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From Ecological Supply to Realized Value: Spatial Mismatch of Forest Ecological Products in Guangdong Province, China

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Abstract

Forest ecological product value realization depends on ecological resource endowment, human demand, and value-conversion capacity. This study developed a dual-scale framework to assess supply–demand mismatch and value realization of forest ecological products in Guangdong Province, China, from 2012 to 2022. At the 1-km grid scale, ecological supply was represented by forest cover and forest NPP intensity, while human demand was characterized by impervious surface, summer land surface temperature, and nighttime lights. At the prefecture-level city scale, grid-based indicators were linked with forestry industry output value to evaluate realized economic value, relative value-realization efficiency, supply–realization mismatch, and city typology. OLS regression and random forest models were used to identify driving factors. Results showed that ecological supply was concentrated in mountainous areas of northern, eastern, and western Guangdong, whereas demand and value-conversion capacity were clustered in the Pearl River Delta and coastal urbanized areas. Impervious surface ratio, forest NPP intensity, GDP, and population were key predictors. These findings reveal the spatial decoupling between ecological resource spaces and value realization spaces and support differentiated forest ecological product governance.

Keywords: forest ecological products; supply–demand mismatch; value realization efficiency; dual-scale assessment

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1. Introduction

Forest ecosystems provide diverse ecological products and services, including carbon sequestration, water conservation, soil retention, climate regulation, recreation, and forest-derived material products [1,2]. In the Chinese policy context, forest ecological products generally refer to ecological goods and services generated by forest ecosystems that can support human well-being and be transformed into socioeconomic benefits under appropriate institutional and market conditions. Because these products involve both ecological functions and market-related outputs, their empirical assessment requires operational indicators that can characterize ecological supply, human demand, and realized value at comparable spatial and temporal scales [3,4]. Rapid urbanization and land-use transformation have increasingly separated ecological supply areas from socioeconomic demand

centers. Forest ecological resources are often concentrated in mountainous or peripheral areas, whereas population, infrastructure, consumption demand, and value-conversion opportunities are concentrated in urban cores. This spatial separation indicates that forest ecological products should be examined through the coupled relationships among supply, demand, value realization, and spatial mismatch.

Conceptually, forest ecological products are closely related to forest ecosystem services, but the two terms emphasize different aspects. Forest ecosystem services mainly describe the ecological functions and benefits provided by forest ecosystems, whereas forest ecological products, as used in the Chinese policy context, emphasize the identification, valuation, exchange, compensation, and socioeconomic transformation of these services and related forest resources. In this sense, forest ecosystem services provide the ecological basis of forest ecological products, while forest ecological products represent a product-oriented and value-realization-oriented expression of forest ecosystem services [5,6].

Ecosystem service supply–demand assessment provides an important basis for identifying spatial imbalances between ecological provision and human needs. Early studies developed conceptual and operational frameworks to distinguish ecosystem service supply, demand, capacity, pressure, and flow [7,8]. Subsequent urban-scale studies showed that ecosystem service deficits are closely related to uneven distributions of green infrastructure, beneficiaries, and demand pressure [9,10]. In rapidly urbanizing regions, supply–demand mismatch is usually shaped by land development intensity, population concentration, spatial governance, and scale effects [11–14]. These studies suggest that ecosystem service mismatch is not merely an ecological phenomenon, but a coupled outcome of ecological resource distribution and socioeconomic spatial organization.

Recent studies have further incorporated multi-source data, urbanization indicators, and scale-sensitive methods into ecosystem service supply–demand assessment. For example, multi-source ecological and socioeconomic indicators have been used to identify ecosystem service matching patterns in arid and urbanized regions [15,16]. Urbanization has also been reported to generate scale- and location-dependent effects on ecosystem service supply–demand relationships, with distinct responses observed in established urban cores, newly urbanized zones, and surrounding non-urban areas [17,18]. Composite-indicator and multi-scale approaches have also been applied to diagnose supply–demand mismatch under environmental pressure and spatial heterogeneity [19,20]. At broader scales, recent evidence suggests that ecosystem service mismatch is jointly driven by climate change and human activity, and that refined ecosystem management requires attention to cross-scale imbalance [21–23]. Nevertheless, these studies mainly focus on ecological service supply, human demand, or their spatial balance, while the transformation of ecological resources into realized socioeconomic value remains insufficiently integrated.

In China, realizing the value of forest ecological products has increasingly been incorporated into policy discussions on ecological civilization construction and green development. Different from conventional ecosystem service assessment, value realization focuses not only on ecological supply capacity, but also on whether ecological resources can be transformed into economic, social, and ecological benefits through market access, industrial systems, infrastructure, and institutional mechanisms [24,25]. Previous research has examined this issue from multiple perspectives, including ecological product valuation, implementation pathways, forest-based ecological industries, and supporting policy instruments [26,27]. Evaluation frameworks based on DPSIR, effectiveness assessment, and efficiency analysis further indicate that value realization depends on policy support, market response, industrial transformation, and regional development conditions [28–30]. However, most studies have been conducted at administrative scales, and relatively little

attention has been paid to how fine-scale ecological supply and human demand patterns are linked with city-level value realization efficiency.

The scale mismatch between ecological processes and socioeconomic value realization remains a key methodological challenge. Remote sensing data can capture fine-scale spatial heterogeneity in forest cover, vegetation productivity, impervious surface, land surface temperature, and nighttime lights [31–35]. In contrast, city-level socioeconomic statistics are more suitable for evaluating industrial output, population demand, and value realization capacity. Composite indicator construction provides a practical way to integrate multi-source variables with different units, while machine-learning methods can help identify nonlinear driving factors [36–39]. However, grid-scale ecological indicators are often weakly connected to administrative-scale value realization, and city-level studies may obscure local ecological gradients and demand pressure. Therefore, a dual-scale analytical framework is needed to link grid-scale ecological supply and human demand with city-scale value realization, supply–realization mismatch, and driving mechanisms.

Guangdong Province provides a suitable case for addressing this issue. The province contains the highly urbanized Pearl River Delta (PRD), rapidly developing coastal zones, and extensive mountainous forest ecosystems in northern, eastern, and western Guangdong. This spatial structure creates a strong contrast between ecological supply areas and socioeconomic demand centers. Forest-rich mountainous cities may have strong ecological supply but limited value-conversion capacity, whereas highly urbanized Pearl River Delta cities may have stronger market demand and industrial transformation capacity despite relatively limited ecological supply. Recent studies have shown that ecological product value realization is closely associated with green finance, digital economy, institutional performance, and regional development capacity [40–43]. These characteristics make Guangdong an appropriate region for examining the spatial disconnection among forest ecological resource endowment, human demand, and value realization capacity.

This study develops a dual-scale framework to assess forest ecological product supply–demand mismatch and value realization in Guangdong Province from 2012 to 2022. At the 1 km grid scale, ecological supply is represented by forest cover proportion and forest NPP intensity, while human demand is characterized by impervious surface proportion, summer land surface temperature, and nighttime lights. At the prefecture-level city scale, grid-scale supply and demand are aggregated and linked with forestry output data to construct value realization, value realization efficiency, and supply–realization mismatch indicators. Furthermore, OLS regression with year fixed effects and city-clustered robust standard errors is combined with random forest modelling and cross-validation to identify linear and nonlinear driving mechanisms [44]. The objectives are to: (1) identify the spatial distribution and temporal evolution of ecological supply, human demand pressure, and supply–demand mismatch; (2) evaluate city-scale value realization efficiency and supply–realization mismatch; (3) identify different value realization types; and (4) reveal the main ecological, urbanization, climatic, topographic, and socioeconomic drivers of value realization efficiency and mismatch.

2. Materials and Methods

2.1. Study Area

Located in southern mainland China, Guangdong Province comprises 21 prefecture-level cities and represents one of the country's most economically dynamic and rapidly urbanizing regions, while also showing marked spatial heterogeneity in ecological resource distribution (Figure 1). The province contains the highly urbanized PRD, rapidly developing coastal zones, and extensive mountainous and hilly ecological spaces in northern, eastern, and western Guangdong. Forest resources are mainly distributed in mountainous

and hilly areas, whereas construction land, population, and economic activities are concentrated in the PRD and coastal cities. Previous studies have shown that urbanization in the PRD has reshaped ecosystem service supply and demand, intensified ecological pressure, and increased the need for supply–demand-oriented ecological management [45,46]. Mountainous cities generally have relatively high forest cover and ecological productivity but weaker market access and industrial transformation capacity. In contrast, the PRD has relatively limited ecological supply space but stronger population, capital, infrastructure, and consumption demand. This spatial contrast provides a typical case for examining the mismatch among forest ecological product supply, demand, and value realization.

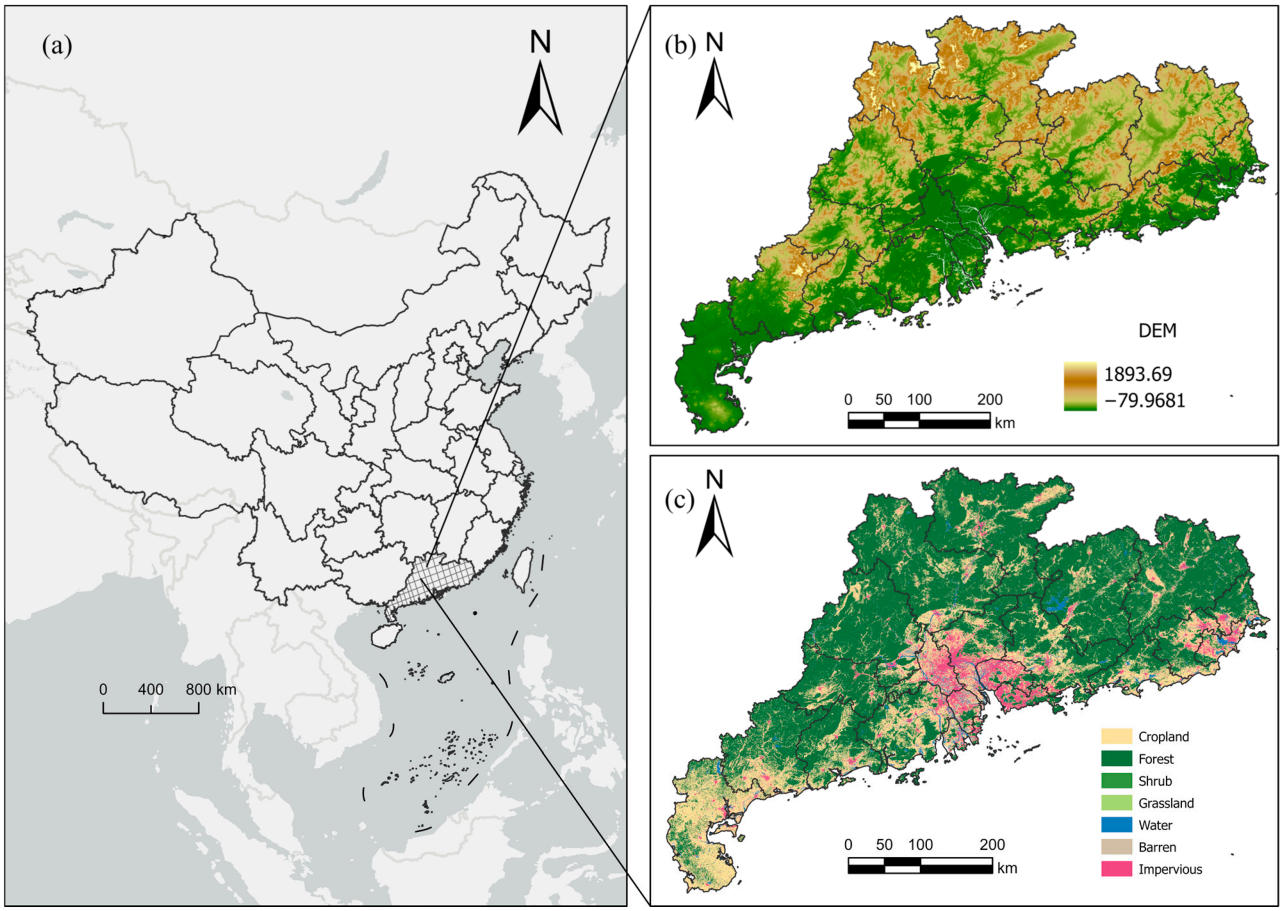


Figure 1. Overview of the Study Area. (**a**) Spatial Location of Guangdong Province, (**b**) DEM, (**c**) Land Use.

2.2. Data Sources and Preprocessing

This study covers the period from 2012 to 2022 and integrates land use, vegetation productivity, urbanization, human activity, climate, topography, and socioeconomic statistics to construct a forest ecological product supply–demand–value realization framework. The raster datasets include the China Land Cover Dataset (CLCD), net primary productivity (NPP), summer land surface temperature (LST), nighttime lights (NTL), impervious surface, air temperature, precipitation, potential evapotranspiration (PET), digital elevation model (DEM), and slope. Socioeconomic data include prefecture-level GDP, permanent population, and forestry industry output value (Table 1). Considering data availability, forestry industry output value was used as a proxy for the realized economic value of forest ecological products at the prefecture-level city scale. Non-commercial or weakly marketized components, such as carbon trading, ecological compensation, forest recreation, cultural services, biodiversity conservation, and payments for ecosystem services, were

not included in the value realization indicator. Administrative boundary data were used to match raster-based indicators with prefecture-level cities. These datasets were used to characterize forest ecological supply, human demand intensity, climatic and topographic conditions, urbanization level, socioeconomic development, and the realized value of forest ecological products.

Table 1. Data Source.

Data Name	Year	Spatial Resolution	Data Source (All Accessed on 11 July 2026)
CLCD	2012–2022	30 m	https://zenodo.org/records/12779975
NPP	2012–2022	500 m	https://developers.google.com/earth-engine/datasets/catalog/MODIS_061_MOD17A3HGF?hl=zh-cn
LST	2012–2022	1 km	https://developers.google.com/earth-engine/datasets/catalog/MODIS_061_MOD11A2?hl=zh-cn
NTL	2012–2022	500 m	https://data.harvard.edu/dataverse
Temp	2012–2022	1 km	https://www.ncdc.ac.cn/portal/
Prec	2012–2022	1 km	https://www.ncdc.ac.cn/portal/
PET	2012–2022	1 km	https://www.ncdc.ac.cn/portal/
DEM	2009	500 m	https://www.nasa.gov/
GDP	2012–2022	-	https://stats.gd.gov.cn/gdtjnj/index.html
Population	2012–2022	-	https://stats.gd.gov.cn/gdtjnj/index.html
Output value of the forestry industry	2012–2022	-	https://stats.gd.gov.cn/gdnctjnj/index.html

To ensure spatial comparability across multiple datasets, a unified 1 km grid was generated based on CLCD. All raster datasets were clipped, reprojected, resampled, and aligned to this grid. Categorical datasets were aligned to the unified grid using nearest-neighbor resampling, whereas continuous datasets were harmonized through bilinear interpolation or grid-level averaging according to their original spatial resolution and data characteristics. Variables with highly skewed distributions, such as nighttime lights, GDP, and population, were log-transformed before model analysis to reduce the influence of extreme values. All variables used for composite indicator construction were normalized to the range of 0–1 using pooled min–max normalization across the full 2012–2022 dataset [47]. This procedure allowed the normalized indicators to be compared across both cities and years. Finally, grid-scale indicators were aggregated to prefecture-level cities by calculating the arithmetic mean of all valid 1-km grid cells within each city boundary, and the resulting city-level indicators were matched with socioeconomic statistics to construct the city-level panel dataset for value realization assessment, typology identification, and driving mechanism analysis. The technical route is shown in Figure 2.

2.3. Dual-Scale Analytical Framework and Indicator Construction

This study developed a dual-scale analytical framework that integrates the 1 km grid scale and the prefecture-level city scale. The grid scale was used to identify fine-scale spatial patterns of forest ecological supply, human demand, and supply–demand mismatch. The city scale was used to assess ecological supply, human demand, realized value, value realization efficiency, supply–realization mismatch, and value realization typology. Because ecological supply, human demand, and value realization are multidimensional concepts, they cannot be fully represented by a single variable. Ecosystem service mapping studies generally rely on spatial indicators derived from land cover, vegetation conditions, biophysical processes, and socioeconomic variables, while composite indicators provide a practical way to integrate multiple dimensions into comparable indices [48,49]. Therefore, this study constructed operational composite indicators after normalization. Equal weighting was adopted to ensure that each component had the same initial contribution

to the composite index [50]. This weighting scheme provides a transparent baseline for composite-indicator construction, while the resulting index values may still be affected by alternative weighting assumptions.

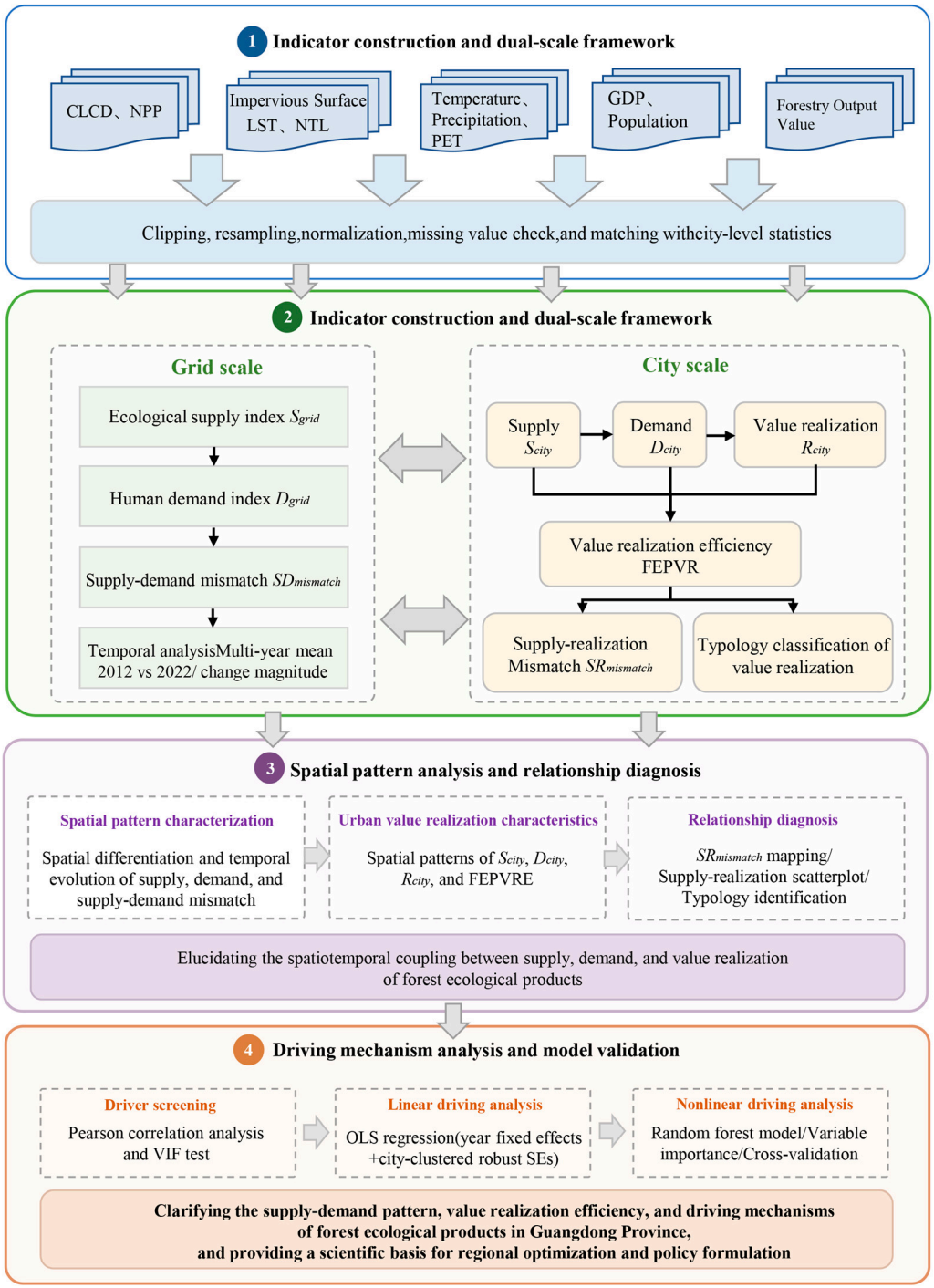


Figure 2. Methodological workflow of the dual-scale assessment framework.

At the grid scale, the ecological supply index S_{grid} was represented by forest cover proportion and forest NPP intensity. Forest cover proportion reflects the spatial quantity of forest ecological resources, whereas forest NPP intensity reflects ecosystem productivity and biomass production capacity. Together, these two indicators mainly capture the forest resource base and ecosystem productivity dimension of ecological supply. Other dimensions of forest ecological products, such as water regulation, soil retention, biodi-

versity conservation, recreation, and cultural services, were not directly measured in the supply index. Forest cover and vegetation productivity are commonly used to characterize the spatial basis and functional capacity of ecosystem service supply, and NPP has been widely applied to quantify terrestrial ecosystem productivity and human appropriation of ecosystem production [51]. The two standardized indicators were combined as follows:

$$S_{grid} = \frac{F_{grid} + NPP_{grid}}{2} \quad (1)$$

where F_{grid} denotes the forest cover proportion, and NPP_{grid} denotes forest NPP intensity.

The human demand index D_{grid} was constructed using impervious surface proportion, summer LST, and NTL intensity. These variables were used to represent urbanization-related demand pressure that can be consistently measured from remote sensing data. Impervious surface proportion reflects built-up land expansion and ecological space occupation. Summer LST indicates urban thermal stress and potential demand for cooling and climate-regulation services. NTL intensity reflects the spatial concentration of population, economic activity, and consumption capacity. These indicators therefore link urban land occupation, thermal environmental pressure, and socioeconomic activity intensity with potential demand for forest ecological regulation, ecological compensation, carbon-offset-related services, recreation, and forest-derived products. Impervious surface, thermal infrared-derived LST, and nighttime lights have been widely used as indicators of land development intensity, urban environmental pressure, and human socioeconomic activity, respectively [52–54]. These three standardized indicators were combined as follows:

$$D_{grid} = \frac{I_{grid} + LST_{grid} + NTL_{grid}}{3} \quad (2)$$

where I_{grid} denotes impervious surface proportion, LST_{grid} denotes summer land surface temperature, and NTL_{grid} denotes nighttime light intensity. To quantify the spatial imbalance between potential ecological supply and human demand pressure, the supply–demand mismatch index was calculated as follows:

$$SD_{mismatch} = D_{grid} - S_{grid} \quad (3)$$

A positive $SD_{mismatch}$ indicates that human demand exceeds ecological supply, suggesting demand-dominated pressure. A negative value indicates that ecological supply exceeds human demand, suggesting supply-dominated conditions. Difference- or balance-based indicators have been widely used to identify ecosystem service surplus, deficit, and mismatch areas by comparing supply and demand surfaces [55–57]. Based on this index, this study analyzed the multi-year mean pattern from 2012 to 2022, the contrast between 2012 and 2022, and the magnitude of change during the study period.

At the city scale, S_{city} and D_{city} were calculated as the arithmetic means of S_{grid} and D_{grid} across all valid 1-km grid cells within each prefecture-level city. The city-level supply–demand mismatch was calculated as the arithmetic mean of grid-level $SD_{mismatch}$ values within each city. The city-level value realization index R_{city} was constructed using forestry industry output value. Forestry industry output value generally records the economic output of forestry-related production and industrial activities, such as forest cultivation, forest product harvesting, forest-product processing, and forestry-related services. Accordingly, R_{city} represents the measurable economic output associated with forest resources and forestry-related industries. This indicator was used as an operational proxy for forest ecological product value realization, rather than a complete measure of all forest ecosystem services. Forest ecological product value realization is closely related to forest ecosystem

service valuation, ecological product accounting, and the transformation of ecological resource endowment into socioeconomic benefits [58,59]. Considering data availability, non-commercial and weakly marketized components were not included in R_{city}. To measure the relative value-conversion capacity per unit ecological supply, the forest ecological product value realization efficiency index (FEPVRE) was defined as:

$$FEPVRE = \frac{R_{city}}{S_{city}} \quad (4)$$

where R_{city} denotes the city-level value realization index, and S_{city} denotes the city-level ecological supply index. A higher FEPVRE indicates greater realized economic value per unit of ecological supply. In this study, FEPVRE is interpreted as a relative value-realization intensity based on the ratio between R_{city} and S_{city}. It describes the proportional relationship between city-level realized economic value and ecological supply and is used to compare value-conversion performance across cities.

To characterize the mismatch between ecological supply and realized value, the supply–realization mismatch index was further defined as:

$$SR_{mismatch} = S_{city} - R_{city} \quad (5)$$

A positive $SR_{mismatch}$ indicates that ecological supply is higher than realized value, suggesting that ecological resources have not been sufficiently transformed into socioeconomic value. A negative value indicates that realized value is higher than ecological supply, reflecting stronger value-conversion capacity. Based on the median thresholds of S_{city}, D_{city}, and R_{city}, cities were classified into three value realization types. The median threshold was used to provide a transparent and relatively balanced classification rule for the limited sample of 21 prefecture-level cities. This typology was used to identify the main constraints and optimization directions for forest ecological product value realization across cities.

2.4. Driving Mechanism Analysis and Robustness Considerations

To identify the factors associated with FEPVRE and supply–realization mismatch, candidate explanatory variables were selected from five dimensions: ecological supply basis, urbanization intensity, climatic conditions, topography, and socioeconomic development. Ecological factors included forest cover proportion and forest NPP intensity. Urbanization factors included impervious surface proportion, summer LST, and NTL intensity. Climatic factors included annual mean air temperature, precipitation, and PET. Topographic factors included elevation and slope. Socioeconomic factors included GDP and permanent population.

For the linear driving analysis, ordinary least squares regression was used to estimate the statistical associations between explanatory variables and the two dependent variables, namely FEPVRE and $SR_{mismatch}$. Year fixed effects were included to control for common temporal shocks during the study period. City fixed effects were not included in the main specification because this study focused on cross-city differences in forest ecological product value realization, and several key explanatory variables, such as elevation, slope, and forest resource endowment, mainly vary across cities rather than within cities over time. Including city fixed effects would absorb much of this spatially stable cross-city variation and reduce the interpretability of these factors. City-clustered robust standard errors were used because observations from the same city across years may have correlated errors, and

clustering adjustment is recommended when unobserved cluster-level components may affect inference [60]. The model was specified as follows:

$$Y_{it} = \alpha + \sum_{k=1}^{n} \beta_k X_{kit} + \gamma_t + \varepsilon_{it} \quad (6)$$

where Y_{it} denotes FEPVRE or $SR_{mismatch}$ for city i in year t; X_{kit} denotes the k-th explanatory variable; γ_t represents year fixed effects; and ε_{it} is the error term. Continuous variables were standardized before modelling to allow comparison of coefficient magnitudes across different explanatory variables.

Because forest ecological product value realization may involve nonlinear relationships and interactions among ecological, urbanization, and socioeconomic factors, random forest modelling was used as a complementary nonparametric approach. The random forest models were implemented in Python 3.10.12 using the scikit-learn package. The main hyperparameters were set as follows: n_estimators = 500, max_features = "sqrt", min_samples_leaf = 3, max_depth = None, bootstrap = True, and random_state = 42. Model performance was evaluated using five-fold grouped cross-validation, with prefecture-level cities used as grouping units to reduce information leakage from repeated observations within the same city. Grouped cross-validation is appropriate for ecological and socioeconomic panel data with hierarchical or spatial dependence, because ignoring such dependence can lead to overly optimistic prediction errors [61]. Predictive accuracy was quantified using cross-validated R^2 and RMSE. To examine the sensitivity of FEPVRE to small denominators, city-year observations with the lowest 5% of S_{city} values were excluded, and the resulting city-level FEPVRE ranking was compared with the original ranking. In addition, a weighting sensitivity analysis was conducted by assigning double weight to forest cover proportion, forest NPP intensity, and NTL intensity, respectively, and the resulting city-level rankings were compared with the equal-weight results using Spearman correlation coefficients. Global Moran's I was calculated for the main city-level indices, including ecological supply, human demand, realized value, FEPVRE, and supply–realization mismatch, to examine spatial autocorrelation at the prefecture-level city scale.

3. Results

3.1. Grid-Scale Spatial Patterns and Temporal Evolution of Supply–Demand Mismatch

Figure 3 shows a pronounced spatial mismatch between forest ecological product supply and human demand at the 1 km grid scale in Guangdong Province. Areas with strong ecological supply were predominantly found in the mountainous and hilly landscapes of northern, eastern, and western Guangdong, where high-value patches formed relatively contiguous supply belts. By comparison, weaker supply capacity was mainly observed in the PRD and other coastal zones characterized by intensive urban development. Human demand pressure displayed a contrasting spatial configuration, with high-intensity clusters concentrated in the PRD urban agglomeration and several coastal built-up zones, while northern Guangdong and inland mountainous regions generally showed much lower pressure levels. These patterns indicate that ecological supply was primarily associated with the spatial distribution of forest resources, whereas human demand was closely related to urbanization intensity and the concentration of human activities.

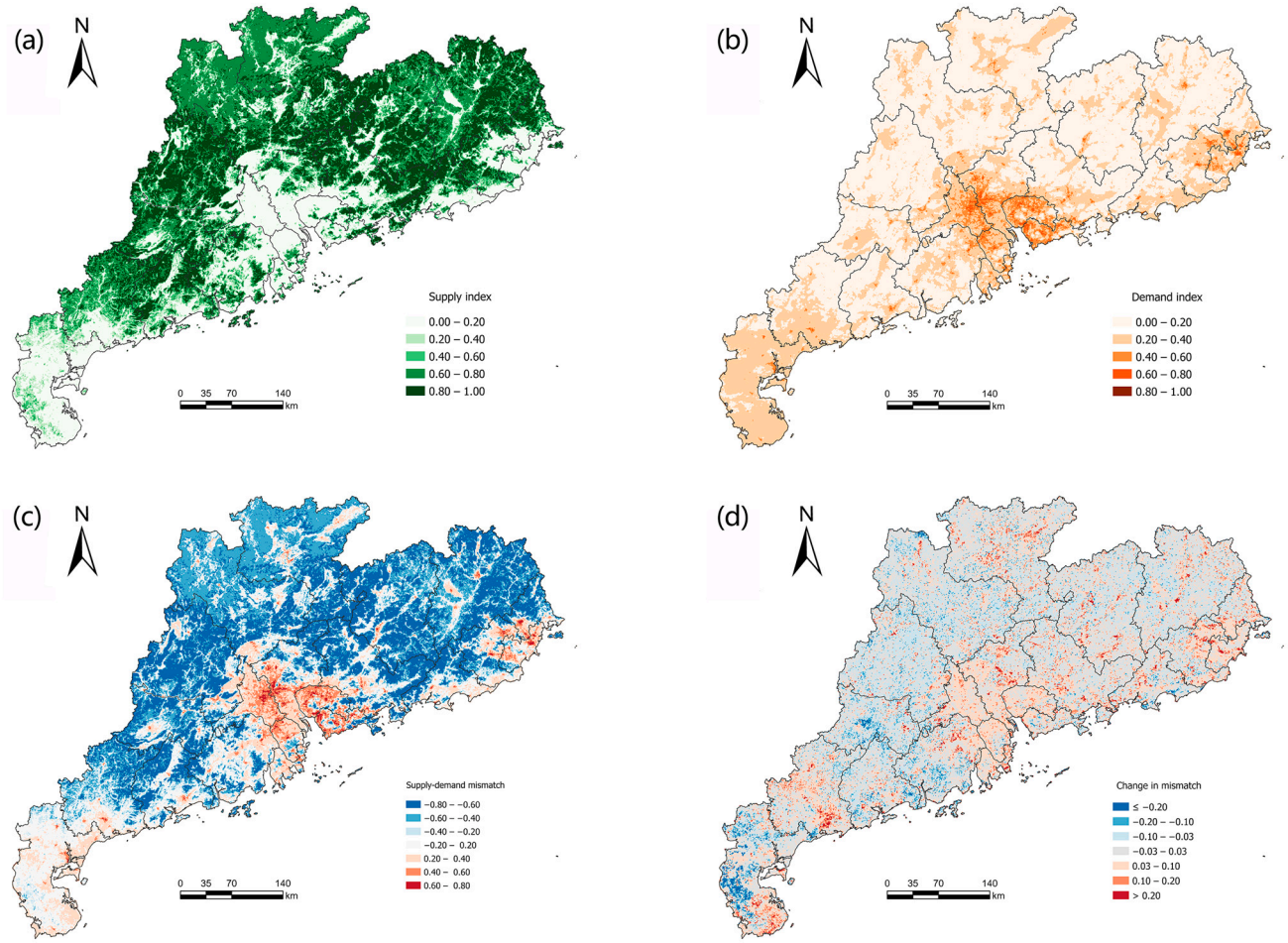


Figure 3. Grid-scale spatial patterns of ecological supply, human demand, supply–demand mismatch, and mismatch changes in Guangdong Province. (**a**) Mean ecological supply index during 2012–2022; (**b**) mean human demand index during 2012–2022; (**c**) mean supply–demand mismatch during 2012–2022; (**d**) change in supply–demand mismatch from 2012 to 2022.

The supply–demand mismatch pattern further revealed the spatial disconnection between ecological resource-rich areas and demand-intensive areas. Northern, eastern, and western Guangdong generally showed supply-dominated conditions, whereas the PRD core exhibited stronger demand pressure. Changes in supply–demand mismatch from 2012 to 2022 were spatially fragmented, with more evident changes occurring around the periphery of the PRD, coastal expansion zones, and mountain–plain transition areas. This suggests that temporal changes in supply–demand relationships were mainly associated with localized urban expansion and adjustments in ecological spatial structure. Overall, Guangdong exhibited a clear pattern of "peripheral concentration of ecological supply, core concentration of human demand, and spatial mismatch between supply and demand."

Figure 4 further compares the typical-year patterns of forest ecological product supply, human demand, and supply–demand mismatch in 2012 and 2022. The distribution of ecological supply showed limited temporal variation over the study period, as high-supply areas continued to be concentrated in the mountainous and hilly regions of northern, eastern, and western Guangdong. The PRD core and highly urbanized coastal areas consistently showed relatively low ecological supply. In contrast, human demand exhibited stronger urban clustering. High-demand areas were already concentrated in the core cities of the PRD in 2012, and this pattern persisted in 2022, with slight expansion toward the peripheral PRD and several coastal urbanizing areas.

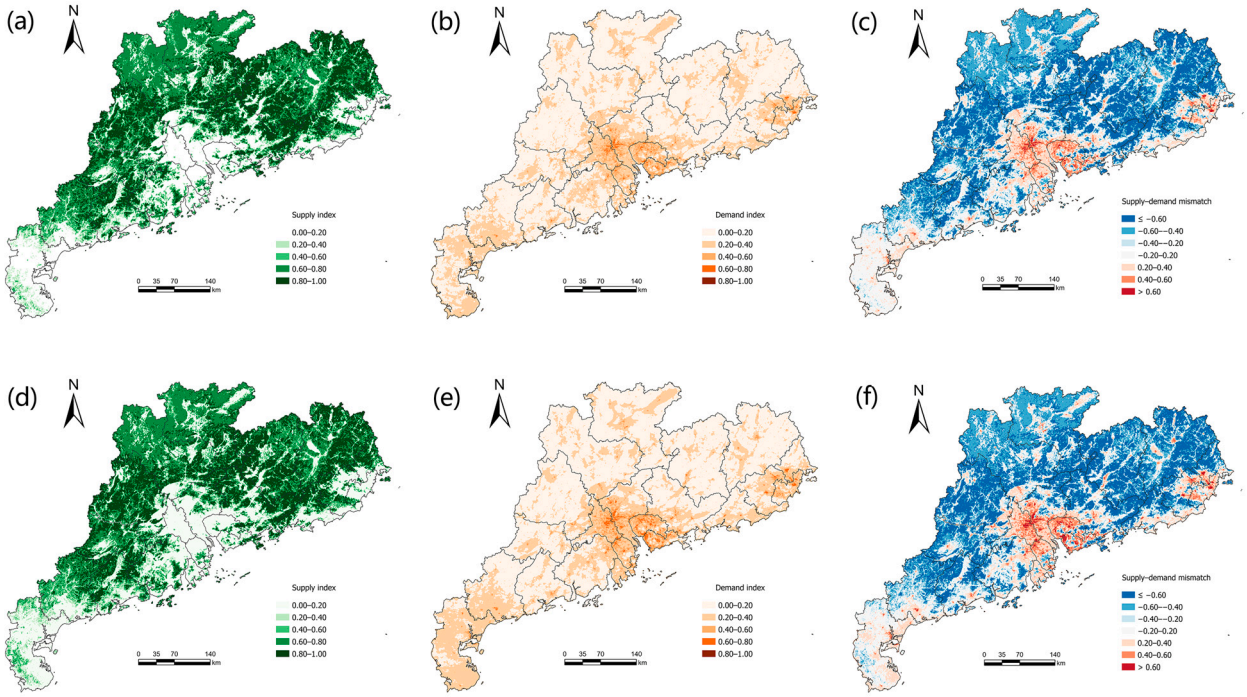


Figure 4. Grid-scale comparison of ecological supply, human demand, and supply–demand mismatch in typical years. (**a**–**c**) Ecological supply index, human demand index, and supply–demand mismatch in 2012; (**d**–**f**) ecological supply index, human demand index, and supply–demand mismatch in 2022.

The supply–demand mismatch pattern also showed strong spatial continuity between the two years. Supply-dominated areas were mainly located in peripheral mountainous ecological spaces, whereas demand-dominated areas were concentrated in the PRD and coastal urbanized zones. Compared with 2012, mismatch patches became more apparent in some urban expansion areas and mountain–plain transition zones in 2022, suggesting that local urbanization may have intensified the spatial mismatch between ecological supply and human demand. Overall, the supply–demand structure in Guangdong did not undergo a fundamental shift during the study period; rather, local increases in demand pressure were superimposed on a stable regional differentiation pattern.

3.2. City-Scale Patterns of Supply, Demand, Value Realization, and Efficiency

At the city scale, forest ecological product supply, demand, value realization, and value realization efficiency exhibited distinct spatial differentiation (Figure 5). High ecological supply values were primarily observed in northern Guangdong and in some mountainous and hilly cities of eastern and western Guangdong, whereas the PRD core and several coastal cities showed lower values. This pattern indicates that city-level ecological supply was still largely controlled by the forest resource base. In contrast, human demand showed an almost opposite pattern, with high values concentrated in the PRD core and its neighboring cities, while peripheral mountainous cities had relatively low demand. This result confirms that urbanization intensity and the concentration of human activities were the dominant spatial features of city-level demand.

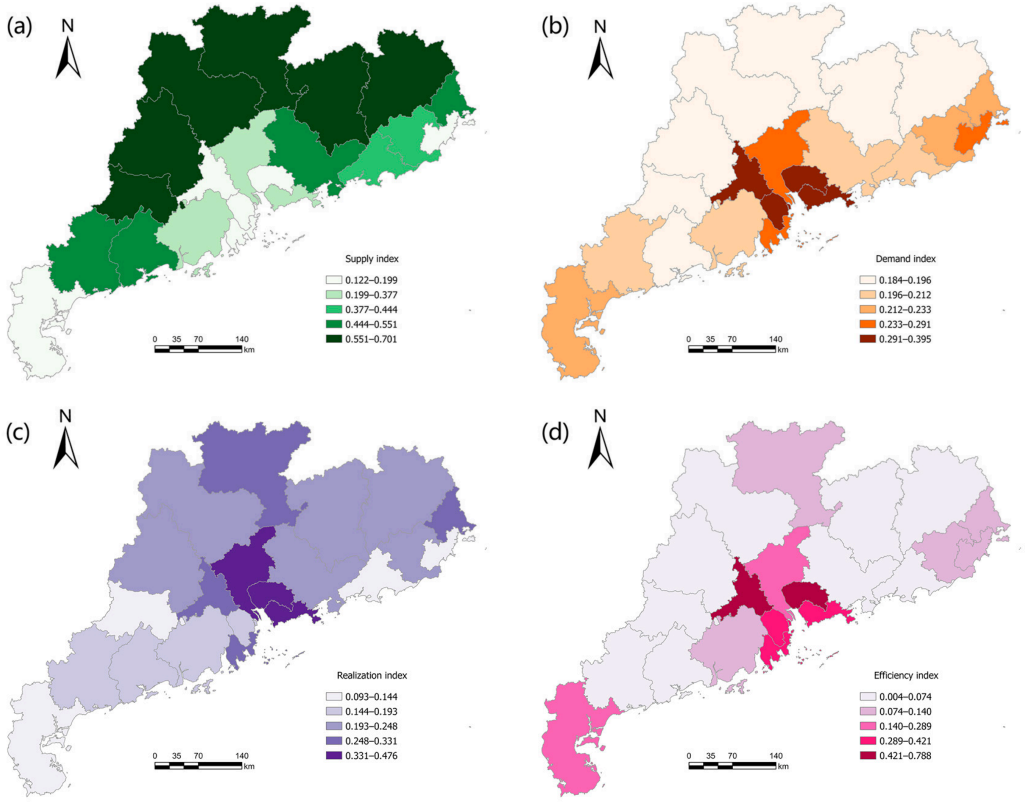


Figure 5. City-scale spatial patterns of ecological supply, human demand, value realization, and value realization efficiency in Guangdong Province. (**a**) Ecological supply index; (**b**) human demand index; (**c**) value realization index; (**d**) Value realization efficiency.

The spatial distributions of value realization and value realization efficiency did not simply increase with ecological supply. High value realization was mainly concentrated in the PRD and several surrounding cities, suggesting that actual value conversion depended more strongly on urban economic conditions, market demand, and industrial absorption capacity. High FEPVRE values were also mainly observed in the PRD core and several coastal cities, whereas some cities with high ecological supply in northern Guangdong showed relatively low value-realization intensity. These results indicate that FEPVRE varied substantially among cities with different ecological supply levels. The conversion of ecological resource endowments into measurable economic returns remains dependent on the level of urban development, the strength of the industrial base, and the degree of market accessibility.

3.3. Supply–Realization Mismatch and Value Realization Typology

The supply–realization mismatch of forest ecological products showed clear regional differentiation in Guangdong Province (Figure 6). Cities showing strong positive supply–realization mismatch were concentrated mainly in northern and western Guangdong, as well as in parts of eastern Guangdong, suggesting that these areas possessed relatively abundant ecological supply but had not yet converted it into sufficient economic realization. Negative mismatch areas were mainly located in the core cities of the PRD and their surrounding areas, suggesting that these cities had relatively limited ecological supply but stronger value-conversion capacity. The scatterplot further showed that ecological supply and value realization did not follow a simple linear relationship. Shenzhen, Guangzhou, Dongguan, Foshan, and several other cities exhibited relatively high levels of value realization, whereas some peripheral cities with higher ecological supply remained at low or moderate levels of realized value.

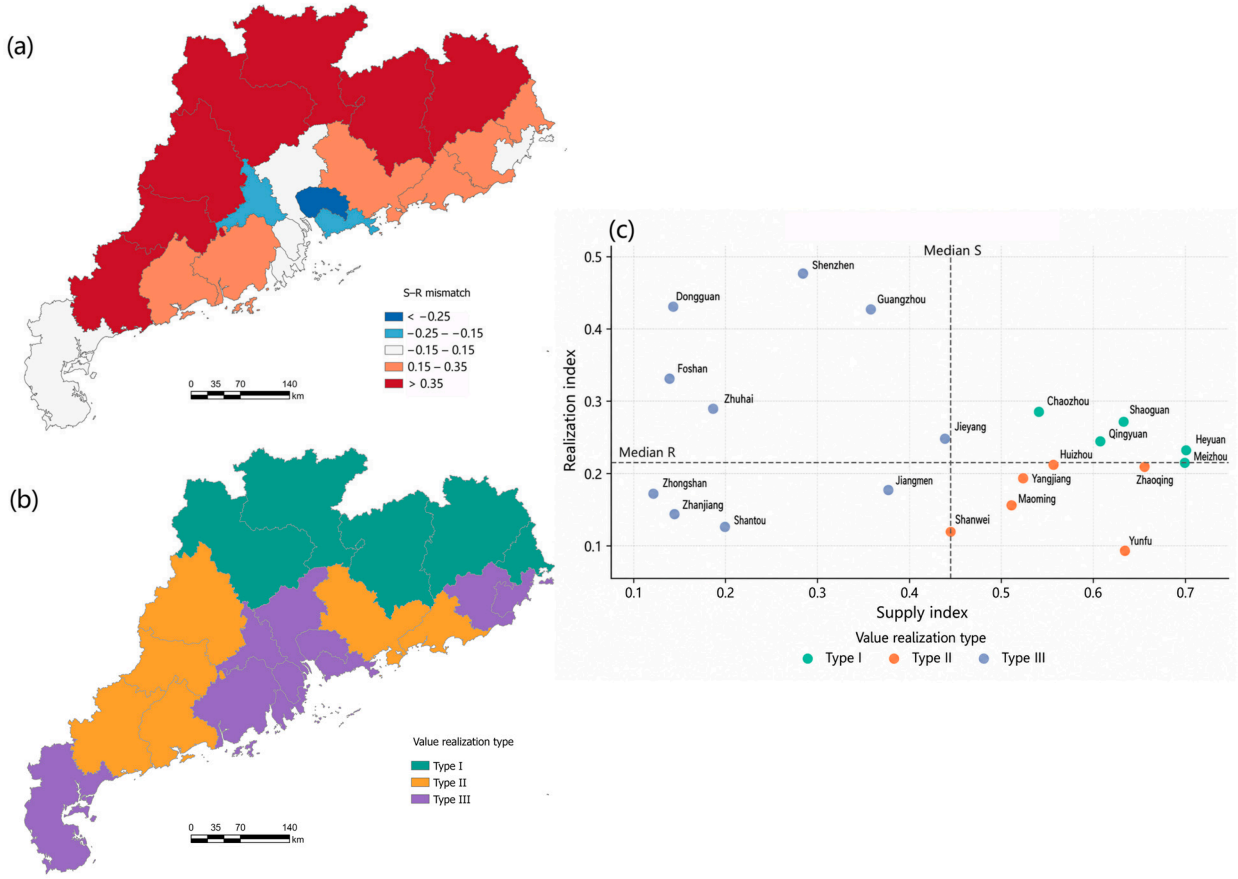


Figure 6. Supply–realization mismatch and value realization types of forest ecological products in Guangdong Province. (**a**) Spatial distribution of supply–realization mismatch; (**b**) value realization types; (**c**) relationship between ecological supply and value realization.

The typology based on supply, realization, and demand relationships identified three major value realization types in Guangdong, while no low-supply–low-realization cultivation area was detected. Type I, representing supply–realization synergy cities, was distributed in northern Guangdong and parts of eastern Guangdong, representing areas where relatively high ecological supply coexisted with relatively high value realization. Type II, representing latent-reserve cities, was mainly distributed in western Guangdong, parts of northern Guangdong, and several peripheral PRD cities, indicating areas with relatively strong ecological supply but insufficient value realization. Type III, representing demand-driven conversion hubs, was mainly concentrated in the PRD core, coastal cities, and parts of eastern Guangdong, reflecting higher demand or stronger value-conversion pressure under relatively limited ecological supply. This broad typology was consistent with the spatial patterns of ecological supply, human demand, value realization, and supply–realization mismatch shown in Figures 5 and 6. Overall, the key issue of forest ecological product value realization in Guangdong is not simply the shortage of ecological supply, but the mismatch between the spatial distribution of ecological resources and the capacity for value conversion.

3.4. Driving Mechanisms of Value Realization Efficiency and Supply–Realization Mismatch

Figure 7a shows that the VIF values of all selected explanatory variables were below 10, indicating that the variables included in the OLS models did not suffer from severe multicollinearity. GDP, summer LST, permanent population, impervious surface ratio, and forest NPP intensity had relatively higher VIF values, suggesting certain correlations among socioeconomic development, urbanization intensity, and ecological-environmental

variables. However, these values remained within an acceptable range. Therefore, the subsequent regression results can be used to identify the main linear associations with value realization efficiency and supply–realization mismatch.

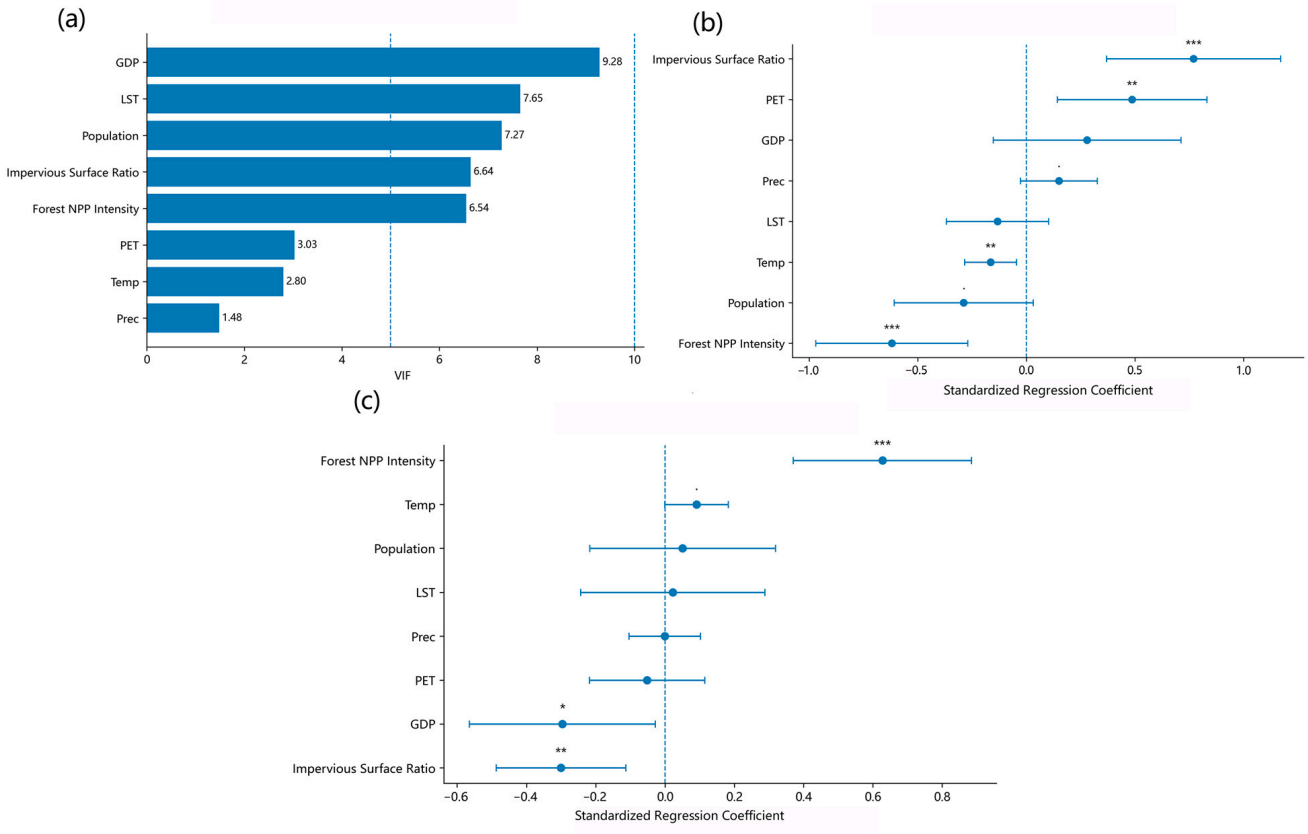


Figure 7. Multicollinearity diagnosis and standardized OLS coefficients for the driving factors of forest ecological product value realization. (**a**) Variance inflation factors of selected explanatory variables; (**b**) standardized OLS coefficients for forest ecological product value realization efficiency; (**c**) standardized OLS coefficients for supply–realization mismatch. Error bars indicate 95% confidence intervals. Significance levels are denoted as *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

The OLS results indicate that FEPVRE was jointly associated with urbanization conditions, climatic factors, and ecological supply characteristics. Impervious surface ratio was significantly positively associated with FEPVRE, whereas forest NPP intensity was significantly negatively associated with FEPVRE. This suggests that areas with stronger urbanization and market-transformation conditions tended to generate greater realized economic value per unit ecological supply. In contrast, regions with high forest productivity may show lower efficiency if ecological resources are not effectively transformed into realized value. For supply–realization mismatch, forest NPP intensity was significantly positively associated with the mismatch index, whereas GDP and impervious surface ratio were significantly negatively associated with it. This indicates that areas with stronger ecological supply but weaker value realization capacity were more likely to exhibit positive mismatch, while cities with larger economic scale and higher urbanization levels were more likely to reduce supply–realization mismatch through market demand, infrastructure, and industrial transformation capacity.

The random forest results further indicate the predictive importance of ecological supply and urbanization-related transformation capacity (Figure 8). For FEPVRE, impervious surface ratio showed the highest predictive importance, with substantially higher permutation importance than the other factors. Forest NPP intensity, GDP, and permanent

population also contributed to model explanation. This indicates that value realization efficiency was not only related to ecological supply conditions but was also strongly shaped by market-transformation conditions represented by urbanization level, economic scale, and population concentration. For supply–realization mismatch, impervious surface ratio and forest NPP intensity had the highest and most similar levels of predictive importance, both clearly exceeding the other variables. This suggests that the mismatch pattern was jointly shaped by ecological supply capacity and urban value-conversion capacity, while GDP, summer LST, and population provided secondary explanatory contributions.

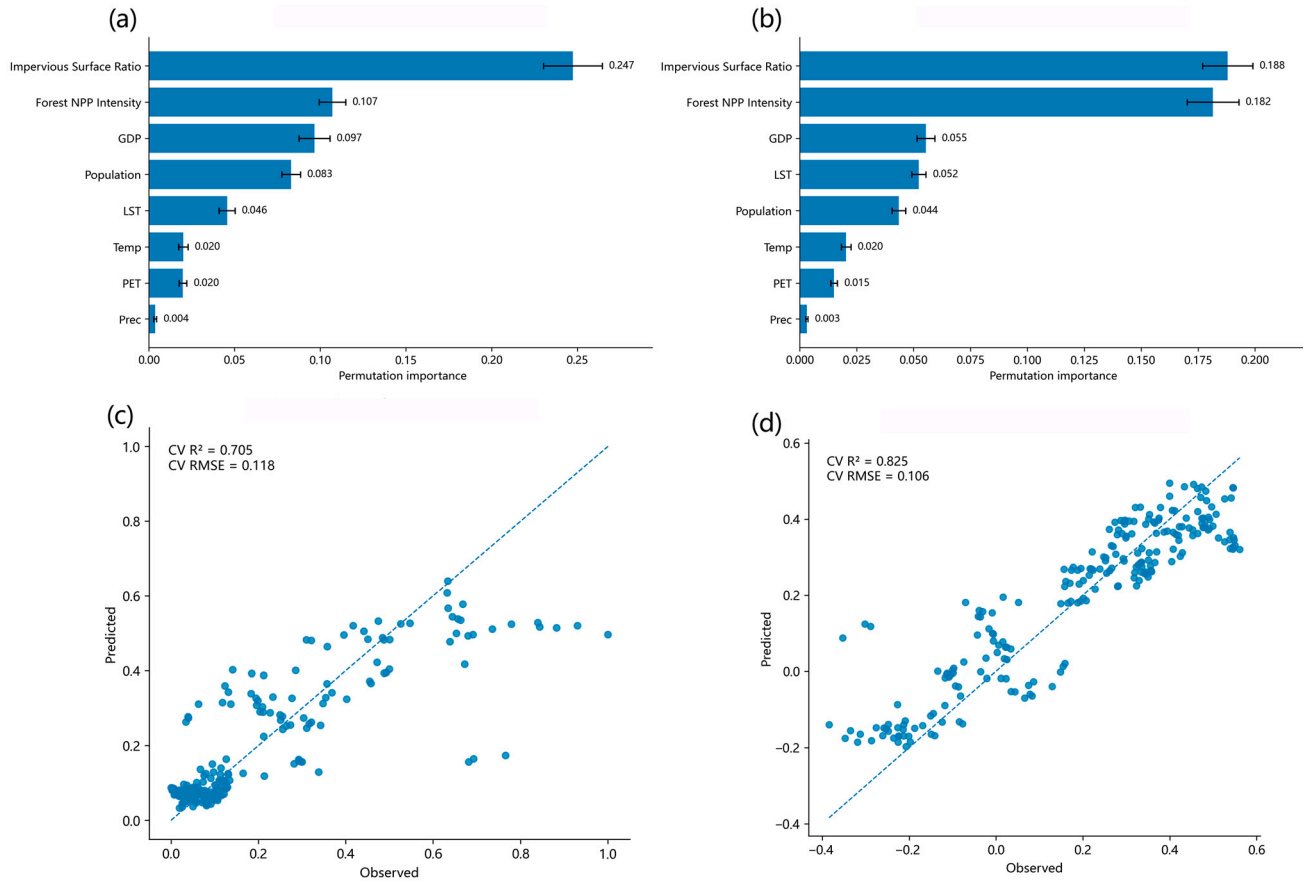


Figure 8. Random forest variable importance and cross-validation performance for forest ecological product value realization. (**a**) Permutation importance for value realization efficiency; (**b**) permutation importance for supply–realization mismatch; (**c**) cross-validation performance for value realization efficiency; (**d**) cross-validation performance for supply–realization mismatch. The dotted lines in panels (**c**,**d**) represent the 1:1 reference line between observed and predicted values.

Model validation showed that the random forest models had good predictive performance for both dependent variables. For the FEPVRE model, grouped cross-validation yielded an R^2 of 0.705 and an RMSE of 0.118, suggesting that the random forest model was able to explain a substantial proportion of the nonlinear variation in value realization efficiency. The supply–realization mismatch model performed better, with predicted values generally closer to the 1:1 reference line. This suggests that supply–realization mismatch was more directly explained by ecological supply, urbanization, and socioeconomic variables than the efficiency indicator. These findings further indicate that forest ecological product value realization in Guangdong is not constrained by ecological resources alone, but is shaped by the combined effects of ecological supply and urban economic transformation capacity. After excluding city-year observations with the lowest 5% of S_{city} values, the city-level FEPVRE ranking remained highly consistent with the original result, with

a Spearman correlation coefficient of 0.996 ($p < 0.001$). The highest FEPVRE values were still concentrated in Dongguan, Foshan, Shenzhen, and Zhuhai, supporting a stable spatial interpretation of FEPVRE after removing observations with very low ecological supply. The weighting sensitivity analysis also showed stable results. The city-level supply ranking remained highly consistent after assigning double weight to forest cover proportion or forest NPP intensity, with Spearman correlation coefficients of 0.999 and 0.995, respectively. The demand ranking also remained highly consistent after assigning double weight to NTL intensity, with a Spearman correlation coefficient of 0.995. The main spatial pattern of peripheral ecological supply and PRD-centered demand was therefore stable under alternative weighting assumptions.

Global Moran's I further confirmed the spatial structure of the main city-level indices (Table 2). Human demand, realized value, and supply–realization mismatch showed significant positive spatial autocorrelation at the 5% level, with Moran's I values of 0.313, 0.293, and 0.293, respectively. Ecological supply and FEPVRE also showed positive spatial autocorrelation, with Moran's I values of 0.238 and 0.219, respectively, although their significance was marginal at the 10% level. These results indicate that the city-level patterns of forest ecological product supply, demand, value realization, and supply–realization mismatch were spatially clustered rather than randomly distributed.

Table 2. Global Moran's I results for the main city-level indices.

Indicator	Moran's I	Expected I	z-Score	*p*-Value
Ecological supply	0.238	−0.050	1.820	0.069
Human demand	0.313	−0.050	2.378	0.017
Realized value	0.293	−0.050	2.254	0.024
FEPVRE	0.219	−0.050	1.853	0.064
Supply–realization mismatch	0.293	−0.050	2.184	0.029

4. Discussion

4.1. Mechanisms of Spatial Decoupling Between Forest Ecological Supply and Human Demand

The spatial mismatch between forest ecological product supply and human demand in Guangdong does not simply reflect insufficient ecological supply, but rather the joint effect of long-term divergence between the natural ecological pattern and the urbanization pattern. Mountainous and hilly areas maintain relatively high forest cover and ecological productivity, thereby constituting the main supply spaces of forest ecological products. In contrast, the PRD and coastal urbanized areas concentrate population, construction land, industrial activities, and consumption demand, forming high-intensity demand centers. Previous studies on ecosystem service supply and demand in urban agglomerations have shown that rapid urbanization tends to strengthen the spatial separation between ecological supply areas and demand centers, increasing the dependence of core cities on surrounding ecological spaces [62,63]. In the context of forest ecological products, this separation becomes more pronounced: forest-resource-rich areas mainly provide ecological supply, whereas areas with concentrated population, capital, and industries generate stronger demand pressure. Therefore, the supply–demand relationship of forest ecological products is not equivalent to that of ordinary urban green-space services; rather, supply, demand, and value realization often occur across different spatial units.

From 2012 to 2022, the overall supply–demand mismatch pattern in Guangdong remained relatively stable, while local changes were mainly concentrated around the periphery of the PRD, coastal expansion zones, and mountain–plain transition areas. This suggests that the key issue is not a province-wide structural shift, but the continuous disturbance near urban expansion frontiers. Previous research has shown that urban sprawl

can reduce ecosystem service supply capacity and increase the risk of supply–demand imbalance [64]. Meanwhile, urbanization and ecosystem services interact spatially, and the flow of ecosystem services from supply areas to demand areas is an important intermediary process for understanding regional supply–demand relationships [65,66]. In Guangdong, the supply–demand relationship of forest ecological products does not change monotonically with urbanization intensity. Instead, it shows a chain-like structure characterized by peripheral supply advantages, core demand advantages, and high sensitivity in transition zones. This feature indicates that future supply–demand governance should not focus only on the PRD core, but should also pay close attention to the interface between urban expansion frontiers and ecological barriers, where supply–demand tensions are more likely to accumulate and intensify.

4.2. Why Ecological Endowment Does Not Directly Translate into Value Realization

One important result of this study is that ecological supply advantages do not necessarily translate into higher value realization efficiency. Conventional ecosystem service assessment mainly focuses on the quantity or capacity of services that ecosystems can provide, whereas forest ecological product value realization further concerns whether ecological resources can be transformed into actual benefits through property-right clarification, value accounting, market transactions, industrial absorption, and consumption processes. Recent research on realized ecosystem services has emphasized that potential supply, actual flow, and final use are not equivalent; ecosystem services are more directly linked to human well-being and socioeconomic systems only when they enter processes of use and transformation [66]. This logic helps explain the spatial differentiation within Guangdong: ecological-resource-rich areas such as northern Guangdong may have strong supply capacity, but their value realization efficiency can remain limited if market access, industrial platforms, and capital investment are insufficient. Ecological resource advantages should therefore be regarded as a necessary foundation for value realization, rather than a sufficient condition for generating realized benefits.

The association analysis further indicates that forest ecological product value realization is related to both ecological foundations and conversion capacity. The positive effect of forest NPP intensity on supply–realization mismatch suggests that areas with high ecological productivity are more likely to experience "high supply–low realization" resource accumulation if effective value-conversion pathways are absent. By contrast, urbanization-related factors represented by impervious surface ratio, GDP, and population agglomeration should not be interpreted as ecological benefits themselves. Rather, they reflect stronger market capacity, infrastructure, consumption demand, and industrial organization. Recent evidence from China also suggests that urbanization, economic development, technological support, and resource endowment jointly shape the value realization efficiency of forest ecological products [67,68]. Therefore, regional differences in forest economic realization of ecological products in Guangdong cannot be explained solely by ecological resource endowment. Market connectivity, industrial absorption, capital input, and institutional support must also be considered. The spatial mismatch between ecological resource spaces and value realization spaces therefore provides an important explanation for differences in value realization efficiency across the province.

4.3. Policy Implications

The above findings suggest that forest ecological product value realization in Guangdong requires differentiated policies that link ecological supply, human demand, and value-conversion capacity rather than relying on uniform ecological protection measures.

(1) For supply-advantaged but under-realized cities, especially Type II cities, policies should strengthen value-conversion capacity through ecological product accounting, certification, regional branding, forest carbon sinks, eco-tourism, understory economy, and forest-product processing. These measures can help transform ecological resources into identifiable and income-generating products [69].
(2) For the spatial separation between ecological supply areas and demand centers, cross-regional compensation and cooperation mechanisms should be improved. Horizontal ecological compensation, carbon trading, ecological product procurement, and regional industrial cooperation can better connect providers, beneficiaries, and ecosystem service flows [70].
(3) For different value realization types, differentiated governance is needed. Supply–realization synergy cities (Type I) should consolidate supply–realization synergy, Type II cities should improve market access and industrial transformation, and Type III cities should enhance green infrastructure, ecological restoration, and external ecological product inputs. Incorporating supply–demand mismatch into land-use optimization can support more targeted spatial governance [71].

4.4. Limitations

This study has three main limitations. First, ecological supply, human demand, and value realization were represented using composite indicators. The supply index was based on forest cover proportion and forest NPP intensity, which mainly captured forest resource quantity and ecosystem productivity. Other dimensions of forest ecological products, such as water regulation, soil retention, biodiversity conservation, recreation, and cultural services, were not directly measured. In addition, because forest NPP intensity and impervious surface proportion were also involved in index construction, some model associations may partly reflect mechanical links among variables rather than fully independent causal mechanisms. Although normalization and equal weighting improved comparability, indicator selection, weighting, aggregation, and the modifiable areal unit problem associated with grid-to-city aggregation may still influence spatial patterns and typology identification [36]. Second, the value realization indicator was based on forestry industry output value and therefore mainly captured the realized economic component of forest ecological product value realization. Considering data availability, carbon trading, ecological compensation, forest recreation, cultural services, biodiversity conservation, certification income, payments for ecosystem services, and other non-commercial or weakly marketized values were not included. Third, the demand index did not include sociocultural dimensions, such as place identity, environmental attitudes, ecological preferences, willingness to pay, or perceived ecosystem service demand. Thus, the current demand index mainly represents biophysical and urbanization-related demand pressure. Moreover, spatial dependence was not explicitly modeled using spatial econometric methods, and the observational design limits causal interpretation beyond statistical associations. Although Global Moran's I was used to examine the spatial autocorrelation of the main city-level indices, residual spatial dependence was not further modeled using spatial econometric methods and may still affect statistical inference. The observational design also limits causal interpretation beyond statistical associations.

Future research should further examine indicator and typology robustness using alternative weighting schemes, normalization methods, threshold settings, clustering approaches, uncertainty analysis, and alternative model specifications. More detailed data on carbon markets, ecological compensation, eco-tourism, enterprise operation, and ecological product certification should also be incorporated. In addition, spatial econometric models, causal inference, and scenario simulations could be used to examine the dynamic effects

of urban expansion, ecological restoration, green finance, and digital platforms on forest ecological product value realization. Future studies could integrate questionnaire surveys, stated-preference methods, tourism behavior data, and social perception data to better capture the sociocultural demand for forest ecological products. The generalizability of the Guangdong case should also be tested in other regions with different ecological resource endowments and development conditions.

5. Conclusions

This study developed a dual-scale framework to assess the supply–demand mismatch and value realization of forest ecological products in Guangdong Province from 2012 to 2022. By integrating multi-source remote sensing data, city-level socioeconomic statistics, grid-scale supply–demand assessment, city-scale value realization evaluation, and linear and nonlinear driving mechanism analysis, this study linked fine-scale ecological supply and human demand patterns with prefecture-level value realization outcomes. The framework helps reveal not only where ecological supply and human demand are spatially mismatched, but also why ecological resource advantages do not necessarily translate into higher value realization efficiency. The main conclusions are as follows:

(1) At the 1 km grid scale, forest ecological supply and human demand exhibited a clear spatial mismatch. Ecological supply was mainly concentrated in the mountainous and hilly areas of northern, eastern, and western Guangdong, whereas human demand was highly clustered in the PRD and coastal urbanized areas. From 2012 to 2022, the overall supply–demand structure remained relatively stable, while local changes were more evident in the PRD periphery, coastal expansion zones, and mountain–plain transition areas.

(2) At the city scale, ecological supply, human demand, value realization, and value realization efficiency showed distinct spatial differentiation. Cities with high ecological supply did not necessarily have high value realization or efficiency. The PRD and several coastal cities showed stronger value realization capacity, while some forest-resource-rich mountainous cities still faced insufficient value conversion. This indicates that forest ecological product value realization depends not only on ecological endowment, but also on market demand, industrial capacity, infrastructure, and socioeconomic development conditions.

(3) The supply–realization mismatch and typology results further revealed the spatial separation between ecological resource spaces and value realization spaces. Positive supply–realization mismatch was mainly observed in ecological supply-advantaged cities, indicating insufficient transformation of ecological resources into realized value. Negative mismatch was mainly concentrated in the PRD, reflecting stronger value-conversion capacity. Three major value realization types were identified, while no low-supply–low-realization cultivation area was detected.

(4) The driving mechanism analysis showed that forest ecological product value realization is jointly shaped by ecological supply and urban transformation capacity. OLS and random forest results consistently indicated that impervious surface ratio, forest NPP intensity, GDP, and population were important explanatory variables. Impervious surface ratio was the most important factor for FEPVRE, while both impervious surface ratio and forest NPP intensity strongly contributed to supply–realization mismatch. These results suggest that improving value realization requires not only maintaining ecological supply, but also strengthening the institutional, industrial, and market pathways through which ecological resources are transformed into realized socioeconomic value.

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Data Availability Statement: The public datasets used in this study are listed in Table 1. The processed city-level indicators, model input tables, and analysis code are available from the corresponding author upon reasonable request.

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