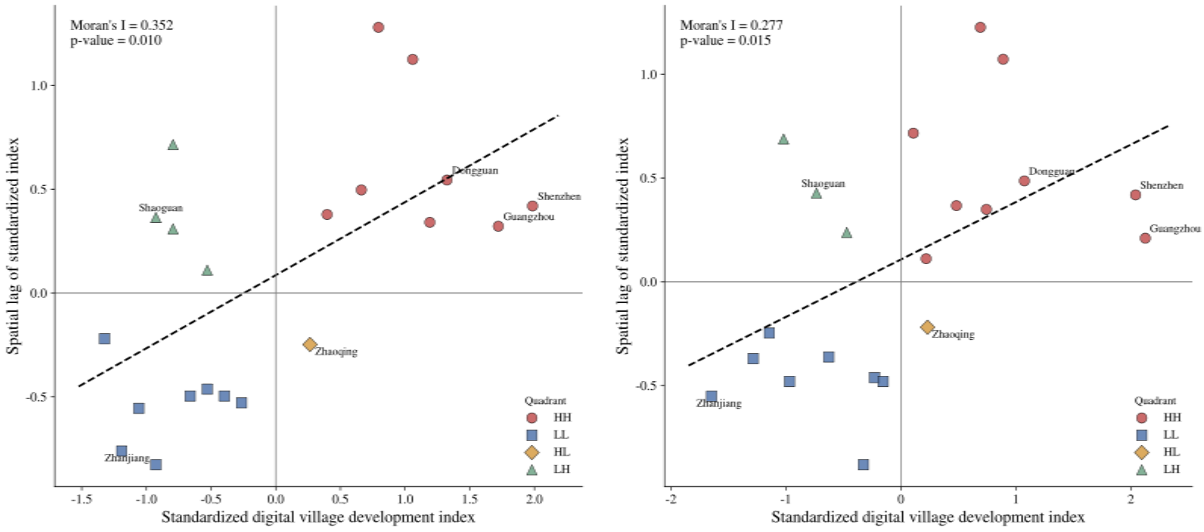
(a) Overall and regional trends

(b) Sub-dimension trends

Figure 3: Detailed changes in the evolution of time.

The results of spatial correlation and agglomeration tests are shown in Figure 4. As shown in Figures 4 (a) and 4 (b), the Moran's I values for 2018 and 2024 were 0.352 and 0.277, respectively, and both passed the significance test, indicating that the development of digital rural areas in Guangdong has always had stable positive spatial correlation characteristics.

High value agglomeration mainly occurs in core cities of the Pearl River Delta such as Guangzhou, Shenzhen, and Dongguan, while low value agglomeration is more distributed in some areas of western and northern Guangdong. By 2024, high-value areas will still maintain a clear linkage, while the spatial cohesion of low value areas has eased, reflecting that some latecomer areas in the province have begun to narrow their weaknesses, but the overall spatial gradient has not yet disappeared. Based on Table 2, it can be seen that the development of digital rural areas in Guangdong presents the basic characteristics of "overall increase, convergence of disparities, and still existing spatial correlations". This also means that subsequent resource allocation cannot be solely based on the logic of average investment, but needs to consider regional development foundations, neighboring spillover effects, and marginal improvement space in different dimensions simultaneously.



(a) Moran scatter plot in 2018

(b) Moran scatter plot in 2024

Figure 4: Results of Spatial Correlation and Agglomeration Test.

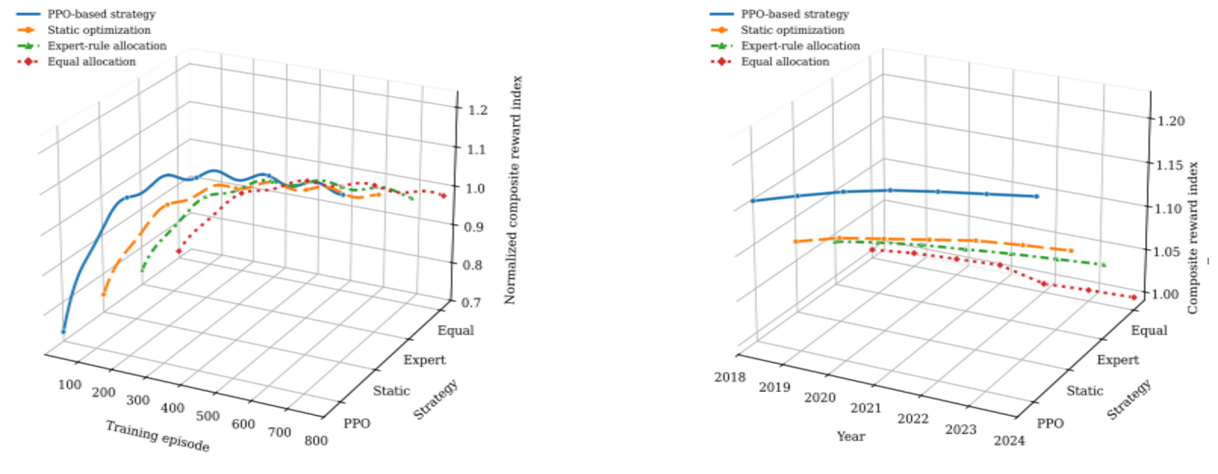
3.2 Optimization performance of reinforcement learning-based resource allocation

The comparison results of optimization performance of different resource allocation strategies are shown in Table 2. It can be seen that PPO based strategy outperforms the three baseline schemes in all key indicators. Compared with equal allocation, the PPO-based strategy increased the composite reward by 19.6%, improved the digital village index (DVI) by 13.4%, improved the sustainable development index (SDI) by 11.2%, and reduced interregional disparity by 15.7%。 Compared to the expert rule allocation, the three improvements mentioned above have increased to 13.4%, 11.2%, and 15.7% respectively, corresponding to baseline values of 10.1%, 7.8%, and 10.2%; Compared to static optimization, PPO still outperforms the Digital Rural Development Index, Sustainable Development Performance Index, and Regional Gap Convergence by 1.5, 2.3, and 3.6 percentage points, respectively. This indicates that the advantages of reinforcement learning strategies are not limited to the comprehensive reward function itself, but rather demonstrate stronger configuration capabilities in three dimensions: development improvement, performance improvement, and regional coordination.

Table 2: Comparison Results of Optimization Performance of Different Resource Allocation Strategies.

Strategy	Reward Improvement (%)	DVI Improvement (%)	SDI Improvement (%)	Interregional Disparity Reduction (%)
Equal allocation	0.0	8.4	6.7	8.3
Expert-rule allocation	6.7	10.1	7.8	10.2
Static optimization	11.3	11.9	8.9	12.1
PPO-based strategy	19.6	13.4	11.2	15.7

The convergence of training and the performance of out of year samples are shown in Figure 5. As shown in Figure 5 (a), the normalized comprehensive return of PPO rapidly increases within the first 200 episodes and stabilizes above the reference level of static optimization after about 260 episodes. After 500 episodes, it basically converges to the range of 1.19-1.21, indicating that the training process has good stability. As shown in Figure 5 (b), in the external sample evaluation from 2018 to 2024, the PPO curve remained at the highest position, and the gap with other strategies further widened in the later stage of the sample, indicating that its advantage has persistence rather than single period fluctuations. From the perspective of budget utilization efficiency, PPO based strategy can generate 0.0086 DVI increments and 0.0069 SDI increments for every additional CNY 1 billion investment, which is higher than the 0.0074 and 0.0059 for equal allocation, and also higher than the 0.0080 and 0.0064 for static optimization. This result indicates that reinforcement learning configuration not only improves overall returns, but also enhances the conversion efficiency of unit budgets.

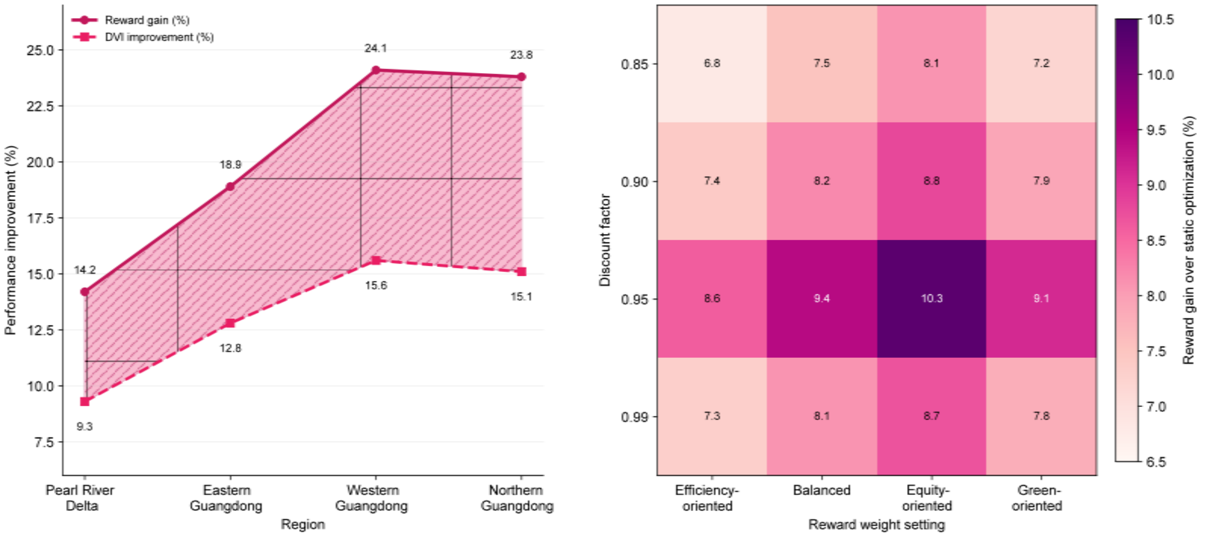


(a) Three-dimensional training convergence performance

(b) Three-dimensional out-of-sample annual performance

Figure 5: Training convergence and performance of out of year samples.

The results of regional heterogeneity and robustness verification are shown in Figure 6. As shown in Figure 6 (a), the gain of PPO relative to equal allocation is more pronounced in underdeveloped areas. The comprehensive return improvement of Western Guangdong and Northern Guangdong reached 24.1% and 23.8% respectively, significantly higher than Pearl River Delta's 14.2%; In terms of DVI improvement, the first two were 15.6% and 15.1%, respectively, which were also higher than the 9.3% in the Pearl River Delta. This indicates that reinforcement learning is better able to identify the weaknesses of latecomer regions and prioritize budget allocation to infrastructure, public services, and skill support areas with higher marginal benefits. As shown in Figure 6 (b), when the discount factor varies between 0.85-0.99 and the reward weight is adjusted between different settings, the return improvement of PPO relative to static optimization always remains in the range of 6.8% -10.3%, with the best performance under the γ=0.95 \ gamma=0.95 γ=0.95 and equity oriented weight settings. From this, it can be seen that the model is insensitive to disturbances in key parameters, and the overall conclusion has good robustness.



(a) Regional heterogeneity of PPO gains

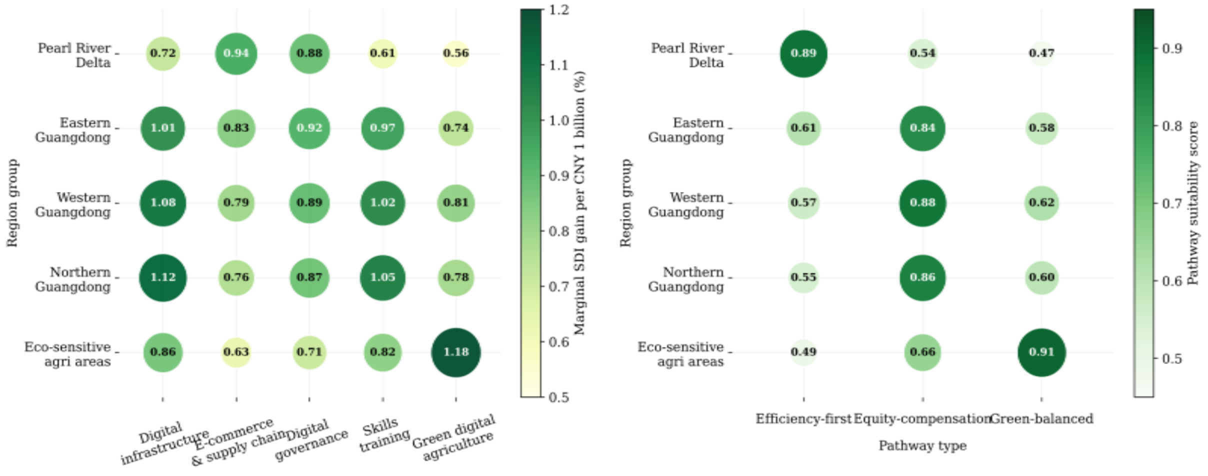
(b) Robustness across parameters

Figure 6: Regional Heterogeneity and Robustness Verification Results.

3.3 Sustainable development pathways and policy implications

After completing the optimization performance comparison, the further question is how different regions can form more targeted promotion paths based on this. Figures 7 and 8 present the results of region type recognition and path verification. Combining the marginal returns of optimized configuration, it can be found that the construction of digital villages in Guangdong is not suitable for a single promotion model, but should form differentiated plans based on development foundations, public service shortcomings, and green constraints. Recent empirical studies have also shown that the impact of digital rural construction has extended to multiple dimensions such as public service supply, governance participation, subjective well-being, and poverty reduction, and the mechanisms of action in different regions exhibit significant heterogeneity.

The path adaptation result is shown in Figure 7. As shown in Figure 7 (a), the marginal SDI gains of the Pearl River Delta region in e-commerce and industrial chain services, as well as digital governance, reached 0.94% and 0.88%, respectively, higher than its 0.72% and 0.56% in digital infrastructure and green agriculture digital applications. This indicates that the region is more suitable for taking the Efficiency first path, continuing to allocate resources towards platform collaboration, digitalization of the industrial chain, and improvement of governance efficiency, in order to unleash the marginal efficiency on the existing foundation. In contrast, the marginal returns on digital infrastructure and skills training in eastern, western, and northern Guangdong are higher, with Northern Guangdong achieving gains of 1.12% and 1.05% in both areas, and Western Guangdong achieving gains of 1.08% and 1.02%, respectively. As shown in Figure 7 (b), the corresponding Equity matching scores for these regions reached 0.84-0.88, significantly higher than the efficiency enhanced path, indicating that their short-term focus should be on network access, public service connectivity, and digital capability compensation. For ecologically sensitive agricultural areas, the marginal gain of green agriculture digital applications reaches 1.18%, corresponding to a Green balanced adaptation score of 0.91, which is higher than the other two paths. This indicates that such areas should not simply replicate the e-commerce priority model, but should incorporate green production, environmental monitoring, and low-carbon constraints into the logic of resource allocation.

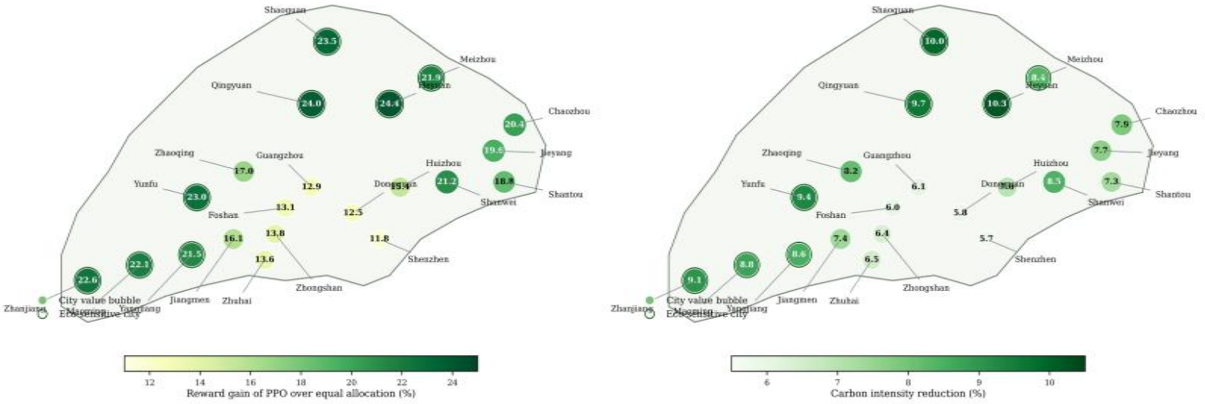


(a) Marginal returns across policy buckets and region groups

(b) Pathway suitability by region group

Figure 7: Path adaptation results.

The further spatial distribution results are shown in Figure 8. As shown in Figure 8 (a), the optimization benefits of PPO relative to equal allocation exhibit a clear spatial gradient in Guangdong. The return increase of core cities in the Pearl River Delta is mostly concentrated in the range of 11.8% to 13.8%, while cities in western Guangdong, northern Guangdong, and some eastern Guangdong are generally in the range of 18.8% to 24.4%, with particularly prominent increases in Qingyuan, Heyuan, Shaoguan, and Yunfu. This indicates that areas with relatively weak development foundations are more sensitive to optimizing allocation, and the marginal benefits of resource allocation are more fully released. It also suggests that the compensation and enhancement path has stronger practical adaptability in these areas. In contrast, although the Pearl River Delta region can also benefit from optimized allocation, its room for improvement is more reflected in industrial chain collaboration, governance efficiency, and high value-added digital applications, making it more suitable for an efficiency improvement path. As shown in Figure 8 (b), the effect of the green collaborative path also has clear spatial differences. The carbon intensity reduction in ecologically sensitive agricultural areas and northern mountainous cities is generally high, mostly in the range of 8.5% to 10.3%, while in the Pearl River Delta cities, it is mainly distributed in the range of 5.7% to 6.5%. Zhanjiang, Maoming, Yangjiang, Shaoguan, and Qingyuan have shown stronger green benefits, indicating that in areas with a higher proportion of agriculture and more prominent ecological constraints, incorporating digital agriculture, environmental monitoring, and low-carbon governance tools into resource allocation can more effectively translate into improved green performance. From this, it can be seen that the construction of digital villages in Guangdong is more suitable for forming an efficiency improvement path centered on the Pearl River Delta, a compensation improvement path with a focus on eastern, western, and northern Guangdong, and a green collaborative path for ecologically sensitive agricultural areas.



(a) Spatial distribution of optimization gains

(b) Spatial distribution of green pathway outcomes

Figure 8: Further Spatial distribution results.

4 Conclusion

In summary, the construction of digital villages in Guangdong has entered a new stage of shifting from scale expansion to structural optimization, and the allocation of resources and the degree of regional adaptation are becoming key factors affecting overall performance.

(1) The development of digital rural areas in Guangdong presents significant regional gradients and dimensional differences. The development index of digital rural areas in the province will increase from 0.310 to 0.565 from 2018 to 2024, but there is still a stable gap between the Pearl River Delta and non Pearl River Delta regions, indicating that the expansion of digital infrastructure will not naturally bring about synchronous improvement in comprehensive performance. The coordinated improvement of digital governance, public services, and digital capacity building is more important.

(2) The resource allocation driven by reinforcement learning is superior to traditional average allocation and experience allocation. The results showed that the PPO strategy increased the comprehensive return by 19.6%, DVI by 13.4%, SDI by 11.2% compared to the average allocation, while also achieving a convergence rate of 15.7% in regional disparities. This indicates that in situations with strong budget constraints and significant regional heterogeneity, dynamic optimization configuration has higher efficiency.

(3) The sustainable development of digital rural areas in Guangdong should not follow a single path. The Pearl River Delta is more suitable for an efficiency improvement path, while eastern, western, and northern Guangdong require a fair compensation path. Ecological sensitive agricultural areas should promote a green collaborative path to form a differentiated and focused promotion mechanism.

However, it should be pointed out that the availability of long-term continuous data at the county level is still limited, and the reinforcement learning environment still relies on historical samples. More fine-grained village data and real-time policy feedback mechanisms still need to be further validated in subsequent research.

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