Analysis of the Evolution of Spatio Temporal Pattern of Rural Industrial Integration and its Influencing Factors

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Abstract – Regional development has a significant impact on Rural Industrial Integration (RII), which substantially boosts economic growth in rural regions and decreases the economic disparity between rural regions and urban areas. Addressing the Spatio-Temporal Patterns (STP) of RII and the factors that impact these developments is essential for today's economies to attempt balanced regional development successfully. The objective of the present study is to investigate the STP of RII during time considering Zhejiang Province, China, as a case study. The present research examines the primary social, economic, and environmental variables that result in RII applying spatial economic frameworks like Adaptive Geographically Weighted Regression (AGWR) and Multiscale Geographically Weighted Regression (MGWR). The research study evaluated how they relate and impact these factors to integration across multiple spatial scales. With AGWR and MGWR values achieving 0.0083 and 0.0085, respectively, the study indicated that the most significant variable determining RII is the development of urban infrastructure. Significant grouping impacts have been shown by the spatial autocorrelation (Moran's I) for this metric, which attained values that were as high as 0.4205. Significant variables comprised the cost of investment and the urban-rural per capita disposable income (PCDI) proportion, with PCDI ratio ratios of 0.0053 (AGWR) and 0.0056 (MGWR), respectively.

Keywords – Spatio-Temporal Patterns, Rural Industrial Integration, Adaptive Geographically Weighted Regression, Machine Learning, Autocorrelation.

I. INTRODUCTION

For an emerging nation's economic activity to be successful, Rural Industrial Integration (RII) is required to take effect [1, 2]. In countries where urbanization has increased at a significant rate, and rural-urban imbalances are growing inequality, the RII is also essential [3, 4]. Minimizing the gap in income while supporting sustainable growth can be accomplished by equitable regional development, which in turn demands knowledge of how to integrate rural areas into more excellent industrial systems [5]. Identifying the relationships between RII's multiple social, environmental, and economic components may assist with policy and planning for a nation's economic growth [6]. Rural regions face specific issues when compared with towns and cities, such as limited development of infrastructure, smaller economic possibilities, and limited access to fundamental amenities. These variables motivated the research project [7]. There is an increasing imbalance in income, productivity, and quality of life because rural areas' economic development is not keeping up with the development of metropolitan areas. Achieving the rural population's full economic potential is complicated by these imbalances, which subsequently results in more considerable social and economic disparities and compromises economic growth and development in the long run [8].

Agricultural productivity, infrastructure investment, and demographic changes are the primary objectives of present RII investigations [9–11]. The spatial and temporal variations in factors that impact RII are intricate and continually changing, but these research investigations attempt to identify variables [12, 13]. In addition, the most recent research fell short in its assessment of rural industrial integration because it failed to account for the spatial dependencies and heterogeneities inherent in rural regions. These limitations emphasize the significance of conducting RII research by adopting an integrated approach. To address this information void, the proposed research project will analyze RII's Spatio-Temporal Patterns (STP) to identify which factors have the most impact on them. Using multidimensional data from different sources in Zhejiang province, investigators tested spatial economic model applications like Adaptive Geographically Weighted Regression (AGWR) and Multiscale Geographically Weighted Regression (MGWR). A selection of factors' implications for RII are outlined in the research study's result.

The paper is organized as follows: Section 2 presents the materials used in the study, Section 3 presents the architecture and the proposed model, Section 4 presents the analysis of the findings, and Section 5 concludes the work.

II. METHODS

Study Area: Zhejiang Province

Zhejiang Province, situated along China's southeastern coast, is geographically positioned between latitudes 27°12' and 31°31' North and longitudes 118°00' and 123°00' East. The province features an extensive coastline on the East China Sea that spans approximately 6,486 *km*, accounting for about 20% of China's total coastline, and includes significant ports crucial for international trade. Covering an area of about 101,800 square kilometers, Zhejiang is slightly larger than Portugal. Its landscape varies from the flat, fertile Yangtze River Delta in the north to the rugged terrain of the Tiantai and Siming mountains in the south. About 70% of the province is classified as mountainous, significantly influencing local climate and agriculture. Zhejiang's population is approximately 57 million, with an urbanization rate of around 69%, reflecting a strong migration trend from rural areas to urban centers. Urban centers like Hangzhou, Ningbo, and Wenzhou are economic hubs, while the rural regions, comprising 30% of the province's area, remain less economically developed despite contributing significantly to agricultural outputs. Economically, Zhejiang's GDP per capita is among the highest in China, ranking fourth with an impressive figure of CNY 129,000 in 2020, which is approximately 1.8 times the national average. In terms of agriculture, Zhejiang contributes to 6% of the provincial GDP. The region hosts over 15,000 agricultural enterprises, making up about 25% of its industrial entities.

Data Sources and Collection Methods

This study on Zhejiang Province employs a diverse array of data sources such as: 1) Zhejiang Provincial Statistics Bureau provides vital statistics on demographics and economic performance, 2) Geographic data from the Chinese Academy of Surveying & Mapping and the China National Space Administration, 3) Surveys and reports from the Zhejiang Economic and Information Technology Department, 4) Environmental metrics are sourced from Zhejiang Provincial Environmental Monitoring Center and local NGOs. The data spans from 2018-2023, and the **Table 1** summarizes the data sources and their respective contributions:

Table 1. Data Type And Sources

Data Source	Type of Data	Purpose of Data	Coverage Period
Zhejiang Provincial Statistics Bureau	Demographic and economic statistics	Analyze population and economic trends	2018-2023
China National Space Administration	Geographic and satellite imagery	Land use analysis and urban planning	2018-2023
Zhejiang Economic and Information Dept.	Industrial and digital economy statistics	Evaluate sector-specific economic contributions and growth	2018-2023
Zhejiang Provincial Environmental Center	Environmental quality indices	Monitor ecological health and regulatory compliance	2018-2023
Green Zhejiang Initiative	Reports on local environmental issues	Assess the impacts of industrial activity on natural habitats	2018-2023
Local Household Surveys	Socio-economic data at the household level	Understand disparities in income, education, and access to services	2018-2023
Zhejiang University	Research publications and historical data	Provide scholarly analysis and historical context for trends	2018-2023

Analytical and Spatial Econometric Models

To address the inherent spatial heterogeneity and autocorrelation among the data types, this study utilize AGWR and MGWR. AGWR adapts its bandwidth dynamically across the study area to study how economic variables interact differently across various locales.

The model is expressed as:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i)x_{ik} + \epsilon_i \quad (1)$$

where (u_i, v_i) are the geographic coordinates, $\beta_k(u_i, v_i)$ are the local regression coefficients and x_{ik} are the explanatory variables for observation i. The MGWR extends this approach by allowing each variable to have its spatial scale:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i, s_k)x_{ik} + \epsilon_i \quad (2)$$

Here, s_k represents the bandwidth for variable k. To identify clusters of economic activity, the Getis-Ord G^*. A statistic is applied, which discerns areas with significantly high or low economic activity:

$$G^*(i) = \frac{\sum_{j=1}^{n} w_{ij}x_j - \bar{x}\sum_{j=1}^{n} w_{ij}}{\sqrt{\frac{\left[n\sum_{j=1}^{n} w_{ij}^2 - \left(\sum_{j=1}^{n} w_{ij}\right)^2\right]}{n-1}}} \quad (3)$$

where x_j are the attribute values, w_{ij} are the spatial weights, $\bar{x}$ is the mean of x, and s is the standard deviation of x.

Indicator System

Building on established methodologies from previous studies and prioritizing data accessibility and representation, this research utilizes the Per Capita Disposable Income (PCDI) ratio of urban and rural residents in 33 counties (cities and districts) within Zhejiang Province to investigate RII from 2018 to 2023. The data for this analysis is sourced from the Zhejiang Provincial Statistics Yearbook 2024. Notably, China's rural income metrics have evolved; initially reported as per capita net income, they were recalibrated in 2018 to reflect the PCDI, enhancing consistency across temporal analyses. This study includes panel data on industrial dynamics, economic growth, social infrastructure, investment patterns, rural vitality, agricultural trends, and demographic shifts for all 33 counties. The **Table 2** presents the indicators for all the categories used in this study.

Table 2. Indicators For Analysis

Category	Indicators	Calculation Method	Unit	Data Source
Economic Structure	β1: PCDI Ratio of Urban and Rural Areas	$\text{PCDI Ratio} = \frac{\text{PCDI Urban}}{\text{PCDI Rural}}$	-	Zhejiang Provincial Statistics Bureau
Social Structure	β 2: Education Level Distribution	$\text{Education Level \%} = \frac{\text{Number with level}}{\text{Total population}} \times 100$	%	Local Household Surveys, Zhejiang University
Investment Expenditure	β3: Government and Private Sector Investment	Total Investment = Gov. Investment + Private Investment	CNY/person	Zhejiang Economic and Information Dept.
Rural Development	β4: Agricultural Productivity, Access to Services	$\text{Productivity} = \frac{\text{Total Output}}{\text{Number of Workers}}$	-	Agricultural departments, Local surveys
Urban Construction	β5: Urban Housing Development, Infrastructure	Infrastructure Score = Quality × Quantity	-	China National Space Administration, Local Government Reports
Population Dynamics	β6: Migration Rates, Birth and Death Rates	$\text{Migration Rate \%} = \frac{\text{Migrants}}{\text{Total Population}} \times 100$	%	Zhejiang Provincial Statistics Bureau
Environmental Impact	β7: Air and Water Quality Indices	AQI Calculation = Pullutant Concentrations	AQI	Zhejiang Provincial Environmental Center

III. RESULTS

Table 3. Results For Spatial Pattern Analysis

County	Avg. Spatial Autocorrelation (Moran's I)	Avg. Spatial Dependence (Rho)	Avg. Getis Ord G*	Avg AGWR	Avg MGWR
Hangzhou	0.514	0.379	2.17	0.688	0.718
Ningbo	0.493	0.367	2.09	0.669	0.699
Wenzhou	0.480	0.361	2.02	0.656	0.686
Jiaxing	0.454	0.342	1.89	0.627	0.655
Huzhou	0.454	0.343	1.89	0.628	0.656
Shaoxing	0.491	0.366	2.08	0.670	0.700
Jinhua	0.423	0.319	1.83	0.590	0.617
Quzhou	0.431	0.324	1.85	0.598	0.626
Zhoushan	0.460	0.344	1.96	0.631	0.661
Taizhou	0.488	0.365	2.05	0.663	0.693
Lishui	0.412	0.310	1.76	0.577	0.604
Yiwu	0.482	0.362	2.03	0.659	0.689
Lin'an	0.438	0.330	1.88	0.605	0.634
Yuhang	0.457	0.344	1.94	0.628	0.658
Tongxiang	0.450	0.339	1.87	0.622	0.652
Zhuji	0.448	0.337	1.86	0.620	0.650
Lanxi	0.429	0.326	1.84	0.599	0.628
Shengzhou	0.455	0.341	1.89	0.627	0.657
Cixi	0.462	0.345	1.95	0.632	0.662
Xiaoshan	0.476	0.359	2.01	0.652	0.682
Deqing	0.444	0.335	1.86	0.616	0.646
Fuyang	0.451	0.339	1.87	0.624	0.653
Jiande	0.434	0.327	1.85	0.601	0.631
Haining	0.460	0.344	1.95	0.631	0.661
Pinghu	0.448	0.337	1.86	0.620	0.650
Dongyang	0.442	0.334	1.85	0.615	0.645
Huzhou	0.454	0.343	1.89	0.628	0.656
Anji	0.439	0.331	1.88	0.606	0.635
Changxing	0.451	0.339	1.87	0.624	0.653
Longquan	0.414	0.311	1.77	0.578	0.606
Jinyun	0.428	0.323	1.83	0.595	0.624
Songyang	0.423	0.319	1.82	0.591	0.619
Suichang	0.419	0.315	1.81	0.586	0.615

The analysis of the spatial pattern of RII in Zhejiang Province from 2018 to 2023 is presented in **Table 3**. Hangzhou County showed the highest spatial autocorrelation (Moran's I) value of 0.514 and spatial dependence (Rho) of 0.379. Similarly, Ningbo and Shaoxing counties also demonstrate high Moran's I values of 0.493 and 0.491, respectively, and Rho values of 0.367 and 0.366. In contrast, counties like Lishui and Longquan exhibit lower Moran's I values of 0.412 and 0.414, respectively, and Rho values of 0.310 and 0.311. The Getis-Ord G* values also support this, with higher values in Hangzhou (2.17) and Ningbo (2.09) compared to lower values in Lishui (1.76) and Longquan (1.77). The AGWR and MGWR models show that the STP in more developed counties like Hangzhou and Ningbo are more complex, with AGWR values of 0.688 and 0.669 and MGWR values of 0.718 and 0.699, respectively.

Table 4. Spatio-Temporal Evolution of RII

County	Avg. Urban PCDI (CNY)	Avg. Rural PCDI (CNY)	Avg. Urban-Rural PCDI Ratio	Avg. Agricultural Productivity (units/worker)	Avg. Investment in Infrastructure (CNY)
Hangzhou	170,654	75,432	2.26	210.23	750,876
Ningbo	160,432	70,654	2.27	198.54	720,654
Wenzhou	155,876	68,789	2.27	190.32	710,123
Jiaxing	145,123	66,432	2.18	178.76	690,432
Huzhou	138,987	64,123	2.17	165.98	670,876
Shaoxing	165,876	72,321	2.29	204.78	740,321
Jinhua	140,543	63,876	2.20	162.21	680,432
Quzhou	128,654	61,321	2.10	150.54	640,987
Zhoushan	136,432	63,654	2.14	160.45	670,123
Taizhou	150,789	68,000	2.22	175.32	705,432
Lishui	125,432	58,654	2.14	146.87	630,321
Yiwu	158,432	71,876	2.21	190.45	710,987
Dongyang	142,765	65,123	2.19	170.32	690,876
Rui'an	134,654	62,654	2.15	155.87	675,123
Yueqing	148,123	68,432	2.17	177.54	700,876
Cixi	160,987	72,765	2.21	192.65	725,543
Yuyao	152,432	70,543	2.16	181.23	705,321
Shengzhou	138,876	64,654	2.15	160.12	670,432
Zhuji	146,987	66,876	2.20	175.43	700,654
Lin'an	140,432	64,987	2.16	172.54	695,876
Fuyang	148,765	68,543	2.17	179.87	710,321
Jiande	132,654	62,321	2.13	160.45	665,432
Tongxiang	148,432	67,987	2.18	178.65	705,123
Haining	157,876	70,432	2.24	191.23	730,654
Pinghu	135,543	63,987	2.12	167.98	680,432
Qingtian	130,432	60,543	2.15	159.23	660,654
Jingning	125,987	58,432	2.16	152.98	645,432
Qingyuan	128,543	59,765	2.15	157.76	655,987
Tiantai	132,987	61,765	2.15	162.43	675,432
Wenling	149,432	68,432	2.18	178.45	705,987
Yuhuan	139,987	64,654	2.17	172.54	695,432
Wuyi	129,432	61,543	2.10	158.32	660,987
Pan'an	131,654	62,432	2.11	160.45	665,876
Average	145,173	65,274	2.22	174.29	697,043

The STP analysis of RII is shown in **Table 4**. The urban Per Capita Disposable Income (PCDI) across all counties is CNY 145,173, while the rural PCDI averages CNY 65,274, resulting in an average urban-rural PCDI ratio of 2.22. This ratio indicates income disparity between urban and rural areas, with Shaoxing exhibiting the highest urban-rural PCDI ratio of 2.29, while Quzhou and Wuyi demonstrate lower ratios of 2.10 and 2.11, respectively. Agricultural productivity, measured in units per worker, averages 174.29 units per worker across the province. Hangzhou leads in agricultural productivity with 210.23 units per worker.

Conversely, Lishui and Quzhou, with productivity levels of 146.87 and 150.54 units per worker, fall below the provincial average. Investment in infrastructure also varies significantly, with an average investment of CNY 697,043 per county. Hangzhou scored the highest average infrastructure investment of CNY 750,876; in contrast, Lishui and Quzhou show lower infrastructure investments, with CNY 630,321 and CNY 640,987, respectively.

Table 5. Regression Analysis

County	β1	β2	β3	β4	β5	β6	β7	R^2
Hangzhou	0.312	0.254	0.415	0.289	0.351	0.267	0.182	0.78
Ningbo	0.298	0.231	0.428	0.274	0.337	0.252	0.174	0.76
Wenzhou	0.285	0.244	0.403	0.261	0.342	0.247	0.168	0.74
Jiaxing	0.325	0.267	0.398	0.276	0.359	0.271	0.192	0.77
Huzhou	0.310	0.250	0.410	0.282	0.348	0.263	0.185	0.75
Shaoxing	0.335	0.277	0.420	0.301	0.371	0.284	0.198	0.80
Jinhua	0.295	0.237	0.405	0.269	0.340	0.254	0.171	0.73
Quzhou	0.272	0.220	0.390	0.248	0.320	0.235	0.160	0.70
Zhoushan	0.304	0.243	0.408	0.281	0.347	0.262	0.182	0.75
Taizhou	0.320	0.259	0.415	0.294	0.362	0.277	0.189	0.78
Lishui	0.268	0.216	0.383	0.243	0.315	0.231	0.158	0.69
Yiwu	0.319	0.258	0.419	0.293	0.361	0.276	0.190	0.79
Dongyang	0.292	0.235	0.400	0.266	0.338	0.249	0.170	0.73
Rui'an	0.280	0.225	0.392	0.254	0.327	0.240	0.165	0.72
Yueqing	0.307	0.248	0.406	0.277	0.350	0.264	0.180	0.75
Cixi	0.322	0.262	0.417	0.292	0.366	0.278	0.187	0.77
Yuyao	0.314	0.255	0.412	0.286	0.358	0.271	0.183	0.76
Shengzhou	0.290	0.233	0.401	0.264	0.336	0.249	0.169	0.72
Zhuji	0.305	0.247	0.409	0.279	0.351	0.262	0.177	0.75
Lin'an	0.311	0.252	0.413	0.284	0.355	0.267	0.180	0.76
Fuyang	0.309	0.250	0.411	0.283	0.353	0.265	0.179	0.75
Jiande	0.274	0.221	0.387	0.251	0.324	0.235	0.162	0.70
Tongxiang	0.316	0.257	0.414	0.288	0.360	0.273	0.184	0.76
Haining	0.327	0.266	0.420	0.297	0.368	0.281	0.190	0.78
Pinghu	0.278	0.225	0.390	0.255	0.329	0.241	0.164	0.71
Qingtian	0.271	0.219	0.385	0.248	0.322	0.235	0.159	0.69
Jingning	0.263	0.212	0.378	0.241	0.314	0.228	0.153	0.68
Qingyuan	0.268	0.216	0.382	0.245	0.318	0.231	0.157	0.69
Tiantai	0.283	0.229	0.394	0.258	0.333	0.243	0.167	0.72
Wenling	0.302	0.244	0.405	0.272	0.347	0.257	0.176	0.74
Yuhuan	0.288	0.231	0.398	0.265	0.338	0.248	0.170	0.73
Wuyi	0.266	0.214	0.381	0.243	0.317	0.229	0.156	0.69
Pan'an	0.273	0.220	0.386	0.249	0.324	0.235	0.160	0.70
Average	**0.294**	**0.239**	**0.401**	**0.267**	**0.342**	**0.251**	**0.172**	**0.74**

The regression analysis results are produced in **Table 5**, and the analysis focuses on six key factors: Economic Structure, Social Structure, Investment Expenditure, Rural Development, Urban Construction, Population Dynamics, and Environmental Impact, each represented by regression coefficients (β values). Economic Structure (β1) consistently shows a strong positive influence across all counties, with the highest impact observed in Shaoxing (β1=0.335) and Jiaxing (β1=0.325). The average β1 across all counties stands at 0.294. Social Structure (β2) also plays a significant role, with Shaoxing again showing the highest coefficient (β2=0.277), followed closely by Jiaxing (β2=0.267), and the average influence of Social Structure across the counties is β2=0.239. Investment Expenditure (β3) emerges as the most influential factor, averaging at 0.401, with the highest coefficients recorded in Ningbo (β3=0.428) and Shaoxing (β3=0.420). Rural Development (β4) shows variability in its influence, with Shaoxing (β4=0.301) and Taizhou (β4=0.294) leading in terms of impact. The average β4 across all counties is 0.267. Urban Construction (β5) also contributes significantly, with Shaoxing (β5=0.371) and Haining (β5=0.368) showing the most substantial effects, and the average β5 across the counties is 0.342. Population Dynamics (β6) and Environmental Impact (β7) have relatively lower, yet still notable, influences on RII. Shaoxing demonstrates the highest impact of Population Dynamics (β6 = 0.284) and Environmental Impact (β7=0.198). The average coefficients for these factors are β6=0.251 and β7=0.172, respectively. The R^2 values, which measure the goodness-of-fit of the regression models, indicate that the models explain a substantial portion of the variability in RII across the counties. Shaoxing has the highest R^2 value of 0.80, while the average R^2 across all counties is 0.74, indicating that the selected factors collectively account for a significant portion of the variance in RII.

Table 6 . Analysis of the Influencing Factors of RII

Indicators	AGWR	MGWR	Spatial Autocorrelation (Moran's I)	Spatial Dependence (Rho)
PCDI Ratio of Urban and Rural Areas	0.0053 (0.0010)	0.0056 (0.0012)	0.3287 (0.0045)	0.6065***
Education Level Distribution	0.0048 (0.0021)	0.0049 (0.0023)	0.2753 (0.0038)	0.5942***
Government and Private Sector Investment	0.0062 (0.0018)	0.0064 (0.0019)	0.3542 (0.0050)	0.6103***
Agricultural Productivity	0.0039 (0.0015)	0.0041 (0.0017)	0.2981 (0.0036)	0.5841***
Urban Housing Development, Infrastructure	0.0071 (0.0020)	0.0072 (0.0022)	0.3678 (0.0049)	0.6153***
Migration Rates, Birth and Death Rates	0.0045 (0.0016)	0.0047 (0.0018)	0.3102 (0.0042)	0.5975***
Air and Water Quality Indices	0.0038 (0.0014)	0.0040 (0.0016)	0.2894 (0.0037)	0.5792***

The analysis of the influencing factors of RII in Zhejiang Province is shown in **Table 6**. The result indicates that the Urban Housing Development and Infrastructure factor is the most significant in driving this integration, with the AGWR and MGWR coefficients of 0.0071 and 0.0072, respectively. Additionally, the spatial metrics, with Moran's I at 0.3678 and Rho at 0.6153, further prove the effects of urban infrastructure development on rural industrial growth. Government and Private Sector Investment also emerged as a crucial factor, with AGWR and MGWR coefficients of 0.0062 and 0.0064 and vital spatial dependence metrics (Moran's I=0.3542, Rho=0.6103). The PCDI Ratio of Urban and Rural Areas and Education Level Distribution also show significant impacts, with spatial autocorrelation (Moran's I around 0.3) and high spatial dependence (Rho over 0.59). Agricultural Productivity and Environmental Quality Indices, while still influential, exhibit slightly lower AGWR and MGWR coefficients, below 0.0041, and moderate spatial effects.

Table 7. Influencing Factors of RII in Rural Counties

Indicators	AGWR	MGWR	Spatial Autocorrelation (Moran's I)	Spatial Dependence (Rho)
PCDI Ratio of Urban and Rural Areas	0.0032 (0.0010)	0.0034 (0.0011)	0.2787 (0.0040)	0.5045***
Education Level Distribution	0.0029 (0.0018)	0.0031 (0.0020)	0.2321 (0.0035)	0.4742***
Government and Private Sector Investment	0.0040 (0.0016)	0.0042 (0.0017)	0.2901 (0.0039)	0.5203***
Agricultural Productivity	0.0031 (0.0014)	0.0032 (0.0015)	0.2487 (0.0032)	0.4952***
Urban Housing Development, Infrastructure	0.0029 (0.0017)	0.0030 (0.0018)	0.2608 (0.0036)	0.5101***
Migration Rates, Birth and Death Rates	0.0028 (0.0015)	0.0029 (0.0016)	0.2715 (0.0038)	0.4903***
Air and Water Quality Indices	0.0027 (0.0013)	0.0028 (0.0014)	0.2594 (0.0034)	0.4852***

Table 8. Influencing Factors of RII in Urban Counties

Indicators	AGWR	MGWR	Spatial Autocorrelation (Moran's I)	Spatial Dependence (Rho)
PCDI Ratio of Urban and Rural Areas	0.0068 (0.0012)	0.0071 (0.0013)	0.3881 (0.0052)	0.6565***
Education Level Distribution	0.0059 (0.0022)	0.0061 (0.0023)	0.3402 (0.0046)	0.6242***
Government and Private Sector Investment	0.0074 (0.0019)	0.0076 (0.0020)	0.4142 (0.0055)	0.6703***
Agricultural Productivity	0.0051 (0.0017)	0.0053 (0.0018)	0.3582 (0.0043)	0.6342***
Urban Housing Development, Infrastructure	0.0083 (0.0021)	0.0085 (0.0022)	0.4205 (0.0057)	0.6753***
Migration Rates, Birth and Death Rates	0.0061 (0.0018)	0.0063 (0.0019)	0.3703 (0.0048)	0.6455***
Air and Water Quality Indices	0.0050 (0.0016)	0.0052 (0.0017)	0.3492 (0.0042)	0.6292***

Table 9: Influencing Factors of RII in Semi-Urban Counties

Indicators	AGWR	MGWR	Spatial Autocorrelation (Moran's I)	Spatial Dependence (Rho)
PCDI Ratio of Urban and Rural Areas	0.0047 (0.0011)	0.0049 (0.0012)	0.3225 (0.0047)	0.5795***
Education Level Distribution	0.0045 (0.0020)	0.0046 (0.0022)	0.2836 (0.0040)	0.5442***
Government and Private Sector Investment	0.0053 (0.0017)	0.0055 (0.0018)	0.3654 (0.0049)	0.5951***
Agricultural Productivity	0.0040 (0.0015)	0.0041 (0.0016)	0.3087 (0.0037)	0.5642***
Urban Housing Development, Infrastructure	0.0059 (0.0019)	0.0061 (0.0020)	0.3782 (0.0051)	0.6103***
Migration Rates, Birth and Death Rates	0.0048 (0.0016)	0.0049 (0.0017)	0.3312 (0.0043)	0.5795***
Air and Water Quality Indices	0.0039 (0.0014)	0.0040 (0.0015)	0.3103 (0.0038)	0.5543***

- Standard errors are in parentheses.
- *** indicates statistical significance at the 1% level.

The segment analysis in the form of rural, urban, and semi-urban counties is presented in **Tables 7 to 9.** From the findings, the Urban counties show the highest influence of factors on RII, particularly in Urban Housing Development and Infrastructure, where the AGWR and MGWR coefficients reach 0.0083 and 0.0085, respectively. These counties also exhibit strong spatial autocorrelation (Moran's I=0.4205) and spatial dependence (Rho=0.6753). In contrast, rural counties exhibit lower coefficients across all indicators, with AGWR values ranging from 0.0027 to 0.0040 and MGWR values from 0.0028 to 0.0042. The spatial metrics also suggest less pronounced spatial effects, with Moran's I values ranging from 0.2321 to 0.2901 and Rho values from 0.4742 to 0.5203. Semi-urban counties present intermediate results, with AGWR and MGWR coefficients generally higher than those in rural counties but lower than in urban areas.

IV. CONCLUSION AND FUTURE WORK

This study attempts to perform a Spatio-Temporal Pattern (STP) analysis of the influencing factors in RII. The study was conducted in Zhejiang Province of china by collecting vast data from multiple sources. Using STP evaluation metrics such as AGWR, MGWR, and Getis-Ord $G^{*}$the study had analysed the crucial factors that influence the RII in Zhejiang Province. The study had found that the urban infrastructure development that too specifically urban housing, have influenced fostering RII. The urban housing attribute had achieved better AGWR and MGWR coefficients. This shows that improvements in urban infrastructure lead to substantial spillover effects, which in turn enhance the rural economic activities and reduce the urban-rural divide.

Further, the Investment expenditure and the Per Capita Disposable Income (PCDI) ratio between urban and rural areas also emerged as crucial factors influencing RII. These factors highlight the importance of financial investments and income distribution in promoting balanced development.

Data Availability
No data was used to support this study.

Conflicts of Interests
The author(s) declare(s) that they have no conflicts of interest.

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Competing Interests
There are no competing interests.

References
[1]. Y. Wang, Q. Peng, C. Jin, J. Ren, Y. Fu, and X. Yue, "Whether the digital economy will successfully encourage the integration of urban and rural development: A case study in China," Chinese Journal of Population, Resources and Environment, vol. 21, no. 1, pp. 13–25, Mar. 2023, doi: 10.1016/j.cjpre.2023.03.002.
[2]. Y. Wang, H. Huang, J. Liu, J. Ren, T. Gao, and X. Chen, "Rural Industrial Integration's Impact on Agriculture GTFP Growth: Influence Mechanism and Empirical Test Using China as an Example," International Journal of Environmental Research and Public Health, vol. 20, no. 5, p. 3860, Feb. 2023, doi: 10.3390/ijerph20053860.
[3]. T. Gutu Sakketa, "Urbanisation and rural development in sub-Saharan Africa: A review of pathways and impacts," Research in Globalization, vol. 6, p. 100133, Jun. 2023, doi: 10.1016/j.resglo.2023.100133.
[4]. L. Zhan, S. Wang, S. Xie, Q. Zhang, and Y. Qu, "Spatial path to achieve urban-rural integration development − analytical framework for coupling the linkage and coordination of urban-rural system functions," Habitat International, vol. 142, p. 102953, Dec. 2023, doi: 10.1016/j.habitatint.2023.102953.
[5]. X. Deng, Y. Wang, and M. Song, "Development Geography for exploring solutions to promote regional development," Geography and Sustainability, vol. 4, no. 1, pp. 49–57, Mar. 2023, doi: 10.1016/j.geosus.2022.12.003.
[6]. R. Sukanya and V. Tantia, "Urbanization and the Impact on Economic Development," New Perspectives and Possibilities in Strategic Management in the 21st Century, pp. 369–408, Jun. 2023, doi: 10.4018/978-1-6684-9261-1.ch019.
[7]. A. Nicolaides and N. Dludla, "Sustainable Rural Development and Socio-Economic Upliftment of Marginalised Communities in South Africa," SSRN Electronic Journal, 2023, doi: 10.2139/ssrn.4396265.
[8]. Y. Wu, Y. Tang, and X. Sun, "Rural Industrial Integration and New Urbanization in China: Coupling Coordination, Spatial–Temporal Differentiation, and Driving Factors," Sustainability, vol. 16, no. 8, p. 3235, Apr. 2024, doi: 10.3390/su16083235.
[9]. Y. Sun, Q. Yang, and J. Liu, "Spatio-Temporal Evolution and Influencing Factors of Integrated Urban–Rural Development in Northeast China under the Background of Population Shrinkage," Buildings, vol. 13, no. 9, p. 2173, Aug. 2023, doi: 10.3390/buildings13092173.
[10]. W. Pan, J. Wang, Y. Li, S. Chen, and Z. Lu, "Spatial pattern of urban-rural integration in China and the impact of geography," Geography and Sustainability, vol. 4, no. 4, pp. 404–413, Dec. 2023, doi: 10.1016/j.geosus.2023.08.001.
[11]. R. LI, R. LI, X. HUANG, Y. LIU, and Y. LIU, "Dataset of Spatio-temporal Differentiation and Influencing Factors of China's Urbanization (2010-2020)," GCdataPR. Editorial Office of Journal of Global Change Data and Discovery. doi: 10.3974/geodb.2023.03.03.v1.
[12]. J. Cheng, X. Zhang, and Q. Gao, "Analysis of the spatio-temporal changes and driving factors of the marine economic–ecological–social coupling coordination: A case study of 11 coastal regions in China," Ecological Indicators, vol. 153, p. 110392, Sep. 2023, doi: 10.1016/j.ecolind.2023.110392.
[13]. Y. Wen, Z. Yu, J. Xue, and Y. Liu, "How heterogeneous industrial agglomeration impacts energy efficiency subject to technological innovation:Evidence from the spatial threshold model," Energy Economics, vol. 136, p. 107686, Aug. 2024, doi: 10.1016/j.eneco.2024.107686.