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The Impact of the Rural Digital Economy on Ecological Product Value Conversion Efficiency from the Perspective of Production–Living–Ecological Functions

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Abstract

The rapid expansion of the rural digital economy (RDE) has introduced new opportunities for enhancing ecological product value conversion efficiency (EPVCE), yet the mechanisms underlying this relationship remain insufficiently understood. Based on provincial panel data from 31 Chinese provinces during 2010–2019, this study constructs an RDE index system and evaluates EPVCE using a super-efficiency slack-based measure (SBM) model. Two-way fixed-effects models, bootstrap mediation analysis, heterogeneity tests, and spatial Durbin models are employed to examine the impact of RDE on EPVCE and explore the underlying mechanisms. The findings reveal that (1) RDE is significantly and positively associated with EPVCE, and this finding remains robust to alternative model specifications and variable measures, controls for climatic factors, a one-period lag of RDE, and an instrumental-variable approach; (2) production, living, and ecological functions constitute key transmission channels, with the ecological function exhibiting a relatively larger indirect effect; (3) the positive relationship is more pronounced in eastern China and non-resource-based provinces, indicating substantial heterogeneity; and (4) spatial analysis reveals that the relationship is primarily characterized by local effects rather than spatial spillovers. From a rural multifunctionality perspective, this study extends research on the RDE–EPVCE nexus and provides empirical evidence for coordinating rural digital transformation with ecological value realization.

Keywords: rural digital economy; ecological product value conversion efficiency; production–living–ecological functions; rural green transformation

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1. Introduction

Ecosystems provide human societies not only with material goods such as food, water, and timber, but also with a wide range of services that support socioeconomic development, including water conservation, climate mitigation, soil protection, biodiversity maintenance, recreational benefits, and cultural values. With advances in ecosystem service valuation and natural capital accounting, ecosystem services have gradually evolved from being viewed merely as an environmental backdrop to being recognized as a form of natural capital that can be identified, quantified, and incorporated into public decision-making [1–4]. In recent years, Gross Ecosystem Product (GEP) accounting has further advanced ecosystem service valuation from theoretical assessment to policy application, providing a valuable

tool for integrating the value of ecological resources into regional development decision-making [5]. Within the context of China's ecological civilization agenda, ecological product value conversion describes how ecosystem-derived products and services are transformed into measurable, tradable, and sustainable socioeconomic benefits through mechanisms such as ecological compensation, market-based transactions, industrial development, green finance, and institutional innovation [6–8]. However, ecological resource endowments do not automatically translate into tangible development outcomes. Constraints related to value accounting, market connectivity, industrial organization, factor allocation, and institutional arrangements have contributed to substantial regional disparities in EPVCE [6,7]. Improving EPVCE has therefore become a key issue in transforming ecological advantages into sustainable development gains.

Among the factors associated with EPVCE, the digital economy, encompassing digital infrastructure, digital platforms, digital finance, and data-driven production elements, is increasingly reshaping resource allocation, industrial organization, and market transactions. Existing research has indicated that digital economic development is closely linked to improvements in green total factor productivity, low-carbon transformation, and rural revitalization through mechanisms including lower information barriers, enhanced innovation capacity, more efficient resource allocation, and industrial restructuring [9–11]. In rural areas endowed with abundant ecological resources but constrained by limited market access, digitalization may further facilitate the conversion of ecological resources into socioeconomic value by expanding marketing channels for ecological products, promoting the integration of ecology-related industries, alleviating financing constraints faced by market participants, and improving factor allocation efficiency [11–13]. Nevertheless, prior studies have mainly examined how digitalization relates to green development, ecological performance, low-carbon transformation, and rural revitalization, while whether and through what mechanisms RDE enhances EPVCE remains insufficiently examined. More importantly, the effects of RDE extend beyond technological diffusion and may also influence ecological product value conversion by reshaping the production, living, and ecological functions of rural systems. Accordingly, this study develops an analytical framework that integrates RDE, rural production–living–ecological functions, and EPVCE.

1.1. Ecological Product Value Conversion Efficiency: Conceptual Evolution and Measurement Advances

EPVCE is conceptually distinct from both the value of ecological products and eco-efficiency in the conventional sense. The value of ecological products mainly represents the monetary or non-monetary value of goods and services provided by ecosystems, whereas eco-efficiency generally focuses on the relationship between economic output and resource consumption or environmental pressure. In comparison, EPVCE highlights how effectively ecological resources, ecological products, and ecological capital are transformed into socioeconomic benefits within particular institutional, market, and industrial contexts. Its central concern is therefore not only the conversion of ecological value into tangible benefits but also the efficiency of this conversion process [6,8].

The theoretical foundations of EPVCE research can be traced to ecosystem service valuation, natural capital theory, and ecological economics. Early studies advanced the identification and quantification of ecological value through ecosystem service valuation, ecosystem function classification, and natural capital accounting [1,2]. Subsequently, research on ecosystem services and natural capital gradually shifted from value identification toward decision-oriented applications, with increasing emphasis on incorporating natural capital into public policy, regional planning, and sustainable development decision-making [4,14]. More recently, GEP accounting has further facilitated the transition of

ecosystem service valuation from theoretical assessment to policy application, providing a useful instrument for integrating ecological value into regional development decisions [5]. However, ecological value accounting primarily addresses the magnitude of ecological resource value, whereas EPVCE further concerns how ecological value is converted into tangible benefits and whether this conversion is achieved efficiently. Accordingly, building on ecological value accounting, EPVCE research places greater emphasis on the interrelationships among ecological capital allocation, industrial transformation, market transactions, and institutional support.

Existing approaches to measuring EPVCE can be broadly classified into two categories. The first treats EPVCE as the ratio of converted economic value to GEP or the potential value of ecological products, thereby highlighting the effectiveness of transforming ecological value into socioeconomic benefits. Although this approach is intuitive and straightforward, it has limited capacity to identify input redundancy, output shortfalls, and efficiency losses during the value conversion process. The second adopts an input–output efficiency perspective by incorporating the value of ecological products or ecological capital as an input, together with traditional inputs including capital and labor, while applying economic returns, social welfare, or ecological benefits as outputs to assess the efficiency with which ecological capital is converted into socioeconomic benefits [6,7]. Compared with the simple ratio approach, the input–output efficiency framework can simultaneously account for the allocation efficiency of multiple inputs, including ecological capital, physical capital, and labor, while identifying input redundancy and output shortfalls in the value conversion process. Therefore, this study adopts an input–output efficiency perspective and conceptualizes EPVCE as the overall efficiency of ecological capital allocation and ecological value conversion.

In recent years, research on EPVCE has gradually shifted from conceptual discussion and policy analysis toward quantitative efficiency assessment and the identification of its determinants. Song and Du [8] examined ecological product value conversion mechanisms from the perspective of green financial intervention and support, providing empirical evidence on the role of financial factors in facilitating ecological product value conversion. Lou et al. [7] developed a serial–parallel nested two-stage network data envelopment analysis (DEA) model to evaluate the efficiency of converting forest ecosystem products into economic value in China. Their findings indicated that the conversion stage exhibited lower efficiency compared with the preceding product supply stage. Deng et al. [6] further measured EPVCE in China's National Key Ecological Function Zones and identified pronounced spatiotemporal disparities and spatial spillover effects, while noting that research on EPVCE remains at an early stage. Collectively, these studies suggest that EPVCE is jointly shaped by technological development, industrial foundations, market mechanisms, ecological compensation, and regional development conditions. Nevertheless, the existing literature has largely concentrated on efficiency measurement, ecological compensation, and value conversion pathways, whereas insufficient attention has been paid to the role of the digital economy as an emerging technological factor in shaping EPVCE.

1.2. Digital Economy and Ecological Product Value Conversion Efficiency

By expanding digital infrastructure, enabling data to function as a productive input, platform-based organization, and digital financial services, the digital economy is profoundly reshaping the organization of economic activities and the efficiency of resource allocation. Existing studies generally suggest that the digital economy has considerable potential to advance environmentally sustainable development. On the one hand, digital technologies can enhance information transparency, improve resource allocation efficiency, and foster green technological innovation, thereby contributing to gains in green total factor

productivity and energy efficiency, as well as improved low-carbon development performance [9,10]. On the other hand, digital finance and digital infrastructure can alleviate financing constraints, facilitate industrial upgrading, enhance market development, and promote the provision of agricultural socialized services, thereby contributing to rural development, rural industrial revitalization, and broader rural revitalization [11–13]. These insights offer an important basis for examining the potential role of the digital economy in ecological product value conversion.

Nevertheless, the pathways linking the digital economy with EPVCE may differ from those associated with conventional indicators of green development performance. Green total factor productivity, eco-efficiency, and low-carbon development performance mainly emphasize resource utilization and environmental pressures associated with economic growth, whereas EPVCE focuses more specifically on the conversion of ecological resource value into socioeconomic benefits. Accordingly, the relationship between the digital economy and EPVCE may be associated with market connectivity, industrial organization, transaction costs, and the capabilities of market participants. Specifically, digital infrastructure can improve information accessibility and market connectivity in rural areas, thereby lowering the costs involved in matching ecological product supply with market demand. Digital platforms and rural e-commerce can broaden marketing channels for ecological products, including specialty agricultural products, ecotourism services, and forest-based health and wellness services, thereby expanding their market reach. Digital finance can ease financing constraints faced by ecological industry operators and strengthen their capacity for ecological product development, branding, and value conversion. Meanwhile, data governance and digital monitoring can facilitate more precise management of ecological resources, thereby enhancing the quality and sustainability of ecological product supply [11–13].

Although previous studies have provided valuable insights into the relationship between the digital economy and green development, several research gaps remain. First, prior research has primarily examined the relationship between digital economy development and eco-efficiency, green total factor productivity, carbon emission efficiency, or rural revitalization, whereas relatively limited attention has been devoted to EPVCE. Second, existing research has predominantly relied on aggregate regional digital economy indices, with insufficient differentiation between urban and rural digital development. This makes it difficult to identify the specific role of digitalization in rural contexts. Third, limited attention has been devoted to the pathways linking digital economy development with EPVCE, particularly from the perspective of rural production, living, and ecological functions. Therefore, whether RDE can enhance EPVCE, as well as the mechanisms and spatial effects associated with this relationship, requires further empirical investigation.

1.3. Functional Structure of Rural Systems and Ecological Product Value Conversion

The impact of RDE on EPVCE should be understood within the functional structure of rural territorial systems. Rural areas are not merely spaces for agricultural production; rather, they constitute complex territorial systems that simultaneously perform multiple production, living, and ecological functions. Research on rural multifunctionality has shown that, as rural areas transition from traditional productivism toward multifunctional development, rural spaces increasingly perform not only agricultural production and economic functions but also a broader range of functions related to residential well-being, ecological conservation, cultural and recreational activities, and environmental protection [15–18]. Among these dimensions, the production function reflects the capacity of rural areas to generate economic output, organize industrial activities, and provide goods and services. The living function captures residents' income, access to public services, consumption capacity, and quality of life, whereas the ecological function reflects the capacity for ecosystem conser-

vation, environmental governance, and ecological product provision. These three functions may generate synergies but may also involve trade-offs, and the degree of coordination among them has direct implications for the sustainability of rural development [16–18].

Incorporating the production–living–ecological function framework into the analysis of EPVCE provides a perspective for understanding the pathways linking RDE with ecological product value conversion. First, the production function links ecological resources with industrial returns and constitutes a key channel through which ecological resources are transformed into marketable products and economic value. By improving digital infrastructure, expanding digital platforms, and promoting industrial digitalization, RDE can strengthen the development capacity of ecology-related industries, such as ecological agriculture, rural tourism, forest-based health and wellness services, and specialty agricultural product processing. These developments can, in turn, enhance the capacity of local industries to utilize ecological resources and convert them into market value. Second, the living function reflects rural residents' income levels, consumption capacity, access to public services, and ability to participate in economic activities, thereby constituting an essential social foundation for ecological product value conversion. Digital finance, e-commerce platforms, and digital public services can strengthen rural residents' ability to engage in the development, production, and operation of ecological products, thereby improving the socioeconomic conditions required for value conversion. Third, the ecological function determines both the quality of ecological product supply and the long-term sustainability of ecological product value conversion. Digital monitoring, information disclosure, and data governance can improve the precision of ecological resource management and strengthen the capacity to supply ecological products. However, if digitalization is accompanied by infrastructure expansion, increased resource consumption, or excessive exploitation of ecology-related industries, it may also place pressure on ecological functions.

Accordingly, the production–living–ecological function framework serves not only as a useful tool for evaluating rural development but also as an analytical framework for explaining how RDE influences EPVCE. Compared with approaches that focus solely on industrial upgrading, green innovation, or digital finance, an analysis based on the functional structure of rural systems provides a more systematic explanation of how RDE affects ecological product value conversion through changes in economic production capacity, residents' living conditions, and the ecological foundation of product supply.

1.4. Research Questions and Marginal Contributions

Based on the preceding discussion, this study investigates three research questions. First, is RDE significantly associated with EPVCE? Second, does RDE affect EPVCE through rural production, living, and ecological functions, and do these three pathways differ in the direction and magnitude of their effects? Third, does the effect of RDE on EPVCE exhibit spatial spillovers?

To address these questions, this study used panel data from 31 provinces in China over the period 2010–2019. An RDE indicator system was developed based on three dimensions: digital infrastructure, rural digital industrialization, and digital transformation of rural industries. EPVCE was evaluated using an SBM approach. Mediation analysis and a spatial Durbin model were subsequently applied to examine the relationship between RDE and EPVCE, its potential transmission pathways, and spatial spillover characteristics.

Relative to previous studies, this research provides three main contributions. First, regarding research focus, this study expands existing analyses beyond conventional indicators, including eco-efficiency, green development performance, and ecological welfare performance, toward EPVCE, thereby emphasizing the transformation of ecological resource values into socioeconomic outcomes. Second, from a mechanism perspective, this study

integrates rural production, living, and ecological functions into the analytical framework connecting RDE with EPVCE, enabling the identification of multidimensional pathways associated with the relationship between RDE and EPVCE. Third, regarding the empirical setting and spatial dimension, this study develops a digital economy measurement system better suited to rural characteristics and further differentiates between local associations and spatial spillover patterns related to RDE and EPVCE. In this way, it offers empirical insights into the coordinated advancement of digital development and ecological civilization.

The structure of the remainder of this paper is outlined as follows. Section 2 develops the theoretical mechanism analysis and corresponding research hypotheses. Section 3 describes the data sources, variable construction, and model settings. Section 4 presents the empirical findings and provides further discussion. Section 5 summarizes the main conclusions, discusses policy implications, and highlights research limitations. Figure 1 provides an overview of the analytical framework adopted in this study.

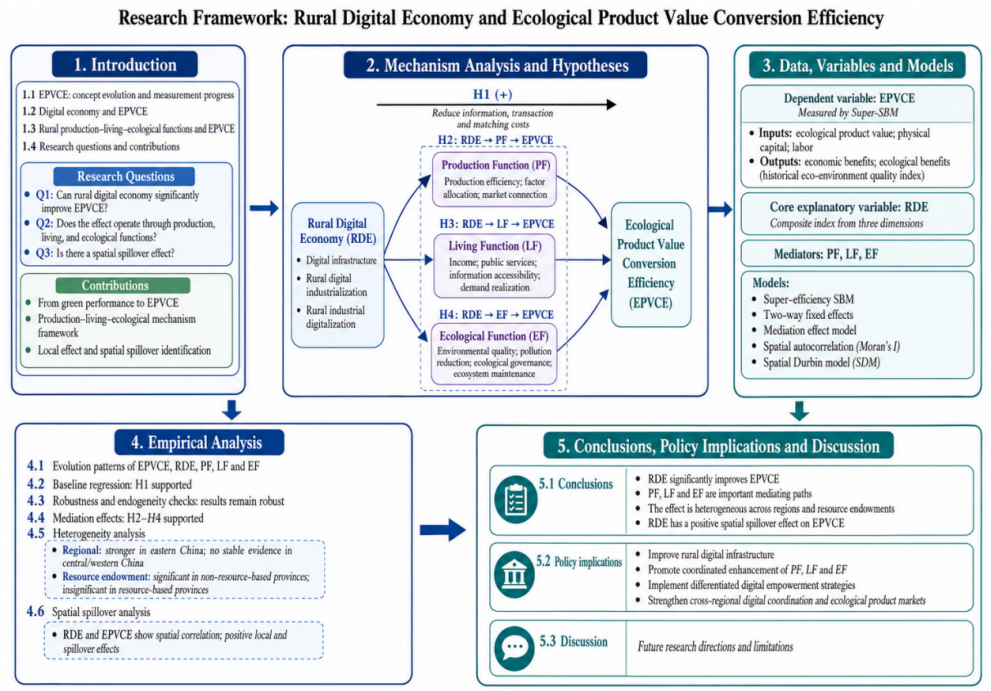


Figure 1. Research Framework of This Study.

2. Mechanism Analysis and Research Hypotheses

2.1. Definition of Production–Living–Ecological Functions and Theoretical Framework

EPVCE reflects the relative efficiency with which ecological product value is converted into realized economic returns and ecological benefits under given constraints of ecological capital, physical capital, and labor inputs. Improvements in EPVCE depend not simply on greater ecological resource endowments, but more fundamentally on whether ecological resources can generate effective supply, actual demand, and sustained ecological support within rural territorial systems. Rural territorial systems are not merely spaces for agricultural production but complex functional systems jointly shaped by production and supply, living support, and ecological regulation. According to multifunctional land-use theory, land-use systems generally perform multiple functions simultaneously, including commodity production, support for social life, and ecological and environmental conservation, with synergies, trade-offs, and spatial interactions among these functions [15,19]. The production–living–ecological function framework further emphasizes that rural areas perform not only agricultural production and economic functions but also functions related

to residential living, public services, human settlements, and ecological regulation. The degree of coordination among these three functions directly affects the sustainability of rural territorial systems [16,17].

In this study, production–living–ecological functions are conceptualized not as general spatial classifications or development outcomes, but as functional conditions underpinning the conversion of potential ecological value into realized economic returns and ecological benefits. Specifically, the production function represents the capacity to generate an effective supply of ecological products; the living function reflects the capacity for stakeholder participation and demand realization; and the ecological function represents the capacity to sustain ecological product provision and provide ecological support. If the production function is weak, ecological resources may fail to generate an effective supply of marketable products. If the living function is insufficient, ecological products may struggle to gain market recognition and translate potential demand into actual payment. Similarly, deterioration of the ecological function may undermine both the sustained supply capacity and market attractiveness of ecological products.

From a temporal perspective, RDE first influences the production, living, and ecological functions of rural territorial systems by reshaping information acquisition, platform connectivity, resource allocation, and governance capacity, and subsequently affects EPVCE. Accordingly, production–living–ecological functions are more appropriately treated as transmission mechanisms rather than merely as background control variables. RDE does not operate independently of rural territorial systems; rather, it becomes embedded in these systems through digital infrastructure, rural digital industrialization, and the digitalization of rural industries. Through this process, RDE affects ecological product value conversion by influencing supply formation, demand realization, and ecological support. Figure 2 presents the theoretical framework proposed in this study.

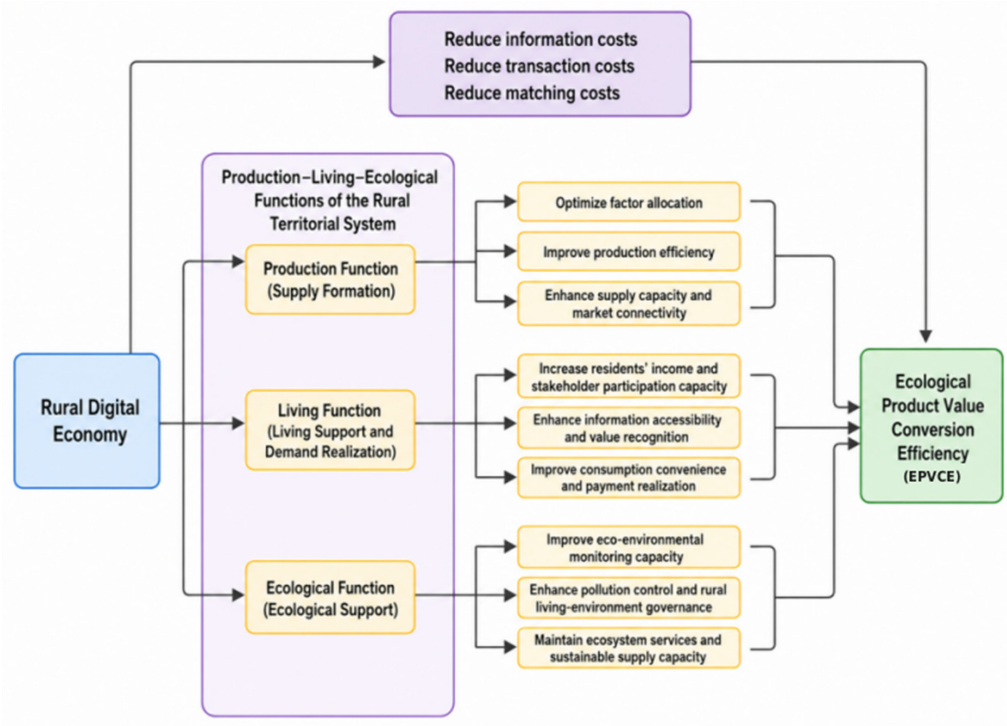


Figure 2. Theoretical Mechanism Framework of the Impact of RDE on EPVCE.

2.2. Direct Effect of the Rural Digital Economy on Ecological Product Value Conversion Efficiency

Improving EPVCE requires reducing information and transaction frictions and enhancing resource allocation throughout the ecological product value conversion process.

Compared with conventional goods, ecological products often exhibit characteristics such as public-good attributes, externalities, spatial immobility, and difficulties in quality identification. Their value conversion is therefore particularly susceptible to information asymmetry, high search costs, difficulties in quality verification, and limited market reach. According to information asymmetry theory, information search theory, and transaction cost theory, when consumers face difficulties in identifying product quality, obtaining market information is costly, or transaction organization involves substantial costs, high-quality products may fail to command prices commensurate with their underlying value, thereby reducing resource allocation efficiency [20–22]. In the case of ecological products, attributes such as ecological quality, environmentally friendly production practices, local landscape value, and broader environmental characteristics are often difficult to identify accurately and communicate credibly to consumers, which may ultimately constrain EPVCE.

RDE may alleviate these constraints through three main channels: information accessibility, market connectivity, and resource allocation. First, digital infrastructure can enhance the visibility and accessibility of information related to ecological products, making information on product origin, production processes, ecological attributes, and quality characteristics more readily available to consumers. Second, e-commerce, digital payment systems, and rural logistics services can expand the market reach of ecological products while reducing supply–demand matching and transaction costs, thereby connecting geographically dispersed rural suppliers with broader consumer markets. Third, digital inclusive finance, agricultural information services, and digital business platforms can help alleviate financing constraints, information disadvantages, and market-entry barriers faced by rural producers and business operators, thereby improving the allocation efficiency of ecological resources. Previous studies have shown that digital infrastructure, digital finance, and broader digital economy development can influence rural and green development outcomes through channels such as industrial upgrading, market development, improved resource allocation, and green technological innovation [9,10,12].

Therefore, holding ecological resource endowments and conventional factor inputs constant, RDE is expected to improve the efficiency with which ecological value is converted into economic returns and ecological benefits by reducing information, transaction, and matching costs throughout the ecological product value conversion process. Accordingly, the following hypothesis is proposed:

H1. *Higher levels of RDE are positively associated with EPVCE.*

2.3. Mediating Role of the Production Function

The production function constitutes the supply-side foundation of ecological product value conversion. The production function captures whether ecological resources can be transformed into a stable supply of high-quality products with relatively low environmental impacts. Under traditional agricultural production conditions, production decisions often rely heavily on experience-based judgments, which may lead to extensive and inefficient use of agricultural inputs. At the same time, quality signals are often difficult to communicate effectively to the market. These limitations not only reduce the allocation efficiency of production factors such as land, labor, and capital but also limit producers' ability to obtain price premiums based on the ecological attributes of their products, making it difficult to fully capture ecological price premiums.

RDE can improve agricultural production decisions through agricultural information services, meteorological data, market price information, technology extension platforms, and digital production services, thereby enhancing the responsiveness of agricultural production to changes in both natural conditions and market demand. Research on precision

agriculture has shown that production management based on site-specific information can optimize the allocation of agricultural inputs while simultaneously improving production efficiency and reducing environmental pressures [23]. Studies on digital agriculture further indicate that big data, the Internet of Things, cloud computing, and platform-based services are becoming increasingly embedded in agricultural production and management. Their effects extend beyond the production process itself to the organization of food supply chains and agricultural innovation networks [24,25].

At the same time, digital platforms and e-commerce channels can strengthen the market connectivity of ecological products, enabling dispersed ecological agricultural products, specialty agricultural products, and rural ecological services to access external markets more effectively. Existing research has indicated that the embeddedness of information and communication technology infrastructure, production networks, and social networks can reshape the spatial organization of rural areas in the context of e-commerce and improve connections between rural products and external markets [26]. The expansion of rural e-commerce can also contribute to higher rural household incomes and enhance market linkages among rural business operators, thereby improving the organizational conditions for rural production and industrial development [27].

Accordingly, RDE may influence the efficiency of transforming ecological resources into economic returns and ecological benefits by increasing agricultural production efficiency, optimizing factor allocation, reducing resource waste, strengthening market connectivity, and enhancing capacity for ecological product supply. In this process, the production function primarily operates as a supply-side mediating mechanism. Based on the above discussion, the following hypothesis is proposed:

H2. *The production function constitutes a potential mediating pathway in the positive relationship between RDE and EPVCE.*

2.4. Mediating Role of the Living Function

The living function constitutes the social foundation for ecological product value conversion. It reflects the capacity of rural areas to provide living support and demand conditions through improvements in income capacity, public services, information accessibility, and consumption patterns. Ecological product value conversion depends not only on the ability to generate marketable products on the supply side, but also on consumers' ability to recognize ecological value, access relevant consumption opportunities, and translate willingness to pay into actual purchases. For ecological products including sustainable agricultural goods, ecotourism services, rural landscape resources, and local cultural offerings, even products with substantial potential ecological value may fail to generate actual economic returns if consumers cannot obtain relevant information in a timely manner, identify ecological attributes, or access appropriate consumption contexts.

RDE can improve income conditions, public service accessibility, and information acquisition capacity among rural residents through digital infrastructure, digital finance, e-commerce platforms, and digital service consumption, thereby strengthening the capacity for stakeholder participation and demand realization required for ecological product value conversion. First, digital finance, e-commerce platforms, and the development of rural digital industries can expand employment and entrepreneurial opportunities for rural households, enhancing their ability to participate in ecological product development, operation, and service provision. Second, the Internet and digital platforms can improve the visibility of ecological products, rural landscapes, and local cultural services, thereby strengthening external consumers' recognition of ecological value. Third, online transactions, digital payment systems, logistics services, and user evaluation mechanisms can

reduce transaction costs between information search and actual purchase, increasing the rate at which potential demand is transformed into effective consumption. Existing studies have shown that the development of rural e-commerce can increase rural residents' income and improve the connectivity between rural products and external markets [26,27]. Furthermore, e-commerce may promote the transition toward green consumption by enhancing consumption capacity, facilitating industrial restructuring, and encouraging enterprises to adopt greener production practices [28].

Therefore, RDE may enhance the market recognition and consumers' willingness and ability to pay, improving public service conditions, enhancing information accessibility, and optimizing consumption structures, thereby improving EPVCE. In this process, the living function primarily operates as a mediating mechanism related to living support and demand realization. Based on the above analysis, the following hypothesis is proposed:

H3. *The living function constitutes a potential mediating pathway in the positive relationship between RDE and EPVCE.*

2.5. Mediating Role of the Ecological Function

The ecological function constitutes the natural foundation for the sustained provision of ecological products. It reflects the capacity for environmental conservation, pollution control, improvement of rural living environments, and ecosystem service provision. Ecological product value conversion should not be understood as the mere exploitation of ecological resources. Rather, it should involve improving the efficiency of ecological value conversion while maintaining ecosystem stability and enhancing environmental quality. If rural areas experience environmental degradation, inadequate pollution control, or deterioration in ecosystem services, both the supply basis and market attractiveness of ecological products are likely to be weakened.

RDE may improve environmental monitoring, pollution detection, and rural environmental management through digital infrastructure, environmental data platforms, information disclosure, digital regulation, and multi-actor governance. Specifically, remote sensing, geographic information systems, environmental data platforms, and digital regulatory tools can improve the observability of changes in ecological quality, pollutant emissions, and resource use, thereby reducing information delays and regulatory blind spots inherent in conventional environmental governance. Zhao et al. [29] found that digital transformation in governmental environmental governance can reduce environmental pollution and improve environmental quality in adjacent areas through spatial interactions. Although the digitalization of governmental environmental governance is not equivalent to RDE, this finding provides relevant empirical evidence that digital technologies can improve environmental monitoring, pollution identification, and governance efficiency.

Nevertheless, the relationship between the digital economy and ecological functions may not always be positive. The expansion of digital infrastructure, logistics networks, and platform-based consumption may also increase energy consumption, packaging waste, and pressure on ecological space. Therefore, whether RDE can improve EPVCE through the ecological function depends on whether greener production practices, environmental governance capacity, and ecological protection constraints are strengthened alongside digital development. Against the backdrop of China's ongoing ecological civilization initiatives and continued improvements in rural living environments, this study expects RDE, on balance, to enhance EPVCE by strengthening environmental monitoring, pollution control, rural environmental management, and ecosystem service maintenance.

Accordingly, RDE may strengthen the foundation for the sustained supply and ecological attractiveness of ecological products by improving environmental quality, reducing

pollution pressures, enhancing the governance of rural living environments, and strengthening ecosystem service maintenance, thereby increasing EPVCE. In this process, the ecological function primarily serves as a mediating mechanism that supports sustained ecological product supply and long-term sustainability. Based on the above analysis, the following hypothesis is proposed:

H4. *The ecological function constitutes a potential mediating pathway in the positive relationship between RDE and EPVCE.*

3. Data Analysis

3.1. Data Sources

This study utilizes provincial panel data covering 31 regions in China during the period 2010–2019. The data were primarily drawn from the China Statistical Yearbook, the China Environmental Statistical Yearbook, the China Forestry Statistical Yearbook, the China Rural Statistical Yearbook, the China Information Almanac, the National Bureau of Statistics of China, the Ministry of Industry and Information Technology, and provincial statistical yearbooks. Data on the digital economy were obtained from the China Information Almanac and statistical bulletins published by provincial communications authorities. Data related to ecological product value conversion and the production, living, and ecological functions were collected from the China Environmental Statistical Yearbook, the China Forestry Statistical Yearbook, and the China Rural Statistical Yearbook. Data for the control variables, including GDP per capita, urbanization rate, fiscal expenditure on agriculture, and forest coverage, were obtained from the China Statistical Yearbook.

The sample period was restricted to 2010–2019 to avoid potential distortions associated with the COVID-19 pandemic. Ecological product value conversion is highly dependent on market conditions, particularly those related to agricultural production, ecotourism, and household consumption. The pandemic caused substantial disruptions to tourism flows, consumer behavior, and service-sector activities from 2020 onward, resulting in abnormal fluctuations in the market-oriented conversion of ecological products. Including the pandemic period could therefore obscure the underlying relationship between RDE and EPVCE. To account for price changes, all monetary variables were converted to constant 2010 prices. Missing observations were imputed using linear interpolation.

3.2. Variable Selection

3.2.1. Dependent Variable: Ecological Product Value Conversion Efficiency

The dependent variable in this study is EPVCE. Following previous research [6], EPVCE is defined as the relative efficiency with which each region obtains actual economic returns and ecological benefits, given its stock of ecological product value and inputs of physical capital and labor, relative to the optimal production frontier. EPVCE was measured using an SBM model.

Specifically, the input indicators include (1) ecological product value, calculated using an ecosystem service valuation approach and covering provisioning, regulating, supporting, and cultural services; (2) physical capital, comprising agricultural capital and tourism capital, which were estimated by allocating fixed-asset investment according to the respective shares of agricultural and tourism output; and (3) labor input, represented by employment levels in the agricultural and tourism sectors.

The output indicators include: (1) economic returns, measured by the gross value of agricultural output and tourism revenue; and (2) ecological benefits, measured using a historical ecological environmental quality index derived from remote sensing data,

as shown in Table 1. Detailed procedures for calculating ecological product value and environmental quality are provided in Supplementary Materials [30].

Table 1. Indicator System for EPVCE.

Primary Category	Secondary Indicator	Tertiary Indicator	Specific Indicator/Description	Reference
Input indicators	Ecological product value	Provisioning services	Food provision, raw material provision, and water supply	[6]
		Regulating services	Gas regulation, climate regulation, environmental purification, and hydrological regulation	
		Supporting services	Soil conservation, nutrient cycling, and biodiversity preservation	
		Cultural services	Agricultural tourism and general tourism	
	Physical capital	Agriculture	Fixed-asset investment × the proportion of agriculture, forestry, animal husbandry, and fisheries output in regional GDP	
		Tourism	Fixed-asset investment × the proportion of tourism revenue in regional GDP	
	Labor	Agriculture	Number of employees engaged in agriculture, forestry, animal husbandry, and fisheries	
		Tourism	Employment estimated according to the share of tourism revenue in the output of tertiary industries, including industry-related tertiary sectors	
Output indicators	Economic returns	Agriculture	Total output of agriculture, forestry, animal husbandry, and fisheries, and value added of the primary sector	
		Tourism	Tourism revenue and tourist arrivals	
	Ecological benefits	Environmental quality	Historical ecological environmental quality data derived from remote-sensing data	

3.2.2. Core Explanatory Variable: Development Level of the Rural Digital Economy

The core explanatory variable is RDE. Unlike broader measures of regional digitalization or rural modernization, RDE is defined in this study as the penetration, application, and integration of digital infrastructure, digital technologies, and digitally enabled services into rural economic activities. Particular emphasis is placed on the role of digital factors in supporting rural production, circulation, and service systems. Accordingly, the measurement

of RDE focuses on digital connectivity, digital service provision, and the adoption of digital technologies across rural industries, rather than on general infrastructure expansion, overall economic development, or rural modernization per se. Based on this conceptual boundary, a composite RDE index is constructed from three dimensions: digital infrastructure, rural digital industrialization, and rural industrial digitalization.

Specifically, digital infrastructure captures the fundamental conditions supporting the adoption and utilization of digital technologies in rural areas, including information network connectivity and access to and use of digital devices. It therefore represents the foundational support for RDE. Rural digital industrialization reflects the development of digital technologies, digital finance, and platform-based services in rural areas, capturing the capacity of the digital sector to provide services and generate economic activity. Rural industrial digitalization measures the extent to which digital technologies are embedded in agricultural production, agricultural product circulation, and other rural industrial activities. It thus reflects the capacity of traditional rural industries to use digital technologies to improve production efficiency and strengthen market connectivity. These three dimensions correspond to digital foundations, digital service development, and the digital transformation of rural industries, respectively, and together provide a comprehensive representation of RDE.

After standardization, the indicators were aggregated using the entropy weighting method to construct RDE index. The detailed indicator system is presented in Table 2.

Table 2. Indicator System for RDE.

Criterion Layer	Indicator Layer	Indicator Code	Calculation Method (Direction)	Unit	Reference
Digital infrastructure	Rural internet penetration rate	X1	Ratio of rural broadband access subscribers to total rural users (+)	%	[31]
	Rural mobile phone penetration rate	X2	Average mobile phone ownership per 100 rural households (+)	Units	
	Rural computer penetration rate	X3	Average computer ownership per 100 rural households (+)	Units	
	Radio and television network coverage rate	X4	Ratio of rural cable radio and television subscribers to total rural households (+)	%	
Rural digital industrialization	Number of agrometeorological observation stations	X5	Number of agrometeorological observation stations (+)	Stations	
	Number of rural digitalization bases	X6	Number of Taobao villages (+)	Villages	

Table 2. *Cont.*

Criterion Layer	Indicator Layer	Indicator Code	Calculation Method (Direction)	Unit	Reference
	Scale of rural online payments	X7	Rural Digital Financial Inclusion Index (+)	—	
	National modern agricultural demonstration projects	X8	Number of national key leading enterprises in agricultural industrialization (+)	Enterprises	
Digital transformation of rural industries	Digital transactions of agricultural products	X9	E-commerce sales revenue (+)	CNY 100 million	
	Digital procurement of agricultural products	X10	E-commerce procurement value (+)	CNY 100 million	
	Coverage of information technology applications, including the Internet of Things	X11	Length of rural postal delivery routes (+)	km	
	Level of postal and communication services	X12	Average weekly frequency of rural delivery services (+)	Deliveries	
	Digital service consumption level	X13	Per capita expenditure of rural residents on transportation and communication (+)	CNY	
	Digital service workforce	X14	Number of agricultural science and technology personnel (+)	Persons	

Note: "+" indicates a positive indicator.

3.2.3. Mediating Variables: Production, Living, and Ecological Functions

To further identify the potential pathways linking RDE and EPVCE, this study constructs three mediating variables—production function (PF), living function (LF), and ecological function (EF)—within the theory of rural territorial multifunctionality.

The PF primarily reflects the capacity of rural territorial systems to undertake agricultural production, allocate production factors, and provide agriculture-related goods and services, with particular emphasis on agricultural production efficiency, labor utilization efficiency, and resource input constraints. The LF mainly captures the capacity of rural areas to support residents' livelihoods, generate income, and provide public services, thereby reflecting rural living conditions and the capacity for demand realization. The EF primarily represents the capacity of rural territorial systems to maintain environmental quality, improve rural living environments, and provide ecosystem services, thereby reflecting the degree of ecological protection and environmental governance in rural areas.

The indicator systems for the three functions were developed with reference to Ren et al. [32], Su et al. [33], and Zhou et al. [18], while also taking into account the characteristics of the present study and the availability of provincial-level panel data. The indicators were aggregated using the entropy weighting method. It should be emphasized that PF, LF, and EF characterize the functional status and development capacity of rural territorial systems across different dimensions, whereas EPVCE measures the effectiveness of con-

verting ecological resource inputs into economic, ecological, and social outputs. The two therefore differ in both conceptual meaning and measurement objectives. Accordingly, PF, LF, and EF are treated in this study as potential mediating mechanisms through which RDE affects EPVCE, rather than as alternative measures of EPVCE itself. The specific indicator framework is provided in Table 3.

Table 3. Indicator System for Production–Living–Ecological Functions.

Functional Dimension	Indicator Code	Indicator Name	Calculation Method	Unit	Direction	References
Production function	P1	Grain yield per unit of sown area	Total grain production divided by grain sown area	kg/ha	+	[32,33]
	P2	Agricultural labor productivity	Value added of agriculture, forestry, animal husbandry, and fisheries divided by primary-sector employment	CNY 10,000/person	+	[33,34]
	P3	Fertilizer application per unit of cultivated land	Fertilizer application measured by pure nutrient content per unit of cultivated land area	t/ha	−	[33,34]
Living function	L1	Per capita disposable income of rural residents	Disposable income of rural residents	CNY/person	+	[18,33,34]
	L2	Number of health professionals per 1000 rural residents	Number of health professionals per rural population	%	+	[18]
	L3	Per Capita Housing Area of Rural Residents	Directly Obtained	m^3/person	+	
	L4	Engel coefficient of rural residents	Ratio of food, tobacco, and alcohol expenditure to total per capita consumption expenditure	%	−	
Ecological function	E1	Rural greening rate	Village green area, including streets, courtyards, parks, and surrounding shelterbelts/administrative area of the village	%	+	
	E2	Composite environmental pollution index	Calculated using the entropy-weight method based on total wastewater discharge, sulfur dioxide emissions, and general industrial solid waste generation	%	−	
	E3	Proportion of administrative villages with domestic sewage treatment	Ratio of administrative villages equipped with domestic sewage treatment facilities to the total number of administrative villages	%	+	[18]
	E4	Sanitary toilet coverage rate	Ratio of rural households using sanitary toilets to the total number of rural households	%	+	[18]

Note: ”+” indicates a positive indicator, and ”−” indicates a negative indicator.

3.2.4. Control Variables

To reduce potential estimation bias arising from omitted variables, this study includes the following control variables (Table 4):

(1) GDP per capita (PGDP): This variable captures regional economic development and accounts for the potential influence of economic growth on ecological value conversion. Regions with stronger economic development may possess greater capacity to invest in ecological conservation, but they may also face greater pressure from resource consumption [35].
(2) Urbanization rate (URB): This variable is measured by the share of urban population in the total population and captures the potential influence of urbanization on ecological value conversion. Urbanization may affect ecosystem service functions through population agglomeration, land-use change, and related processes [35].
(3) Fiscal support for agriculture (AGR): This variable is measured by government expenditure on agricultural support and captures the potential role of agricultural policies in ecological value conversion. Fiscal support for agriculture may influence ecological product supply through agricultural technology extension, ecological compensation, and other channels.
(4) Forest coverage rate (FCOV): This variable reflects regional ecological resource endowments and controls for the effects of natural conditions on ecological value conversion. In general, a higher forest coverage rate is associated with a stronger regional capacity to supply ecological products.

Table 4. Descriptive Statistics

Variable	Symbol	Unit	Mean	Standard Deviation	Min	Max
Ecological product value conversion efficiency	EPVCE	/	0.4796	0.2621	0.0933	1.3398
Rural digital economy	RDE	/	0.1482	0.1029	0.0162	0.7082
GDP per capita	PGDP	CNY per capita	50,239.85	26,572.84	13,066.00	172,373.00
Urbanization rate	URB	%	0.561	0.1358	0.2222	0.9415
Fiscal support for agriculture	AGR	%	0.1146	0.0345	0.0413	0.2094
Forest coverage rate	FCOV	%	0.336	0.1821	0.042	0.668

3.3. Model Specification

3.3.1. Super-Efficiency SBM Model

To measure EPVCE, this study employs the SBM model. Conventional data envelopment analysis (DEA) models can evaluate the relative efficiency of decision-making units (DMUs) within a multiple-input and multiple-output framework. However, they cannot further distinguish among efficient DMUs whose efficiency scores all take a value of 1. The SBM model incorporates input redundancy and output shortfalls into the efficiency assessment, thereby addressing the failure of conventional radial DEA models to account for slack variables. The super-efficiency SBM model additionally removes the evaluated DMU from the reference set. This permits efficient DMUs to obtain efficiency scores greater than 1 and allows a full ranking among all DMUs.

This study treats the 310 province–year observations from 31 provinces during 2010–2019 as DMUs under a common production frontier. This approach improves the discriminatory power of the efficiency measurement and ensures temporal comparability. Suppose that there are n DMUs, each with m input indicators and s desirable output in-

dicators. The input and output vectors of the j DMU are denoted by $\mathbf{x}_j = (x_{1j}, x_{2j}, \ldots, x_{mj})^T$ and $\mathbf{y}_j = (y_{1j}, y_{2j}, \ldots, y_{sj})^T$, respectively. For the evaluated DMUo, the super-efficiency SBM model is specified as follows:

$$\rho_o^* = \min \frac{\frac{1}{m}\sum_{i=1}^{m} \frac{\overline{x}_i}{x_{io}}}{\frac{1}{s}\sum_{r=1}^{s} \frac{\overline{y}_r}{y_{ro}}}$$

subject to

$$\begin{aligned}
\overline{x}_i &\geq \sum_{\substack{j=1 \\ j \neq o}}^{n} \lambda_j x_{ij}, \ \forall i \\
\overline{y}_r &\leq \sum_{\substack{j=1 \\ j \neq o}}^{n} \lambda_j y_{rj}, \ \forall r \\
\overline{x}_i &\geq x_{io}, \ \forall i \\
\overline{y}_r &\leq y_{ro}, \ \forall r \\
\lambda_j &\geq 0, \ j = 1, 2, \ldots, n, \ j \neq o
\end{aligned}$$

where ρ_o^* denotes the EPVCE of DMUo; x_{io} and y_{ro} denote the i input and the r output of DMUo, respectively; $\overline{x}_i$ and $\overline{y}_r$ denote the slack-adjusted input and output variables, respectively; and λ_j is the intensity variable. A value of $\rho_o^* > 1$ indicates that the DMU is super-efficient. A value of $\rho_o^* < 1$ indicates input redundancy or output shortfalls, suggesting that its EPVCE can be further improved.

3.3.2. Two-Way Fixed-Effects Model

To investigate the relationship between RDE and EPVCE, this study specifies the following two-way fixed-effects model:

$$EPVCE_{it} = \alpha_0 + \alpha_1 RDE_{it} + \alpha_2 Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

where $EPVCE_{it}$ denotes the EPVCE of province i in year t; RDE_{it} denotes the level of RDE; and $Controls_{it}$ represents a set of control variables, including GDP per capita, the urbanization rate, fiscal support for agriculture, and the forest coverage rate. Province fixed effects, denoted by μ_i, control for time-invariant regional characteristics. Year fixed effects, denoted by λ_t, control for macroeconomic shocks common to all provinces. The term ε_{it} is the random error term.

The coefficient of primary interest is α_1. A significantly positive $\alpha 1 > 0$ indicates that higher RDE levels are positively related to EPVCE. Province-level cluster-robust standard errors are used in all estimations.

3.3.3. Mediation Effect Model

To further explore the potential pathways linking RDE and EPVCE, this study employs a mediation effect model and applies the bootstrap approach to assess the significance of indirect effects. Compared with the traditional stepwise testing approach, the bootstrap method does not rely on the assumption that indirect effects follow a normal distribution and can therefore improve the statistical power of mediation analysis [36]. Specifically, the following recursive equations are constructed.

First, the total effect of RDE on EPVCE is estimated:

$$EPVCE_{it} = \theta_0 + \theta_1 RDE_{it} + \rho Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

Second, the effect of RDE on the mediating variable is examined:

$$M_{it} = \beta_0 + \beta_1 RDE_{it} + \delta Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

Finally, the mediating variable is incorporated into the baseline model to examine its effect on EPVCE:

$$EPVCE_{it} = \theta_0 + \theta_1 RDE_{it} + \theta_2 M_{it} + \rho Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

where M_{it} denotes the mediating variable, represented by PF_{it}, LF_{it}, and EF_{it}, respectively. The magnitude of the indirect effect is measured by $\beta_1 \times \theta_2$, and its statistical significance is assessed using the bootstrap method. If the confidence interval of the indirect effect does not include 0, the mediation effect is considered statistically significant.

3.4. Analysis of Spatial Spillover Effects

3.4.1. Spatial Autocorrelation

Before applying spatial econometric models, it is necessary to determine whether the core variables exhibit spatial autocorrelation. This study uses the global Moran's I index, which is calculated as follows:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i=1}^{n}(x_i - \overline{x})^2}$$

where n denotes the number of provinces, xi denotes the observed value for province i, $\overline{x}$ denotes the sample mean, and w_{ij} denotes an element of the spatial weight matrix. Moran's I takes values between −1 and 1. A value greater than 0 indicates positive spatial autocorrelation, whereas a value below 0 indicates negative spatial autocorrelation.

3.4.2. Spatial Econometric Model Specification

To investigate the spatial spillover patterns associated with RDE and EPVCE, this study constructs a SDM. Following Elhorst [37], the model is specified as follows:

$$EPVCE_{it} = \rho\sum_{j=1}^{n} w_{ij}Y_{jt} + \beta_1 RDE_{it} + \theta_1\sum_{j=1}^{n} w_{ij}RDE_{jt} + \gamma \mathrm{Controls}_{it} + \theta_2\sum_{j=1}^{n} w_{ij}\mathrm{Controls}_{jt} + \mu_i + \lambda_t + \varepsilon_{it}$$

where ϱ is the spatial autoregressive coefficient, which captures the effect of EPVCE in spatially connected regions on local EPVCE. The coefficient β_1 represents the coefficient of the core explanatory variable, while θ_1 is the coefficient of the spatially lagged explanatory variable and reflects the effect of RDE in neighboring regions on local EPVCE. The term w_{ij} denotes an element of the spatial weight matrix.

3.4.3. Model Selection Strategy

Following the spatial model selection procedure proposed by Elhorst [37], this study uses the Lagrange multiplier (LM), likelihood ratio (LR), and Hausman tests to determine the appropriate spatial econometric model. First, the LM test is conducted to examine the existence of spatial dependence. Second, the LR test is performed to evaluate whether the SDM can be reduced to a spatial autoregressive model or a spatial error model. Finally, the Hausman test is used to determine the appropriate fixed-effects specification. If the test results support the SDM, the model is estimated accordingly, and its direct, indirect, and total effects are further decomposed.

4. Empirical Analysis

4.1. Evolutionary Characteristics of the Main Variables

Figure 3 illustrates the temporal trends and regional variations in RDE, EPVCE, and PF, LF, and EF based on panel data from 31 Chinese provincial-level regions during 2010–2019.

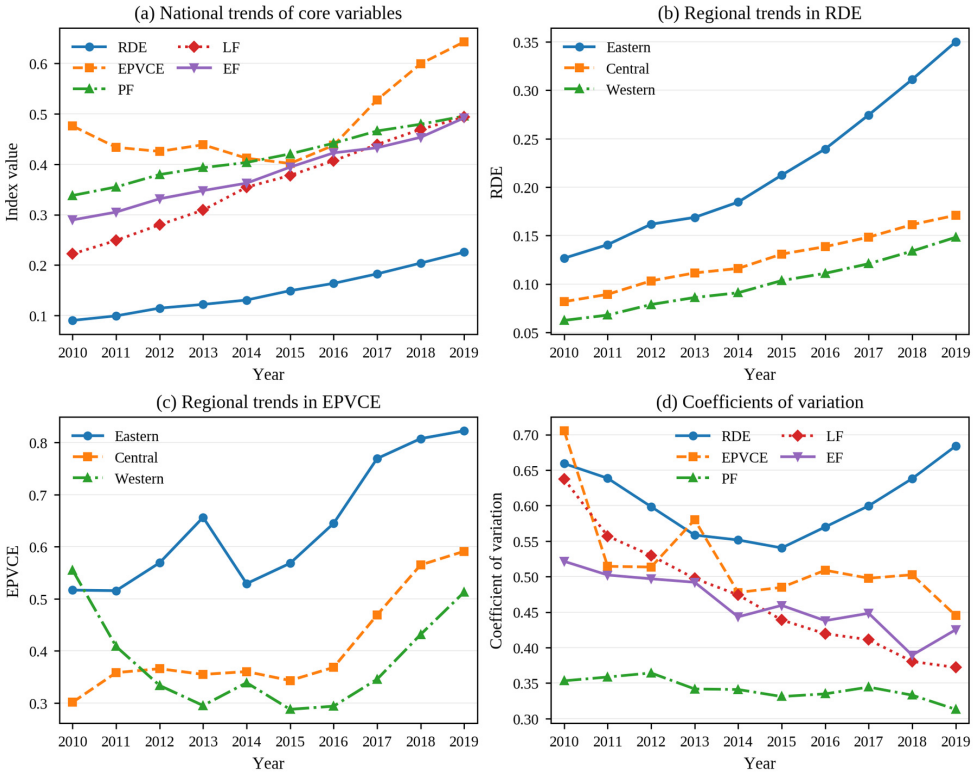


Figure 3. Temporal evolution and regional differentiation of core variables during 2010–2019: (**a**) presents the national temporal evolution trends of RDE, EPVCE, and PF, LF, and EF; (**b**,**c**) illustrate the regional evolution patterns of RDE and EPVCE across eastern, central, and western China; and (**d**) reports the changing trends of coefficients of variation for the core variables, reflecting interprovincial disparities.

At the national level, RDE, EPVCE, PF, LF, and EF all exhibit an overall upward trend, although their evolutionary patterns differ considerably. RDE increased from 0.0902 in 2010 to 0.2257 in 2019, representing an increase of approximately 150.2%. The index shows a sustained upward trend, with growth accelerating after 2015. This pattern is consistent with the expansion of rural digital infrastructure, digital service provision, and the adoption of digital technologies in rural industries. In contrast to the steady increase in RDE, EPVCE displays more pronounced stage-specific fluctuations. Its national average rose from 0.4760 in 2010 to 0.6430 in 2019, an increase of approximately 35.1%. Specifically, EPVCE generally declined between 2010 and 2015 before rebounding markedly after 2016. This pattern suggests that changes in EPVCE do not simply move in parallel with the process of digitalization and may also reflect differences in ecological resource endowments, industrial foundations, market conditions, and institutional environments.

Meanwhile, all three rural functions show sustained increases over the study period. PF increased from 0.3381 in 2010 to 0.4956 in 2019, representing an increase of approximately 46.6%. This increase is consistent with an overall strengthening of rural production capacity, factor allocation conditions, and the foundations for industrial development. LF increased from 0.2222 to 0.4935, representing an increase of approximately 122.1% and the largest increase among the three rural functions. The upward trend is consistent with improvements

in livelihood conditions, income-generating capacity, and public service provision in rural areas. EF rose from 0.2896 to 0.4920, an increase of approximately 69.9%, indicating a general upward trend in the ecological-function index. Notably, by 2019, PF, LF, and EF had reached 0.4956, 0.4935, and 0.4920, respectively, with the gaps among the three functions narrowing substantially. This pattern points to increasing similarity in the levels of the three rural functions toward the end of the study period.

At the regional level, RDE exhibits a pronounced gradient. In 2010, the average RDE values in eastern, central, and western China were 0.1267, 0.0818, and 0.0624, respectively; by 2019, these values had increased to 0.3501, 0.1710, and 0.1483. Throughout the study period, eastern China consistently recorded higher RDE levels than the central and western regions, while the absolute gaps widened in later years. These differences reflect persistent regional disparities in digital infrastructure, digital-industry development, and the application of digital technologies. By comparison, the regional evolution of EPVCE is more heterogeneous. EPVCE increased from 0.5167 to 0.8226 in eastern China and from 0.3015 to 0.5912 in central China. In western China, however, EPVCE changed from 0.5551 to 0.5128, indicating a slight overall decline accompanied by considerable fluctuations. These contrasting trajectories may be associated with regional differences in ecological resource endowments, industrial organization, market connectivity, and the conditions for ecological product value conversion.

The degree of interprovincial dispersion also varies across the main variables. The coefficient of variation (CV) for RDE initially declined from 0.659 in 2010 to 0.540 in 2015, but subsequently increased to 0.684 by 2019. This indicates that relative interprovincial disparities in RDE narrowed during the first half of the study period but widened again after 2015, with dispersion at the end of the period exceeding that at the beginning. In contrast, the CV of EPVCE decreased from 0.705 to 0.445, indicating an overall decline in interprovincial dispersion. The CVs of PF, LF, and EF also declined overall. Specifically, the CV of PF decreased from 0.353 to 0.313, indicating only a modest reduction in dispersion; that of LF declined from 0.637 to 0.372, representing the largest reduction in dispersion among the three functions; and that of EF decreased from 0.522 to 0.425.

4.2. Baseline Regression Analysis

The baseline relationship between RDE and EPVCE is examined using a two-way fixed-effects model, with the results reported in Table 5. Model (1) includes only the core explanatory variable while controlling for province and year fixed effects. Models (2)–(5) sequentially PGDP, URB, AGR, and FCOV to assess the robustness of the estimated results.

Across all model specifications, the coefficient estimates of RDE remain positive and statistically significant. Moreover, its sign and statistical significance remain stable as the control variables are introduced sequentially. In Model (1), the estimated coefficient of RDE is 1.2604, reaching statistical significance at the 5% level. After incorporating the full set of control variables, the coefficient increases to 1.7543 in Model (5), with significance at the 1% level. These results suggest a stable positive association between RDE and EPVCE after accounting for regional economic development, urbanization, fiscal support for agriculture, forest coverage, and province and year fixed effects.

Regarding the control variables, the coefficient estimate of FCOV in Model (5) is 4.6780 and remains positive and statistically significant at the 5% level. This finding suggests that forest coverage is positively related to EPVCE under the baseline specification.

With the gradual inclusion of control variables, R^2 increases from 0.6433 to 0.6725, while adjusted R^2 rises from 0.5903 to 0.6181, indicating an improvement in model explanatory capacity. Overall, the baseline regression results provide support for a statistically significant positive relationship between RDE and EPVCE, which is consistent with H1. However,

these estimates should be interpreted as conditional associations rather than definitive causal effects.

Table 5. Baseline regression results for the relationship.

Variable	(1)	(2)	(3)	(4)	(5)
RDE	1.2604 **	1.4216 ***	1.4776 **	1.4835 **	1.7543 ***
	(0.5480)	(0.5443)	(0.6069)	(0.6251)	(0.6292)
PGDP	—	−0.0000	−0.0000	−0.0000	−0.0000
	—	(0.0000)	(0.0000)	(0.0000)	(0.0000)
URB	—	—	0.5142	0.5186	0.4898
	—	—	(1.9015)	(1.9097)	(1.8613)
AGR	—	—	—	0.0550	0.0372
	—	—	—	(0.3880)	(0.3462)
FCOV	—	—	—	—	4.6780 **
	—	—	—	—	(1.8553)
Province fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Province-clustered robust standard errors	Yes	Yes	Yes	Yes	Yes
Observations	310	310	310	310	310
R^2	0.6433	0.6448	0.6454	0.6454	0.6725
Adjusted R^2	0.5903	0.5904	0.5896	0.5881	0.6181

Note: Province-clustered robust standard errors are reported in parentheses. ***, and ** denote statistical significance at the 1%, and 5%, levels, respectively. All models include province and year fixed effects.

Compared with previous studies, these findings are broadly consistent with the existing literature documenting a positive relationship between the digital economy and green development performance [9,10]. However, previous studies have mainly considered green total factor productivity, eco-efficiency, or green innovation efficiency as outcome variables.

4.3. Robustness Checks and Endogeneity Treatment

Although the baseline results reveal a positive relationship between RDE and EPVCE, concerns remain regarding model dependence, measurement choices, omitted variables, and potential endogeneity. Accordingly, robustness checks and endogeneity tests are conducted to assess the stability of the baseline findings.

4.3.1. Robustness Checks

To further examine the robustness of the baseline findings, this study conducts four robustness checks involving alternative model specifications, an alternative measure of the core explanatory variable, additional controls for climatic factors, and a one-period lag of RDE. The results are presented in Table 6.

First, the baseline fixed-effects specification was replaced with a random-effects model while retaining year fixed effects. The coefficient estimate of RDE is 1.1713, remaining positive and statistically significant at the 1% level. This result suggests that the observed positive relationship between RDE and EPVCE is not sensitive to the choice of estimation framework.

Second, considering that RDE can be quantified using different measurement approaches, the Digital Financial Inclusion Index (DIFI) was adopted as an alternative proxy. DIFI reflects regional digital development through multiple dimensions, including digital financial coverage, usage depth, and associated digital services. The coefficient of DIFI is 0.6541 and remains positive and significant at the 1% level, suggesting that the baseline result is consistent when an alternative measure of the explanatory variable is applied. This

finding is also consistent with previous evidence that digital financial inclusion improves agricultural green total factor productivity [38].

Table 6. Results of robustness checks.

Variable	(1) RE Model	(2) Alternative Variable	(3) TEMP	(4) PREC	(5) TEMP + PREC	(6) L.RDE
	RE model	Alternative variable	Add temperature	Add precipitation	Add temperature and precipitation	Lagged explanatory variable
L.RDE	—	—	—	—	—	1.6556 ***
	—	—	—	—	—	(0.5663)
RDE	1.1713 ***	0.6541 ***	1.6032 ***	1.7702 ***	1.6210 ***	—
	(0.2786)	(0.2318)	(0.5705)	(0.6424)	(0.5821)	—
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Province effects (μ_i)	Random	Yes	Yes	Yes	Yes	Yes
Year effects (ν_t)	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.6395	0.6610	0.6841	0.6731	0.6858	0.7584
F/Wald statistic	106.68 ***	5.97 ***	3.83 ***	4.25 ***	3.47 ***	—

Note: Province-clustered robust standard errors are reported in parentheses. *** denote statistical significance at the 1% levels, respectively. RE denotes the random-effects model, FE denotes province fixed effects, DIFI denotes the Digital Financial Inclusion Index, TEMP and PREC denote temperature and precipitation, respectively, and L.RDE denotes the one-period lag of RDE.

Third, given the potential relevance of environmental conditions to EPVCE, temperature (TEMP) and precipitation (PREC) were additionally included in the regression models. Under all three specifications, the RDE coefficient remains positive and statistically significant at the 1% level, suggesting that the baseline relationship persists after accounting for climatic factors.

Finally, considering the persistence of RDE and potential temporal delays in its association with EPVCE, contemporaneous RDE is replaced with its one-period lagged value (LRDE). The coefficient estimate of LRDE is 1.6556, remaining positive and statistically significant at the 1% level. This result suggests that the relationship between RDE and EPVCE is not substantially altered when the explanatory variable is lagged by one period.

4.3.2. Endogeneity Treatment

Despite the stability of the preceding estimates, potential endogeneity may remain. Rural digitalization may evolve simultaneously with the economic and institutional conditions associated with ecological product value conversion. Conversely, regions with higher EPVCE may also have better digital infrastructure, stronger market demand, or more favorable conditions for digital investment, giving rise to potential reverse causality. In addition, unobserved factors may jointly influence RDE and EPVCE. Therefore, an instrumental variable (IV) estimation based on the two-stage least squares (2SLS) method is implemented to further address potential endogeneity.

Following related studies [39], a historical communication infrastructure-based instrument was developed. Specifically, the instrument is defined as the interaction between the

total volume of postal and telecommunications services in each province in 1984 and the one-period-lagged average RDE of all other provinces. The historical communications measure captures cross-provincial differences in earlier communications infrastructure, while the leave-one-out lagged average captures broader changes in RDE outside the focal province.

Table 7 presents the results of the IV estimation. Based on the same sample, the FE-OLS specification produces an RDE coefficient of 1.4095, which remains positive and significant at the 1% level. Under the IV-2SLS specification, the estimated RDE coefficient is 3.1525 and reaches significance at the 10% level. The positive sign of the IV estimate is consistent with the baseline regression, suggesting that the relationship between RDE and EPVCE remains positive after addressing potential endogeneity.

Table 7. Endogeneity treatment: Instrumental-variable two-stage least squares estimates.

Variable	(1) FE-OLS	(2) 2SLS (IV)
RDE	1.4095 ***	3.1525 *
	(0.4546)	(1.6373)
Controls	Yes	Yes
Province fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Kleibergen–Paap rk Wald F statistic	—	9.3327
Kleibergen–Paap rk LM test (*p*-value)	—	0.0069
Anderson–Rubin test (*p*-value)	—	0.0271
Durbin–Wu–Hausman test (*p*-value)	—	0.1329
Observations	279	279

Note: Province-clustered robust standard errors are reported in parentheses. ***, and * denote statistical significance at the 1%, and 10% levels, respectively.

The diagnostic tests offer additional evidence regarding instrument relevance and identification. The Kleibergen–Paap rk LM test yields a *p*-value of 0.0069, rejecting the null hypothesis of underidentification. The Kleibergen–Paap rk Wald F-statistic equals 9.3327, which is close to the conventional threshold value of 10. This indicates instrument relevance, although potential weak-instrument concerns remain. To further evaluate this concern, the weak-instrument-robust Anderson–Rubin test was additionally performed. The test produces a *p*-value of 0.0271, allowing rejection of the null hypothesis that the RDE coefficient equals zero at the 5% level. The Durbin–Wu–Hausman test reports a *p*-value of 0.1329, suggesting that the null hypothesis of RDE exogeneity is not rejected. Overall, these findings are consistent with the baseline results. However, any causal interpretation remains dependent on the validity of the instrument, especially the exclusion restriction and instrument strength.

4.4. Mechanism Analysis: Mediating Effects of Production, Living, and Ecological Functions

To further explore the potential mechanisms underlying the relationship between RDE and EPVCE, this study draws on the functional theory of rural territorial systems and considers PF, LF, and EF as potential mediators. Specifically, the analysis examines whether the relationship between RDE and EPVCE is consistent with transmission through these three functional dimensions. A stepwise regression approach was first used to examine the association between RDE and each mediator and, after introducing the corresponding mediator into the EPVCE model, the association between the mediator and EPVCE and the change in the estimated coefficient of RDE. A province-clustered bootstrap procedure with 5000 replications was subsequently performed to obtain the indirect effect estimates and their corresponding confidence intervals. The results are presented in Tables 8 and 9.

Table 8. Results of the mediation analysis for production, living, and ecological functions.

Variable	(1) EPVCE	(2) PF	(3) EPVCE	(4) LF	(5) EPVCE	(6) EF	(7) EPVCE
RDE	1.7673 ***	0.1470 **	1.6544 ***	0.1581 ***	1.7105 ***	0.3967 ***	1.5673 ***
	(0.632)	(0.057)	(0.548)	(0.053)	(0.608)	(0.167)	(0.531)
PF			1.1629 **				
LF					1.4334 ***		
EF							0.7016 *
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	310	310	310	310	310	310	310

Note: Province-clustered robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are winsorized at the 1% level in both tails. All specifications control for PGDP, AGR, FCOV, and URB and include both year and province fixed effects.

Table 9. Bootstrap results for the indirect effects.

Mediator	Indirect Effect	90% Bootstrap CI	95% Bootstrap CI	Inference
PF	0.1710	[0.0184, 0.3768]	[−0.0028, 0.4384]	Supported at the 90% confidence level
LF	0.2266	[0.0647, 0.4768]	[0.0346, 0.5765]	Significant
EF	0.2784	[0.0536, 0.5849]	[0.0037, 0.7018]	Significant

4.4.1. Mediating Effect of Production Function

The production-function pathway is examined using Columns (2) and (3) of Table 8 and the results in Table 9.

First, Column (2) of Table 8 indicates that RDE has a coefficient estimate of 0.1470 for PF, which is significant at the 5% level, indicating that RDE is positively associated with the production function of rural territorial systems. Furthermore, after PF is incorporated into the EPVCE model in Column (3), the PF coefficient is 1.1629 and remains significant at the 5% level, indicating a significant positive relationship between enhanced production function and higher EPVCE. Meanwhile, the estimated coefficient of RDE decreases from 1.7673 in the baseline mediation specification to 1.6544 but remains significant at the 1% level. This pattern suggests that RDE retains a significant direct association with EPVCE after controlling for PF, while production function may constitute one of the transmission channels linking RDE to EPVCE.

The bootstrap results provide additional evidence for this mechanism. As shown in Table 9, when PF is treated as the mediator, the estimated indirect effect of RDE on EPVCE is 0.1710, with a 90% bootstrap confidence interval of [0.0184, 0.3768]. Because this interval excludes zero, the indirect effect through production function is statistically supported at the 90% confidence level.

These findings suggest that RDE may strengthen the capacity to generate ecological products by improving access to agricultural information, optimizing factor allocation, enhancing production decision-making efficiency, and strengthening market connectivity, thereby facilitating the conversion of ecological resources into economic returns and ecological benefits. This finding is consistent with previous studies showing that digital village development and digital financial inclusion can promote agricultural green productivity and green agricultural development [38,40]. Therefore, Hypothesis H2 is supported.

4.4.2. Mediating Effect of Living Function

The results for the living-function pathway are presented in Columns (4) and (5) of Table 8 and in Table 9.

Column (4) indicates that RDE has a coefficient estimate of 0.1581 for LF, significant at the 1% level, suggesting that RDE is positively associated with improvements in the living function of rural territorial systems. Column (5) further incorporates LF into the EPVCE model. LF has a coefficient estimate of 1.4334 and remains significant at the 1% level, suggesting that improvements in living function are positively associated with higher EPVCE. At the same time, after LF is included, the estimated coefficient of RDE declines from 1.7673 to 1.7105 but remains significant at the 1% level. These results indicate that RDE is related to EPVCE both directly and indirectly through improvements in rural living function.

The bootstrap results further support this transmission mechanism. As reported in Table 9, the indirect effect through LF is 0.2266, with a 95% bootstrap confidence interval of [0.0346, 0.5765]. Because the interval does not include zero, the mediating effect of living function is statistically significant at the 5% level.

These findings indicate that the rural digital economy operates not only through the production side but also by improving rural residents' income conditions, access to public services, information accessibility, and consumption convenience. Such improvements may strengthen both the recognition of ecological product value and the capacity to realize market demand for ecological products. Previous research on digital villages has similarly emphasized that rural digitalization can affect agricultural green development performance through agricultural informatization and improvements in human capital [40]. Extending this literature, the present study identifies living function as a demand-realization pathway through which ecological product value conversion may be enhanced. This highlights that the conversion of ecological product value depends not only on production-side efficiency but also on the living conditions, service capacity, and consumption connectivity of rural areas. Therefore, Hypothesis H3 is supported.

4.4.3. Mediating Effect of Ecological Function

The ecological-function pathway is examined using Columns (6) and (7) of Table 8, together with the bootstrap results reported in Table 9.

First, Column (6) of Table 8 indicates that RDE has a coefficient estimate of 0.3967 for EF, which is significant at the 1% level, suggesting a positive relationship between RDE and the ecological function of rural territorial systems. Furthermore, Column (7) indicates that EF has a coefficient estimate of 0.7016 in the EPVCE model, with significance at the 10% level, suggesting a positive relationship between improvements in ecological function and EPVCE. After EF is introduced into the model, the estimated coefficient of RDE decreases from 1.7673 to 1.5673 but remains statistically significant at the 1% level. This result suggests that ecological function may constitute another important transmission pathway through which RDE is associated with EPVCE.

The bootstrap test provides further support for this mechanism. As shown in Table 9, the estimated indirect effect through EF is 0.2784, with a 95% bootstrap confidence interval of [0.0037, 0.7018]. Since the confidence interval does not include zero, the indirect association through EF is statistically significant at the 5% level.

These findings suggest that RDE may strengthen the sustained provision of ecological products by improving environmental monitoring capabilities, enhancing the efficiency of environmental governance, promoting the digitalization of ecological conservation, and facilitating the management of rural human settlements. Previous research on ecological product value realization has emphasized that this process involves not only market transactions and value accounting but also institutional and governance conditions related

to ecological conservation, ecological compensation, environmental governance, and the conversion of natural-resource value [41,42]. The results further suggest that improvements in ecological function represent an important mechanism linking RDE to higher EPVCE. Therefore, Hypothesis H4 is supported.

To further verify the robustness of the mediation findings, robustness checks based on the Wild Cluster Bootstrap, Leave-One-Province-Out, and Leave-One-Region-Out approaches were conducted, with detailed results provided in Supplement A. The indirect effects through PF, LF, and EF remain positive across alternative inference procedures and province-exclusion specifications, while the corresponding point estimates are generally stable. Under the region-exclusion tests, the estimated directions of all three pathways also remain unchanged, indicating that the baseline mediation results exhibit satisfactory robustness to alternative sample compositions.

4.5. Heterogeneity Analysis

The baseline findings reveal a positive and statistically significant association between RDE and EPVCE. However, Chinese regions differ considerably in economic development, digital infrastructure, industrial structure, and resource endowments. Accordingly, the relationship between RDE and EPVCE may vary across different types of regions.

To investigate this heterogeneity, subgroup regressions are performed based on two dimensions: geographical location and resource endowment. The corresponding results are presented in Table 10.

Table 10. Heterogeneity analysis of the relationship.

Variable	(1) Eastern	(2) Central	(3) Western	(4) Resource-Based Provinces	(5) Non-Resource-Based Provinces
RDE	0.8950 *	−4.2921	3.2398	0.2676	1.6519 **
	(0.5209)	(6.2005)	(3.8198)	(4.8153)	(0.7774)
Constant	3.7326 **	−2.5353	−6.6847 ***	−4.4446 ***	0.0051
	(1.8822)	(2.8688)	(1.6861)	(1.2025)	(1.4891)
Controls	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Province-clustered robust standard errors	Yes	Yes	Yes	Yes	Yes
Observations	110	80	120	90	220
Number of clusters	11	8	12	9	22
Within R^2	0.5050	0.4976	0.5733	0.5374	0.3354

Note: Robust standard errors clustered at the province level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The control variables include PGDP, URB, AGR, and FCOV. Resource-based provinces include Heilongjiang, Inner Mongolia, Shanxi, Guizhou, Shaanxi, Yunnan, Qinghai, Ningxia, and Xinjiang (9 provinces), while the remaining 22 provinces are classified as non-resource-based provinces. The eastern region includes Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan, and Liaoning; the central region includes Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan; and the western region includes Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang.

4.5.1. Regional Heterogeneity

The regional subgroup regressions reveal differences in the estimated relationship between RDE and EPVCE across eastern, central, and western regions.

In eastern China, the RDE coefficient is estimated at 0.8950 and remains significant at the 10% level, suggesting a positive association with EPVCE. Given the relatively advanced level of digital development in eastern China, this pattern may be related to better-developed digital infrastructure and market systems that provide favorable conditions for ecological value conversion.

In contrast, the coefficient estimate for RDE in the central region is −4.2921 and does not reach statistical significance. Thus, the current sample does not provide sufficient statistical evidence of a stable relationship between RDE and EPVCE in this region. One possible explanation is that central China is undergoing industrial restructuring and agricultural modernization, while the integration of the digital economy with ecological industries remains incomplete. Coordination among rural digital infrastructure, platform-based economic activities, and market-based mechanisms for ecological products may therefore remain insufficient, which could constrain the conversion of digital development into ecological value realization.

In western China, the estimated coefficient of RDE is 3.2398 but is also statistically insignificant. Although the coefficient is positive, the evidence is insufficient to establish a statistically robust positive relationship between RDE and EPVCE in western China. The western region generally possesses substantial ecological resources and considerable potential for ecological product supply. However, geographical constraints, transportation conditions, limited market connectivity, and relatively weaker digital infrastructure may impede the conversion of ecological resource advantages into realized economic returns and ecological benefits.

Overall, the subgroup estimates indicate that the positive association between RDE and EPVCE is statistically evident in the eastern region, while the coefficients for the central and western regions do not reach statistical significance. This pattern is broadly consistent with previous studies on digital villages and the digital economy, which suggest that the effectiveness of digitalization depends on local conditions such as digital infrastructure, market development, human capital, and industrial capacity [40]. Accordingly, the capacity of the digital economy to facilitate ecological product value conversion may depend on complementary industrial foundations, market institutions, and application scenarios for digital technologies.

4.5.2. Heterogeneity by Resource Endowment

The sample is additionally classified into resource-based and non-resource-based provinces to examine whether the association between RDE and EPVCE differs according to resource dependence.

Among resource-based provinces, the estimated coefficient of RDE is 0.2676 and does not reach conventional levels of statistical significance, indicating that no statistically stable relationship between RDE and EPVCE is observed within this subgroup. In contrast, the RDE coefficient for non-resource-based provinces is 1.6519 and is significant at the 5% level, indicating a stronger positive association between RDE and EPVCE in this group.

One possible interpretation is that resource-based provinces have long depended on traditional resource industries, such as energy and minerals, which may have contributed to stronger industrial path dependence and greater ecological restoration pressures. In some of these regions, the foundations for green industries and market-based mechanisms for ecological products may also remain relatively underdeveloped. Under such conditions, improvements in digital development alone may be insufficient to overcome structural constraints associated with traditional resource-dependent industries in the short term, and the corresponding relationship with ecological product value conversion may therefore be less evident. In contrast, non-resource-based provinces tend to have more diversified industrial

structures and lower dependence on extractive activities. They may consequently face fewer structural barriers to integrating the digital economy with ecological agriculture, rural tourism, green consumption, and modern service industries. Rural digitalization may therefore facilitate ecological product value conversion more effectively through enhanced market connectivity, digital finance, platform-based transactions, and information dissemination.

Taken together, these findings suggest that the relationship between RDE and ecological product value conversion is conditional on regional characteristics. Previous research on production–living–ecological spaces and regional endowments has shown that natural conditions, geographical location, and infrastructure can shape the evolution and spatial coordination of rural functions [43]. The present study further suggests that such differences in regional endowments may also condition the extent to which RDE is associated with EPVCE. Relative to resource-based provinces, non-resource-based provinces exhibit a clearer positive association between RDE and EPVCE. For resource-based provinces, enhancing digital infrastructure may therefore need to be accompanied by industrial restructuring, ecological restoration and governance, and institutional innovation in market-based mechanisms for ecological products.

4.6. Spatial Econometric Analysis

4.6.1. Spatial Autocorrelation Tests

Global Moran's I was employed to examine whether RDE and EPVCE exhibit spatial autocorrelation. A spatial contiguity matrix (W1) was adopted as the baseline spatial weight matrix to capture direct spatial linkages between regions sharing a common administrative boundary. The results are presented in Table 11.

Table 11. Global Moran's I statistics for RDE and EPVCE, 2010–2019.

Year	RDE Moran's I	*p*-Value	EPVCE Moran's I	*p*-Value
2010	0.0412	0.5292	0.2112 **	0.0391
2011	0.0770	0.3516	0.0184	0.6622
2012	0.1266	0.1771	0.1990 **	0.0499
2013	0.1036	0.2478	0.2816 ***	0.0079
2014	0.1644 *	0.0952	0.2296 **	0.0265
2015	0.1861 *	0.0641	0.3844 ***	0.0004
2016	0.1994 **	0.0496	0.4181 ***	0.0001
2017	0.1838 *	0.0670	0.5306 ***	<0.0001
2018	0.2094 **	0.0406	0.2055 **	0.0439
2019	0.2280 **	0.0274	0.1503	0.1213

Note: The *p*-values are based on two-sided normal-approximation tests for Moran's I. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

The results show that the Moran's I statistics for RDE are positive throughout the study period, although their statistical significance varies over time. Spatial clustering begins to receive statistical support from 2014 onward. Specifically, Moran's I is significant at the 10% level in 2014, 2015, and 2017 and at the 5% level in 2016, 2018, and 2019. These findings suggest that positive spatial clustering of RDE is primarily evident during the middle and later stages of the sample period. As digital infrastructure, e-commerce platforms, and digital financial services become increasingly widespread, regions with relatively advanced digital economies may become spatially connected with neighboring regions through technology diffusion, market linkages, and information transmission.

Spatial autocorrelation is more pervasive for EPVCE. With the exception of 2011 and 2019, the Moran's I statistics are positive and statistically significant at least at the 5% level

in all years. Overall, the results indicate pronounced positive spatial dependence in EPVCE across provinces.

Given that both RDE and EPVCE exhibit spatial dependence to varying degrees, spatial econometric models are further employed to distinguish the local effects of RDE from potential spatial spillover effects on EPVCE.

4.6.2. Model Specification Tests for Spatial Econometric Analysis

To select an appropriate spatial econometric specification, Lagrange Multiplier (LM), likelihood-ratio (LR), Wald, and Hausman tests were conducted. The results are reported in Table 12.

Table 12. Specification tests for spatial econometric models.

Test	Statistic	*p*-Value	Decision
LM-lag	11.5980 ***	0.0007	Reject
Robust LM-lag	1.6073	0.2049	Fail to reject
LM-error	10.0123 ***	0.0016	Reject
Robust LM-error	0.0217	0.8829	Fail to reject
Hausman	25.0887 ***	0.0001	Supports fixed effects
Wald: SDM → SAR	11.2022 **	0.0475	Reject
Wald: SDM → SEM	12.3556 **	0.0302	Reject
LR: SDM → SAR	10.9549 *	0.0523	Reject at the 10% level
LR: SDM → SEM	11.9803 **	0.0351	Reject

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Both the LM-lag and LM-error statistics are significant, indicating potential spatial lag and spatial error dependence. However, the robust LM tests do not provide statistically significant evidence at conventional levels. Therefore, the LM diagnostics do not offer sufficient evidence to distinguish between the spatial autoregressive model (SAR) and the spatial error model (SEM). The more general Spatial Durbin Model (SDM) was selected as the candidate specification, followed by Wald and LR tests to assess whether it could be reduced to the SAR or SEM form.

The Wald and LR tests suggest that the SDM cannot be simplified into either the SAR or SEM specification. This result implies that the SDM is more appropriate for accounting for spatial dependence in the dependent variable and spatial interactions among explanatory variables. Hence, the SDM is used in the subsequent spatial estimations.

The Hausman test rejects the null hypothesis at the 1% level and supports the fixed-effects specification for the spatial model. Given potential time-invariant regional heterogeneity and common temporal shocks, both regional and year fixed effects are incorporated.

Overall, the spatial autocorrelation results, LM diagnostics, Hausman test, and Wald and LR tests jointly justify the adoption of a two-way fixed-effects SDM as the baseline spatial specification.

4.6.3. Two-Way Fixed-Effects SDM Estimation and Spatial Effect Decomposition

Table 13 presents the estimates from the two-way fixed-effects SDM under three alternative spatial weight matrices: the spatial contiguity matrix (W1), the inverse geographic distance matrix (W2), and the economic–geographic nested matrix (W3).

Table 13. Parameter estimates from the two-way fixed-effects Spatial Durbin Model.

Variable	W1: Contiguity Matrix (Baseline)	W2: Geographic Distance Matrix	W3: Economic–Geographic Matrix
ϱ	0.2708 *** (0.0741)	−0.1812 (0.2381)	−0.0199 (0.2085)
RDE	1.2930 *** (0.3677)	1.4981 *** (0.4598)	1.3166 *** (0.4248)
PGDP	−0.0728 *** (0.0258)	−0.0692 ** (0.0287)	−0.1140 *** (0.0287)
URB	−0.3769 (0.7039)	0.4330 (0.7196)	0.2092 (0.6672)
AGR	0.0770 (0.2667)	0.0307 (0.3001)	−0.0603 (0.2798)
FCOV	3.8151 *** (1.1318)	5.9690 *** (0.9971)	6.1529 *** (0.9380)
W × RDE	0.0058 (0.6514)	2.0841 (2.9648)	3.9931 (2.7618)
W × PGDP	0.1256 ** (0.0599)	0.0620 (0.2142)	0.1248 (0.2097)
W × URB	3.1608 ** (1.2838)	−8.7898 (5.4157)	−7.3014 (5.5636)
W × AGR	−0.6209 (0.5584)	−2.5282 (2.2585)	−5.1792 *** (1.8897)
W × FCOV	0.6804 (1.8429)	−4.6404 (6.1374)	−4.8611 (6.4478)
Region fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	310	310	310

Note: ***, and ** denote statistical significance at the 1%, and 5% levels, respectively.

Across the three spatial weight matrices, the coefficient of RDE remains positive and significant, suggesting that the association between RDE and EPVCE is robust to alternative spatial specifications. Under the baseline contiguity matrix W1, the spatial autoregressive parameter (ϱ) is positive and significant, indicating the presence of spatial dependence in EPVCE. This implies that EPVCE values in neighboring regions display spatial correlation. However, the spatial autoregressive parameter is insignificant under W2 and W3. This suggests that the detected spatial dependence of EPVCE varies with the choice of spatial weight matrix and appears to be stronger under localized geographic interactions than under broader spatial connections.

The RDE coefficients remain positive, statistically significant, and comparable in magnitude across all three spatial weight matrices. This result suggests that the positive association between RDE and EPVCE persists after accounting for regional heterogeneity, temporal shocks, control variables, and spatial dependence, providing further support for the baseline findings.

Meanwhile, the spatially lagged RDE term (W × RDE) does not achieve statistical significance under any of the three spatial weight matrices. However, within the SDM framework, the coefficient of a spatially lagged explanatory variable does not directly represent the size of the spatial spillover effect, because regional feedback effects operate through the spatial multiplier. Therefore, the impacts of RDE are further decomposed into direct, indirect, and total effects based on the spatial partial-derivative approach. The decomposition results are reported in Table 14.

First, the direct effect of RDE is positive and statistically significant under all three spatial weight matrices, with estimates falling within a relatively narrow range. This indicates a robust positive association between improvements in RDE and higher EPVCE within the same region after accounting for other covariates and spatial interactions. Regardless of whether spatial relationships are defined in terms of administrative contiguity, geographic distance, or combined economic–geographic linkages, the sign, statistical significance, and magnitude of the direct effect remain highly consistent. This provides strong evidence that the estimated local effect is robust to alternative spatial weight specifications.

Second, although the indirect effects of RDE are positive under all three matrices, none reaches conventional levels of statistical significance. The current sample therefore does not provide sufficient evidence of a stable cross-regional effect of RDE on EPVCE in

spatially connected regions. The estimated relationship appears to operate primarily within regions, while the magnitude of cross-regional transmission remains subject to considerable statistical uncertainty. Accordingly, the positive point estimates of the indirect effects should not be interpreted as evidence of statistically significant positive spatial spillovers.

Table 14. Direct, indirect, and total effects of RDE.

Spatial Effect	W1: Contiguity Matrix (Baseline)	W2: Geographic Distance Matrix	W3: Economic–Geographic Matrix
Direct effect	1.3176 ***	1.4828 ***	1.3124 ***
p-value	0.0007	0.0009	0.0021
Indirect effect	0.4637	1.5499	3.8937
p-value	0.5973	0.5384	0.1751
Total effect	1.7813	3.0327	5.2060 *
p-value	0.1137	0.2754	0.0939

Note: The *p*-values are reported in the row immediately below each corresponding effect. ***, and * denote statistical significance at the 1%, and 10% levels, respectively. The direct, indirect, and total effects are obtained from the spatial partial-derivative decomposition of the SDM.

Finally, the total effects display some variation across spatial weight specifications. Under W1 and W2, the estimated total effects are not statistically significant. Under the economic–geographic nested matrix W3, the total effect is statistically significant only at the 10% level. This result suggests that RDE may exhibit a broader overall spatial association with EPVCE when both economic linkages and geographic proximity are incorporated into the spatial structure. However, because this finding is not consistent across the three spatial weight matrices, the statistical evidence for such an aggregate spatial effect remains limited.

Overall, the results indicate that the positive direct effect of RDE on local EPVCE is highly robust, whereas evidence of spatial spillover effects remains insufficient and inconsistent across alternative spatial weight specifications. This finding further suggests that the relationship between RDE and EPVCE is primarily manifested through within-region effects, while cross-regional transmission may be jointly constrained by the form of spatial connectivity, regional heterogeneity, and other transmission mechanisms.

5. Conclusions, Policy Implications, and Research Limitations

5.1. Conclusions

This study examines the relationship between RDE and EPVCE, and the main findings are summarized as follows.

First, RDE is significantly and positively associated with EPVCE. The baseline regression results show that this positive association remains statistically significant after controlling for economic development, urbanization, fiscal support for agriculture, forest coverage, and province and year fixed effects. The finding is also robust to alternative model specifications and proxy variables, the inclusion of climatic controls, and the lag-based robustness specification. Overall, the results provide consistent evidence of a positive relationship between RDE and EPVCE.

Second, the production, living, and ecological functions of rural systems represent potential transmission pathways linking RDE to EPVCE. The mediation analysis yields positive indirect-effect estimates for all three functions. The results are consistent with the possibility that the RDE–EPVCE relationship operates partly through stronger ecological product supply capacity, improved living conditions and demand-side participation, and enhanced ecological governance and ecosystem service provision. The indirect effects through the living and ecological functions are statistically significant at the 5% level, while the evidence for the production-function pathway is weaker and is supported at

the 10% level. Among the three pathways, the ecological function yields the largest point estimate of the indirect effect, although differences across the three indirect effects are not formally tested.

Third, the estimated relationship between RDE and EPVCE varies across regional and resource-endowment groups. The positive association is statistically significant in the eastern subsample, whereas no statistically significant relationship is detected in the central or western subsamples. Similarly, a significant positive association is found in non-resource-based provinces, whereas such evidence is not observed in resource-based provinces. These subgroup results indicate differences in the statistical patterns across regional contexts; however, differences in significance levels alone should not be regarded as sufficient evidence of coefficient differences across groups.

Fourth, RDE and EPVCE exhibit spatial dependence to varying degrees, while the relationship between them appears to be primarily local. Global Moran's I indicates positive spatial autocorrelation for both variables in at least part of the study period, although the temporal consistency of the spatial patterns differs between RDE and EPVCE. The Spatial Durbin Model further suggests that the estimated direct effect of RDE remains positive and statistically significant under alternative spatial weight matrices, whereas the indirect effects are not statistically significant. The available evidence therefore does not support a stable cross-regional spatial spillover relationship between RDE and EPVCE.

5.2. Policy Implications

First, rural digital infrastructure and digital service systems should continue to be strengthened, while greater policy attention should be directed toward the effective use of digital technologies rather than infrastructure expansion alone. Further improvements in rural broadband and communication networks, digital payment systems, smart logistics, and agricultural information services may help strengthen information linkages between ecological product suppliers and consumer markets. Such improvements may also facilitate the integration of digital technologies with ecological agriculture, green agricultural product distribution, rural e-commerce, and ecological resource management.

Second, greater attention should be given to integrating digitalization with the production, living, and ecological functions of rural areas. In the production dimension, digital technologies can be applied more extensively to agricultural production management, market information acquisition, and factor allocation. In the living dimension, improvements in digital public services, rural e-commerce, and digital finance may enhance rural residents' access to services and participation in market activities. In the ecological dimension, digital technologies can be further applied to ecological monitoring, resource surveys, environmental governance, and ecological product traceability. At the same time, potential environmental pressures associated with digital infrastructure expansion, increased logistics activity, and intensified production should also be taken into account.

Third, place-based digital development strategies should be adopted in accordance with regional development conditions and resource endowments. Regions with relatively advanced digital infrastructure and well-developed market systems may further promote the integration of digital technologies with ecological product standardization, branding, and market expansion. Central and western regions may prioritize the enhancement of digital infrastructure, rural logistics systems, and market connectivity. Resource-based regions may need to better align digital development with industrial restructuring and the green transition, thereby strengthening the alignment between digital investment, local industrial foundations, and ecological resource conditions. These recommendations should be interpreted in light of the subgroup evidence, which identifies different empirical patterns

across regional contexts but does not by itself establish statistically significant differences between group-specific coefficients.

Fourth, cross-regional digital connectivity and market coordination for ecological products should be further strengthened. Although the spatial econometric results do not provide consistent evidence of statistically significant cross-regional spillovers, the production, circulation, and consumption of ecological products often extend across regional boundaries. Improving interregional digital connectivity, harmonizing ecological product standards, strengthening logistics coordination, and facilitating market information sharing may help reduce barriers to cross-regional transactions and strengthen regional market linkages.

5.3. Research Limitations and Future Directions

This study is subject to several limitations. First, owing to data constraints, the analysis relies on provincial-level panel data and therefore cannot fully capture heterogeneity across counties, villages, firms, households, and other economic actors. Measurement error may also arise in the construction of the RDE index, the production–living–ecological function indices, and the indicators used to measure EPVCE. In addition, the sample period ends in 2019 and therefore does not capture the more recent expansion of digital platforms, livestreaming e-commerce, digital supply chains, and other emerging digital business models. Future studies could incorporate more spatially detailed and updated data, together with alternative indicators, to further evaluate the robustness of the measurement framework.

Second, although two-way fixed-effects models and instrumental-variable estimation are adopted to address potential endogeneity concerns, time-varying omitted variables and reverse causality may remain. In addition, the causal interpretation of the IV estimates depends on the validity of the exclusion restriction and the strength of the instrument. The mediation analysis primarily identifies statistical indirect relationships that are consistent with the proposed theoretical pathways rather than establishing a causal mediation process or its temporal sequence. Future research could exploit appropriate policy pilots, phased digital infrastructure deployment, or other quasi-natural experiments to strengthen causal identification and provide more rigorous evidence on the underlying mechanisms.

Third, this study examines the production, living, and ecological functions primarily as separate mediating pathways and does not fully capture potential complementarities, substitutions, or trade-offs among them. Digitalization may be associated with improvements in production efficiency, public service provision, and environmental governance, but its expansion may also be accompanied by additional environmental pressures arising from infrastructure construction, logistics activity, energy consumption, and intensified production. Future research could therefore investigate interactions among rural multifunctions and their dynamic evolution, with particular attention to potential synergies and trade-offs.

Fourth, this study uses spatial contiguity, geographic distance, and economic–geographic matrices to characterize interregional spatial relationships. These conventional spatial weight matrices, however, may not fully capture actual regional connections generated by digital platforms, logistics networks, trade linkages, and information flows. Future studies could construct spatial weight matrices based on digital connectivity, logistics flows, or interregional trade relationships to more accurately represent regional linkages and examine potential cross-regional associations in the context of digitalization.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/su182110891/s1, Table S1. Ecosystem Service Value Equivalence per Unit Area; Table S2. Wild Cluster Bootstrap results for the mediation effects; Table S3. Leave-One-Province-

Out sensitivity analysis of the mediation effects; Table S4. Leave-One-Region-Out sensitivity analysis of the mediation effects.

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Abbreviations

The following abbreviations are used in this manuscript:

EPVCE	Ecological Product Value Conversion Efficiency
RDE	Rural Digital Economy
PF	Production function
LF	Living function
EF	Ecological function

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