International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 5, 2025
https://theaspd.com/index.php

A Comparison Of Spatial Pattern Of Cities And Towns In Southern India

Dr. G. Kumar[1], Dr. Vincent Raja A[2], Mr. Sukrishnalall Pasha[3], Ms. Maria Christy[4], Dr. A. Subbarayan[5]
[1]Assistant Professor of Statistics, Department of Mathematics, SRM Arts and Science College, Kattankulathur, 603203, India, kumarmat@srmasc.ac.in
[2]Reader, Department of Mathematics, Physics and Statistics, Faculty of Natural Sciences, University of Guyana, Georgetown, Guyana, South America, vincent.anthonisamy@uog.edu.gy
[3]Finance Secretary, Ministry of Finance, Georgetown, Guyana, South America, spasha@finance.gov.gy
[4]Lecturer II, Department of Accounting and Finance, SEBI, University of Guyana, Georgetown, Guyana, South America, maria.christy@uog.edu.gy
[5]Visiting faculty, Dr MGR Educational and Research Institute, Maduravoyal, Chennai, India

Abstract
This exploratory study employed Geary's Contiguity Ratio and Moran's Index to analyze spatial patterns of cities and towns within the four Southern States in India which are characterized by similar geographical features and distinct demographic characteristics. Using the 2001 Census data of India, it found that the cities and towns in Tamil Nadu, Andhra Pradesh and Kerala exhibited a largely random patterns, reflecting the preference of residents in these states for smaller cities that are unique. However, the results are mixed for Karnataka, where a clustering pattern is suggested by Moran's I at the 10% level of significance, but a random pattern revealed by Geary's C. The nuanced findings for the latter highlight the need for further research into this state to resolve the conflicting results.
KeyWords: *Spatial Pattern, Geary's C, Moran's I, Geographic Data and Urban Arrangement*

1. INTRODUCTION

Analysing patterns using spatial statistics is important for several reasons, especially when it comes to understanding and solving real-world problems, whether related to urban planning, disease management, resource distribution, environmental conservation, etc. Such analyses are very effective in identifying patterns, relationships, and trends that may otherwise remain hidden in purely nonspatial analysis. The two main methods for these analyses are showing features on a map and using statistical measures to see how features are clustered, dissimilar across geographic space, or randomly arranged. Statistical measures make it easier to compare patterns across different feature sets over time. The real data values for each feature are used in place of maps, resulting in more accurate identification of patterns without the influence of how the data is displayed. This study builds on the work of Kumar and Subbarayan (2011) by employing Geary's Contiguity Ratio and Moran's Index to analyze the patterns across four states in South India. In their 2011 study, the authors examined Andhra Pradesh and applied Zipf's law, which assumes that the city size is represented by a Pareto distribution. In contrast, the techniques used in this study do not assume any distribution and are more effective in terms of analyzing spatial relationships when compared to Zipf's law used by Kumar and Subbarayan (2011). Importantly, our study also considers multiple states in India, including Andhra Pradesh. To the authors' knowledge, no previous work employed these techniques before to study the spatial patterns of cities and towns in India. The structure of the paper is as follows: Section 2 provides a detailed account of the urban scenario in the southern states of India. Section 3 discusses the theoretical aspects involved in calculating indices used to study the spatial patterns of cities and towns. Section 4 presents the empirical findings, followed by Section 5, which discusses the conclusions based on the study's results.

2. REVIEW OF LITERATURE

In spatial statistics and analysis of geographic phenomenon, various tools are used to explore patterns of distribution and spatial relationships. Among these are, Zipf's law, Geary's Contiguity Ratio and Moran's Index. In particular, these indices are used to explore city size distribution and also allow for in-depth analysis of spatial relationships between observations, such as the spatial clustering or the level of interaction that may exist in spatial data. Auerbach (1913) which applied the Zipf's law to study city size, found an inverse relationship between the population of cities and their ranking. Since the pioneering work of Auerbach, this technique has been successfully employed to describe city-size distribution across various countries (Gan et al, 2006) as well as specific countries such as the United States (Mills and Hamilton, 1994), France (Guerin-Pace, 1995), China (Song and Zhang, 2002), India (Kumar and Subbarayan, 2011) etc at different points in times. Notwithstanding its utility in describing overall city size distribution, Zipf's law has been challenged by both empirical and theoretical research. In a comprehensive review of the literature, Arshad et al (2018) found that Zipf's law: (i) is not always observable even as an approximation of city size distribution, (ii) is inadequate in terms of describing the rank-size relationship, and (iii) the hypothesis of the law is more often rejected resulting in other distributions being sought. Importantly, the Zipf's law is inadequate in terms of analysing geographical patterns and understanding how spatial variables interact with each other, which is where Geary's Contiguity Ratio (GCR) and Moran's Index (MI), are extremely useful. The former provides insights into local spatial relationships, especially when neighbouring areas are more likely to be similar or dissimilar due to geographical proximity. The latter, on the other hand, offers important global overarching perspectives on spatial clustering. The Geary's Contiguity Ratio (GCR) was introduced by Geary (1954). In that study, the author illustrated the utility of the GCR using data for 26 counties of the Republic of Ireland. Since the publication of this seminal work, the technique has been used in numerous countries and a wide range of fields. Getis and Ord (1992), for instance employed the GCR to investigate the sudden infant death syndrome in Counties in North Carolina and the dwelling unit prices in San Diago. In this study the authors argued that the GCR is effective in terms of identifying pockets of dependence that may complement the Moran's I. Comparing the Getis Index (Gi) with GCR, Mynt et al. (2007), found evidence that these statistical techniques were effective when measuring the variability of complex urban land cover and land use. The study revealed that the Gi identified hot spots and cold spots more accurately than the Geary's C. However, Mynt et al (2007) argued that the Gi was not as effective as the Geary's C in detecting degree of dispersion or clustering. Examining various types of crimes in Turkey, Erdogan et al (2011), found the clustering of these activities, except for crimes related to firearm and knifes. According to the authors, the findings confirmed that geographical proximity is relevant in explaining criminal activities. Griffith and Chun (2022), compares the Moran's I with the GCR and introduces the Geary scatterplot to distil properties of the GCR that should encourage its utilisation by spatial econometricians and statisticians. Applying the indices to 2017 mortality rates in the United States, Griffith and Chun confirmed that the GCR is more closely aligned with geostatistics while the Moran's I is aligned with spatial autoregression. The authors argued that the GCR should be a standard computation in standard as Moran's I and be supplemented with GR graphics. More recently, Wywial (2025) applied generalised GCR and MI to several economic variables in neighbouring Polish voivoeships. The study confirmed that the generalised coefficients captures the degree of similarities of neighbouring objects based on the distance between the observed variables in the observation vectors. Like the GCR, the Moran's Index (MI), has been used in spatial analysis to examine the degree to which adjacent areas exhibit similar or dissimilar patterns. Indeed, this technique is more widely employed spatial analysis when compared with the GCR (Chen, 2013).

Bai et al. (2012) examined the inter-regional growth spillovers in China using the Moran's I. It found positive spillover effects among in China. Using the Moran's I, Ferreira (2020), found that population that was vulnerable to the COVID-19 pandemic were spatially distributed in districts with lower salaries, higher concentration of slums and lower population with residents 60 years and older. Arguing that Moran's I was also successfully employed to in hotspot identification of diseases, environmental planning and environmental, Zhang et al., (2008), used this spatial statistical tool to examine pollution hotspots in Galway City in Ireland. Meanwhile, de Almeida et al (2005), employed the Moran's I to examine the distribution of crime rates in 750 municipalities in Brazil, found that crime rates were distributed non-randomly. Ratcliffe (2010), also employed the Moran's I to examine the pattern of crime in Philadelphia. It found evidence of clustering of robberies in the north and inner northeast and the southwest in the city in Philadelphia. More recently, dos Santos et al. (2024), found a high positive correlation between deforestation and CO_2 emissions. The study also showed that above average temperature were identified in municipalities with high deforestation rates. Based on these findings, do Santos et al (2024) argued that Moran's I is an efficient tool that can be applied for similar studies to guide policy decisions to combat deforestation in across the world.

Based on the foregoing, the GCR and Moran's I are used in a variety of contexts and countries to explore spatial patterns. Notwithstanding the extensive use of these tools, their application in India is sparse. This exploratory study will enrich the literature by applying the GCR and MI to patterns of cities in India.

3. The Urban Conditions of South Indian States

India provides a valuable source of data for urban studies through its census records (Kumar and Subbarayan, 2011). These records are available at national, state, and district levels and offer important insights into rural and urban areas, showing the changes that have happened over the past century. Census data is essential for researchers and planners, as it reveals detailed information about demographic, social, and economic changes. It is also useful for studying trends and patterns over time. This data helps us better understand urban development and changes in different regions of India.

3.1 South India's Demographic Profile

South India includes the states of Andhra Pradesh, Karnataka, Kerala, and Tamil Nadu, along with the union territories of Lakshadweep and Puducherry. Together, these states are approximately 635,780 square kilometres (or 245,476 square miles) and cover 19.31% of India's land area. Located on the Deccan Plateau, South India is bordered by the Arabian Sea to the west, the Indian Ocean to the south, and the Bay of Bengal to the east. These states registered growth in population between 1991 and 2001. The urban populations of Tamil Nadu (43.68%) and Karnataka (33.98%) were above the national average for urban populations (27.78%), whereas Andhra Pradesh (27.08%) and Kerala (25.97%) were below this average. It is important to note that various socioeconomic indicators for these states were above the national average, indicating that the social well-being and overall quality of life of residents in these states were superior. Table 1 shows the per capita GDP for the four states in the study area exceeded the national average. This suggest that the average earnings of residents in South India were higher than average for India. The percentage of the population living below the poverty line was lower than the national average, with Tamil Nadu (22.5%), Andhra Pradesh (15.8%), Karnataka (25%), and Kerala (15%), compared with the national average of 27.5% (table 1). This suggests that fewer residents in these states live below the poverty line than the overall average for the country (table 1). The percentage of residents with access to electricity in these states surpassed the national average (table 1). Except for Kerala, the percentage of residents with access to safe drinking water exceeded the national average (table 1).

Table 1: Demographic Profile of South Indian States and India: 2001 Census Insights

State	Population Growth Rate (%)	Urbanization Rate (%)	Per capita GDP (in Rs)	Literacy Rate (%)	Poverty Rate (%)	Access to Electricity (%)	Access to Safe Drinking Water (%)
Andhra Pradesh	13.9	27.08	17,195	60.5	15.8	59.65	80.10
Karnataka	17.3	33.98	18,344	66.6	25.0	72.16	84.60
Kerala	9.4	25.97	20,094	73.5	22.5	71.18	85.60
Tamil Nadu	11.2	43.68	20,972	90.9	15.0	65.53	23.40
India	**21.3**	**27.78**	**16,688**	**64.8**	**27.5**	**43.53**	**77.90**

Source: Preliminary Census Report 2001

3.2 Cities and Towns in South Indian Districts

The 2001 Census categorized the urban population into five distinct classes as follows:

Class	-	Population
I	-	Over 100,000
II	-	50,000 to 100,000
III	-	20,000 to 50,000
IV	-	10,000 to 20,000

V - 5,000 to10, 000
VI - Less than 5,000

Table 2 shows the number of cities and towns in the four South Indian states, according to the 2001 Census. Based on the table, Tamil Nadu has the largest number of cities and towns (832), followed by Karnataka (270), then Andhra Pradesh (211) and Kerala (159). An important observation is that Tamil Nadu predominantly comprised Class IV Cities and Towns, which accounted for 40.8% of the total. However, Class III Cities and Towns were the most prevalent in Andhra Pradesh (26.5%), Kerala (45.3%) and Karnataka (39.3%).

Table 2: Number of Cities and Towns by Size in South Indian States – 2001 Census

	>100,000 (Class I)	50,000 -1,00,000 (Class II)	20,000 -50,000 (Class III)	10,000 -20,000 (Class IV)	5,000 -10,000 (Class V)	< 5000 (Class VI)	**Total**
Tamil Nadu	26	56	183	340	214	13	**832**
Andhra Pradesh	47	52	56	33	21	2	**211**
Kerala	10	24	72	37	15	1	**159**
Karnataka	30	28	106	61	37	8	**270**

Source: Census 2001

Figures 1(a), 1(b), 1(c), and 1(d) depict the maps of Tamil Nadu, Andhra Pradesh, Kerala, and Karnataka, respectively. Each map lists the names of the districts, which are the administrative units of the states. Additionally, tables 3(a), 3(b), 3(c), and 3(d) shows the distribution of the cities and towns within these districts. Based on these tables, cities/towns in within the districts in Tamil Nadu exhibit clustering while the cities/towns in the districts of the other states are more widely dispersed. On average, the number of towns and cities per district in Tamil Nadu was approximately 26, compared with an average of 9 per district in Andhra Pradesh, 11 in Kerala and 10 in Karnataka.

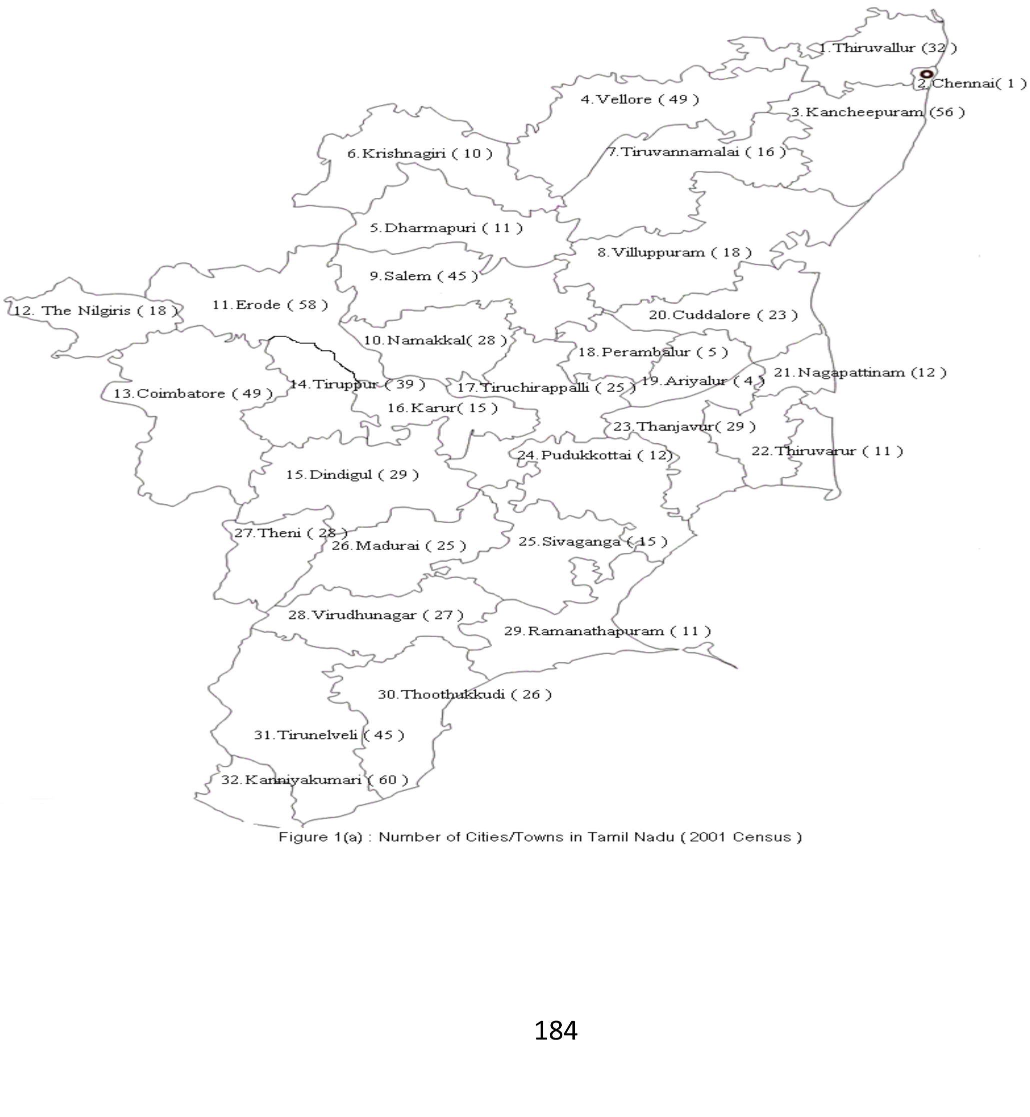


Figure 1(a) : Number of Cities/Towns in Tamil Nadu (2001 Census)

figure 1(b). Number of Cities/Towns in Andhra Pradesh (2001Census)

Figure 1(c) Number of Cities/Towns in Kerala (2001 Census)

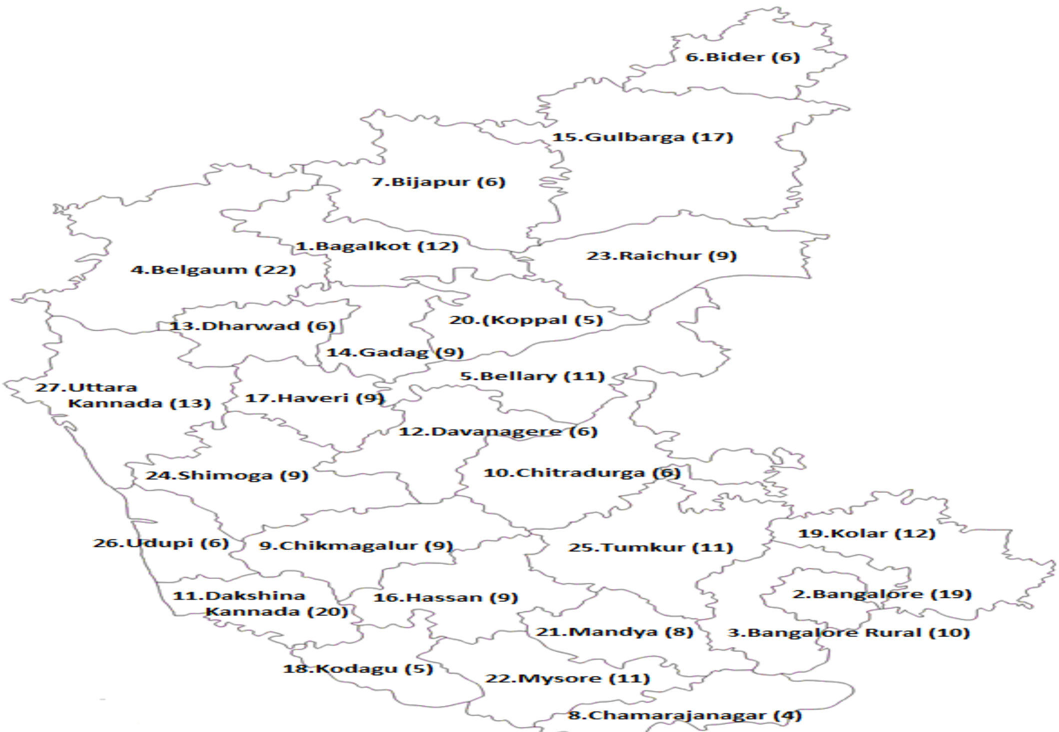


Figure 1(d) Number of Cities/Towns in Karnataka (2001 Census)

Table: 3 (a) District wise Number of Cities and Towns in Tamil Nadu

S.No	District	No. of Cities and Towns
1	Thiruvallur	32
2	Chennai	1
3	Kancheepuram	56
4	Vellore	49
5	Dharmapuri	11
6	Krishnagiri	10
7	Tiruvannamalai	16
8	Viluppuram	18
9	Salem	45
10	Namakkal	28
11	Erode	58
12	The Nilgiris	18
13	Coimbatore	49
14	Tiruppur	39
15	Dindigul	29
16	Karur	15
17	Tiruchirappalli	25
18	Perambalur	5
19	Ariyalur	4
20	Cuddalore	23
21	Nagapattinam	12
22	Thiruvarur	11
23	Thanjavur	29
24	Pudukkottai	12
25	Sivaganga	15
26	Madurai	25
27	Theni	28

28	Virudhunagar	27
29	Ramanathapuram	11
30	Thoothukkudi	26
31	Tirunelveli	45
32	Kanniyakumari	60
	Total	832

Table: 3(b) District wise Number of Cities and Towns in Andhra Pradesh

S.No	District	No. of Cities and Towns
1	Adilabad	15
2	Nizamabad	3
3	Karimnagar	7
4	Medak	11
5	Hyderbad	3
6	Rangareddi	17
7	Mahbubnagar	7
8	Nalgonda	9
9	Warangal	2
10	Khammam	9
11	Srikakulam	6
12	Vizianagaram	12
13	Visakhapatam	9
14	East Godavari	14
15	West Godavari	8
16	Krishna	7
17	Guntur	11
18	Prakasam	8
19	Nellore	5
20	Cuddapah	12
21	Kurnool	10
22	Anantapur	11
23	Chittoor	15
	Total	211

Table: 3(c) District wise Number of Cities and Towns in Kerala

S.No	District	No. Of Cities and Towns
1	Alappuzha	11
2	Ernakulum	25
3	Idukki	2
4	Kannur	45
5	Kasaragod	7
6	Kollam	3
7	Kottayam	6

8	Kozhikode	13
9	Malappuram	5
10	Palakkad	5
11	Pathanamthitta	3
12	Thiruvananthapuram	5
13	Thrissur	28
14	Wayanad	1
	Total	159

Table: 3(d) District Wise Number of Cities and Towns in Karnataka

S.No	District	No. Of Cities and Towns
1	Belgam	22
2	Bagalkot	12
3	Bijapur	6
4	Gulbarga	17
5	Bidar	6
6	Raichur	9
7	Koppal	5
8	Gadag	9
9	Dharwad	6
10	Uttar kannada	13
11	Haveri	9
12	Bellary	11
13	Chitradurga	6
14	Davanagere	6
15	Shimoga	9
16	Udupi	6
17	Chikmagalur	9
18	Tunkur	11
19	Kolar	12
20	Bangalore	19

21	Bangalore (Rural)	10
22	Mandya	8
23	Hassan	9
24	Dakshina Kannada	20
25	Kodagu	5
26	Mysore	11
27	Chamarajanagar	4
	Total	270

4. METHODOLOGY

4.1. Binary Weight Matrix

We started by selecting a district and identifying its neighbouring districts. From this information, we created a binary weight matrix for each state. The spatial binary weight matrix for a specific state is shown in Table 4.1. We have developed these matrices for different states, and they are essential for calculating indices that help study the spatial patterns of cities and towns in South India.

Table 4.1: Binary Weight Matrix

i \ j	1	2	...	j	...	n
1	x_{11}	x_{12}		x_{1j}		x_{1n}
2	x_{21}	x_{22}		x_{2j}		x_{2n}
. . .						
i	x_{i1}	x_{i2}		x_{ij}		x_{in}
n	x_{n1}	x_{n2}		x_{nj}		x_{nn}

In the above table i, j = 1, 2 , ... n. Suppose $x_{ij} = 1$ if j is a neighborhood of i and $x_{ij} = 0$ Otherwise.

Geary's Coefficient is a statistical measure of spatial autocorrelation that checks how similar or different values are at nearby locations. Unlike Moran's Index, which focuses on the covariance of values, Geary's Coefficient looks more closely at the differences between neighboring values. Geary's Coefficient focuses on the differences between values of paired observations. This approach allows Geary's Coefficient to assess the extent of variation among values in adjacent areas.

4.2. Geary's Coefficient

Geary (1954) has given the following expression for computing the following index

$$C = \frac{(n-1)\sum_i \sum_j W_{ij}(x_i - x_j)^2}{2[\sum_i \sum_j W_{ij}](x_i - \bar{x})^2} \qquad \dots \qquad (1)$$

The weight value is applied in both the numerator and denominator to represent the total differences in attribute values between neighbouring features. This approach highlights spatial relationships, unlike standard measures like variance. By multiplying the differences by weights, it becomes clear how close or far apart similar values are. When the difference between neighbouring features is small, it indicates that similar values are clustered closely together. A large difference means similar values are less likely to be near each other. Geary's Coefficient ranges from 0 to 2. Values near 0 show clustering, while values above 1 indicate dispersion. Geary's Coefficient behaves in the opposite way to Moran's Index.

4.3. Moran's Index

The calculation is derived from the cross-products of the deviations from the mean, specifically for n observations of a variable x at positions "i" and "j".

$$I = \frac{n \sum_i \sum_j W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{S_0 \sum_i (x_i - \bar{x})^2} \quad \ldots \quad (2)$$

where " $\bar{x}$ represents the mean of the variable x".

In the weight matrix of the general cross-product statistic, let Wij represent he elements such that

- $W_{ij} = 1$ if the locations "i" and "j" are adjacent.
- $W_{ij} = 0$ if they are not adjacent.
- By convention $W_{ii} = 0$.

1. Positive Sum of Cross-Products: If there are more pairs of similar values than dissimilar ones, the sum of the cross-products will be positive. This means that "I" will be greater than 0, indicating that identical values are grouped.
2. Negative Sum of Cross-Products: If there are more pairs of dissimilar values, the sum of the cross-products will be negative, making "I" less than 0. This indicates that the values are dispersed.

Goodchild (1986) created a table showing possible values of Geary's Coefficient and Moran's Index to help identify these patterns (see Table 4.2).

Table 4.2: Identification of Pattern

Geary's Coefficient	Moran's Index	Pattern
C < 1	I > 0	Clustered (similar values close together)
C = 1	I = 0	Random (no clear pattern)
C > 1	I < 0	Dispersed (high and low values are spread out)

4.4 Testing Geary's Coefficient

The distribution of Geary's Coefficient can be analyzed through analytical expectations and variances, as articulated by Cliff and Ord (1973). Such analyses depend on the neighborhood structure established by the spatial weighting matrix. Both Geary's Coefficient and Moran's Index follow a normal distribution. It therefore means that the results are more predictable and reliable the larger the sample size. This attribute significantly enhances the reliability of statistical analyses in the context of spatial studies.

4.5 Determining the Expected Value of Geary's Coefficient

When there is no spatial autocorrelation, according to the null hypothesis, the expected value of Geary's Coefficient is 1. This means that if data values are randomly spread across the area, Geary's C should be equal to 1.

4.6 Variance of Geary's Coefficient

Assuming normality, we can calculate the variance of Geary's C. Cliff and Ord introduced the formula for this variance in their 1973 study. This formula helps us understand how Geary's Coefficient is distributed under the null hypothesis and is important for statistical testing, $Var_N(C) \left[\frac{1}{2(n+1)S_0^2}\{(2S_1 + S_2)(n-1) - 4S_0^2\}\right]$

The expected value of Moran's Index is given by

$$E_N(I) = -\frac{1}{(n-1)}$$

Under the assumption of normality, the variance of Moran's I, represented as $Var_N(I)$, is calculated as follows,

$$Var_N(I) = \left[\frac{1}{(n^2-1)S_0^2}\{(n^2 S_1 - nS_2 + 3S_0^2)\}\right] - E_N(I)^2$$

The variables outlined in the variance equation are specified as:

n = Number of observations/features

$$S_0 = \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij} = \text{The Sum of the spatial weight matrix}$$

$$S_1 = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\left(W_{ij}+W_{ji}\right)^2}{2} = \text{If the weight matrix is symmetric,}$$

$$\text{then } S_1 = 2\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}$$

$$S_2 = \sum_{i=1}^{n}(W_i + W_i)^2 = \text{The sum of the } (i^{th}\text{column} + i^{th}\text{row})^2 \text{ of weight matrix}$$

If symmetric, then $S_2 = 4\sum_{i=1}^{n} W_i$

4.7 Z-score and Inference for Geary's Coefficient and Moran's Index

(i) Geary's C

We use the test statistic

$$Z_C = \frac{C_0 - C_E}{S_E\ (C_E)} \quad \text{where}$$

C_0 : The observed value of Geary's Coefficient
C_E : The expected value of Geary's Coefficient
$S_E(C_E)$: Standard deviation of Geary's Coefficient

(ii) Moran's Index

Here also we use the test statistic

$$Z_M = \frac{I_0 - I_E}{S_E(I_E)}$$

where
C_0 : The observed value of Moran's Index
C_E : The expected value of Moran's Index
$S_E(I_E)$: Standard deviation of Moran's Index

5. Analysis of the Results

Using the Binary Weight Matrix, we calculated Geary's C and Moran's I values for the states, which are shown in Table 5.1. The results revealed that Geary's Coefficient is positive across all four states. Specifically, the results suggest a clustering pattern for Tamil Nadu, random pattern for Andhra Pradesh and Karnataka and dispersed pattern for Kerala. The Moran's Index statistic presents negative values for Andhra Pradesh, Kerala, and Karnataka, while Tamil Nadu records a positive value. Based on the Moran's I, there is a clustering pattern for Tamil Nadu, and random pattern for the other states. Except for Kerala, the results are consistent for Geary's C and Moran's I. In order to test the statistical significance of the results, Z-score and associated p-values are examined.

Table 5.1: Geary's C and Moran's I for the Cities and Towns in the South Indian States

S.No	State	Geary's C	Moran's I
1	Tamil Nadu	0.772	0.078
2	Andhra Pradesh	1.001	-0.185
3	Kerala	1.111	-0.122
4	Karnataka	1.002	-0.173

Table 5.2 provides the parameters n, S_0, S_1 and S_2, which are utilized in the computation of Mean and Variance for Geary's C and Moran's I for each of the four states.

Table 5.2: Mean and Variance of Geary's C and Moran's I for Cities and Towns in South Indian States

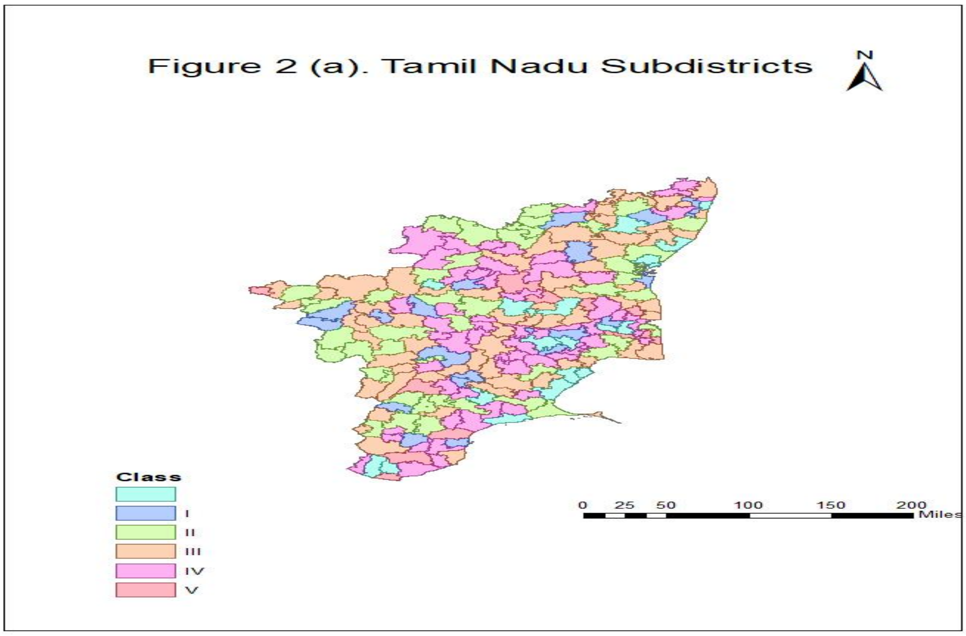
S. No	State	n	S_0	S_1	S_2	Mean		Variance	
						Geary's C	Moran's I	Geary's C	Moran's I
1	Tamil Nadu	32	138	273	2788	1	- 0.032	0.022	0.012
2	Andhra Pradesh	23	84	168	1432	1	- 0.045	0.032	0.019
3	Kerala	14	44	88	616	1	- 0.070	0.044	0.032
4	Karnataka	27	122	244	2416	1	- 0.038	0.019	0.013

Table 5.3 contains the value of Z-score and p-values for the 4 states. The pattern emerged for each state on the basis of the Z-scores and associated p-values are also presented in Table 5.3. Based on these results, Tamil Nadu, Andhra Pradesh, and Kerala exhibited random patterns according to the Geary's C and Moran's I. However, the results for Karnataka are mixed. The Geary's C suggests a random pattern, but Moran's I revealed a clustering pattern at the 10% level of significance (Z-score -1.852, p-value 0.06).

Table: 5.3 Z-Score and Spatial Pattern of Cities and Towns in South Indian States

S.No	State	Z-Score		Pattern
		Geary's C	Moran's I	
1	Tamil Nadu	-1.541 (0.12)	1.004 (0.32)	Random
2	Andhra Pradesh	0.006 (0.99)	-1.014 (0.31)	Random
3	Kerala	0.526 (0.59)	-1.109 (0.26)	Random
4	Karnataka	0.044 (0.96)	-1.852 (0.06)	Mixed results

Figures 2(a), 2(b), 2(c), and 2(d) depict the spatial patterns of Tamil Nadu, Karnataka, Andhra Pradesh, and Kerala. From these figures, it is clear that spatial patterns of all the southern states were generally random. This is consistent with the results from Greary's C and Moran'I.



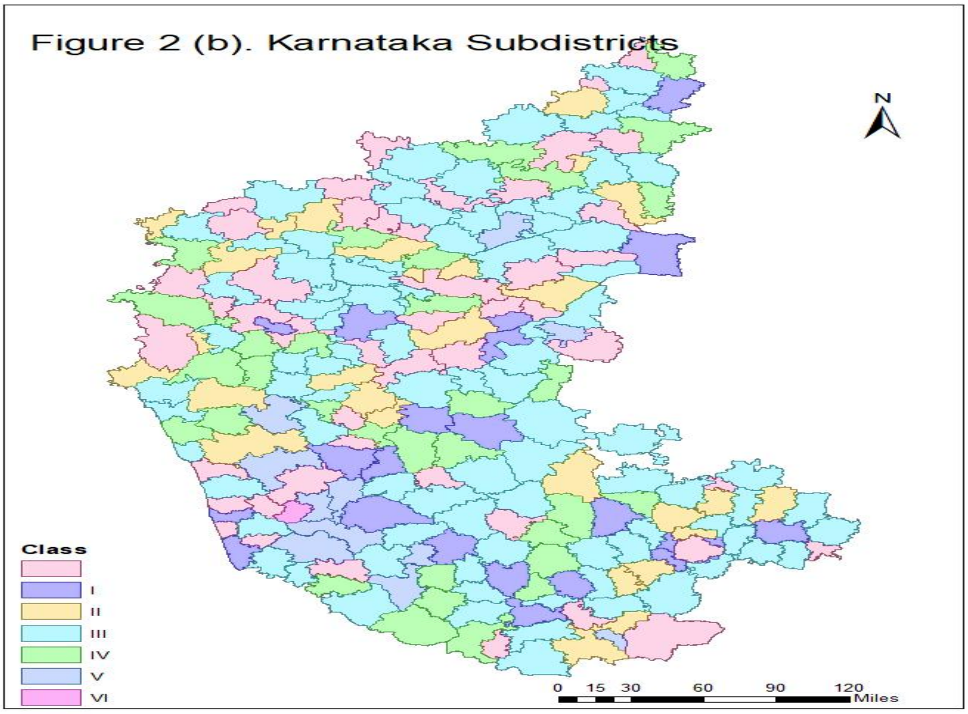


Figure 2 (b). Karnataka Subdistricts
N
Class
I
II
III
IV
V
VI
0 15 30 60 90 120
Miles

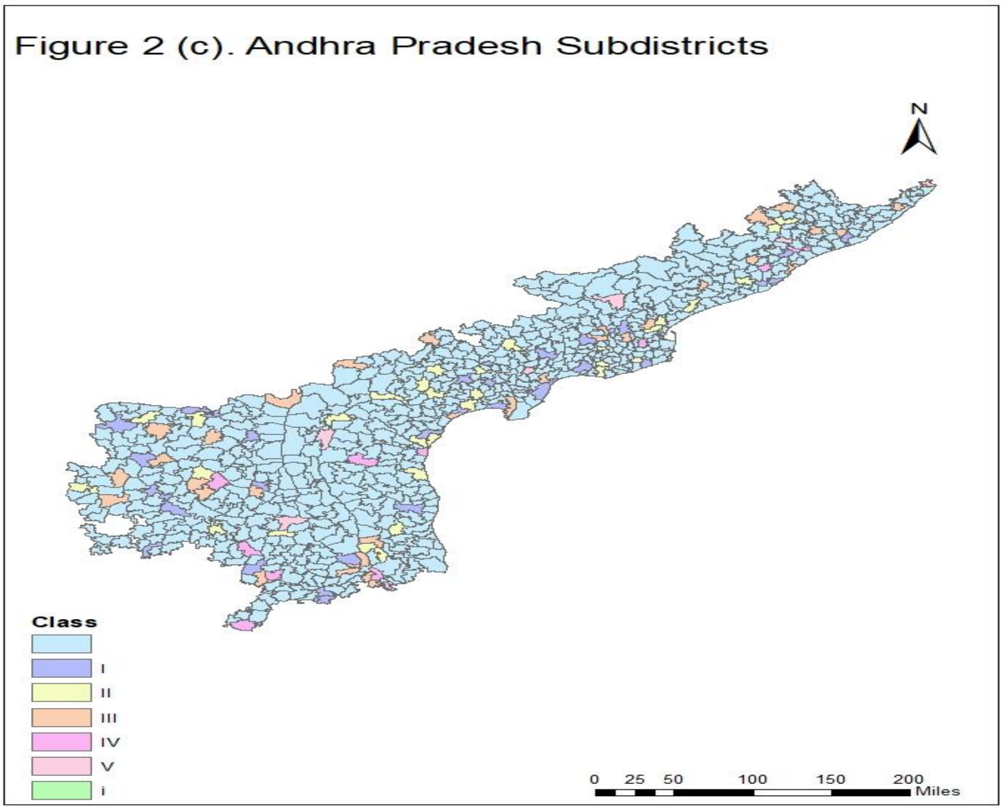
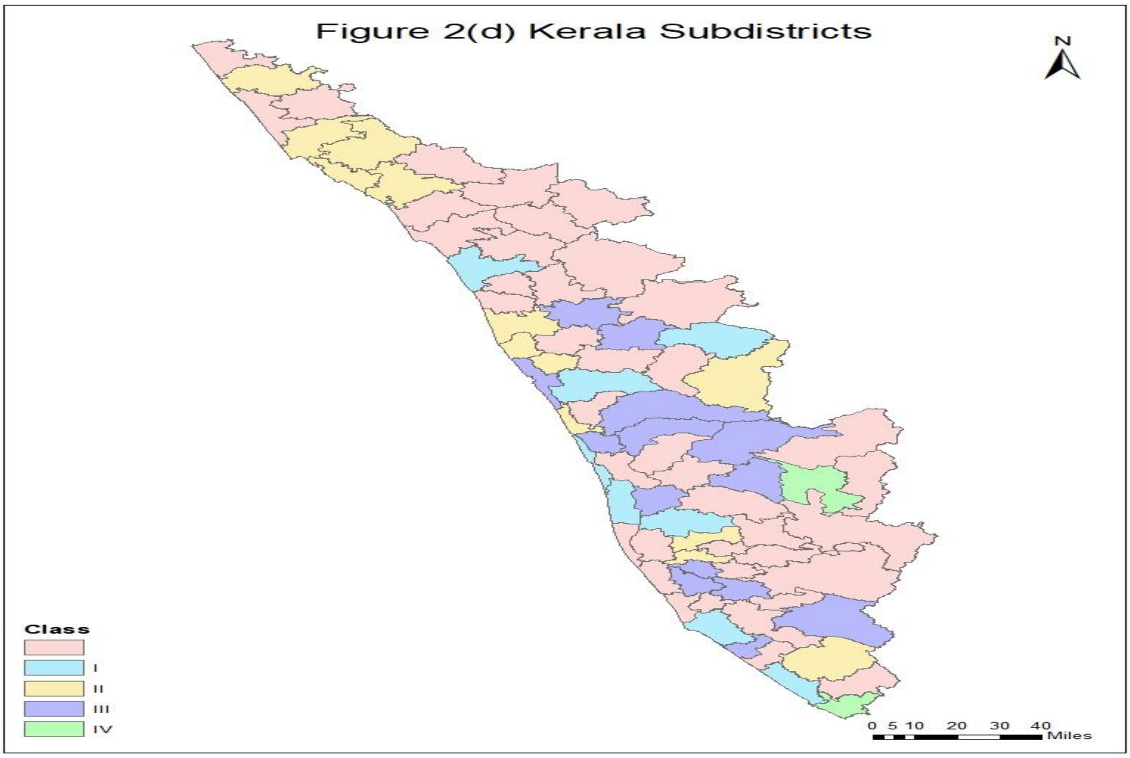


Figure 2 (c). Andhra Pradesh Subdistricts
N
Class
I
II
III
IV
V
i
0 25 50 100 150 200
Miles



6. CONCLUSION

In this paper, we analyzed the spatial patterns of cities and towns in the southern states of India. Using the 2001 Census and the Geary's C and Moran's I and 2001, we found the following:

(i) Tamil Nadu was the Southern state with the largest number of cities and towns, followed by Karnataka, then Andhra Pradesh and Kerala.

(ii) Class IV Cities and Towns were the most prevalent in Tamil Nadu, while the other states predominantly comprised Class III Cities and Towns.

(iii) The spatial patterns in Tamil Nadu, Andhra Pradesh and Kerala exhibited a largely random arrangement of cities and towns. This conclusion is supported by the results from Geary's C and Moran's I, which revealed this pattern. These results suggested that the cities and towns are not clustered together but are rather spread across the respective districts. This may be due to several factors, including the preference for small towns and cities as opposed to large urban centers.

(iv) In contrast, the Karnataka exhibited a dispersed pattern based on the Geary's C but clustering according to Moran's I at the 10% level of significance.

Based on these findings there is conclusive evidence that the spatial pattern is random for three of the four south Indian States, while for Karnataka the evidence is mixed. The latter results highlight the need for further investigation into the reason(s) for the conflicting results.

REFERENCES

1.Arshad, S., Hu, S. and Ashraf, B.N. (2018). Zipf's law and city size distribution: A survey of the literature and future research, Physica A: Statistical Mechanics and its Applications, 492(15), 75-92.

2.Auerbach, F. (1913). Das Geset der Bevolkerungskoncentration Patermanns. Geograpische Mitteilungen, 59(1), 74-76.

3.Bai, C. E., Ma, H., & Pan, W. (2012). Spatial spillover and regional economic growth in China. China Economic Review, 23(4), 982-990.

4.Chen Y (2013) New Approaches for Calculating Moran's Index of Spatial Autocorrelation. PLoS ONE 8(7): e68336. doi:10.1371/journal.pone.0068336

5.Chiff, A.D. & Ord, J.K. (1973). The Spatial Autocorrelation. Pion Press, London.

6.De Almeida, E. S., Haddad, E. A., & Hewings, G. J. (2005). The spatial pattern of crime in Minas Gerais: an exploratory analysis. Economia Aplicada, 9(1), 39-55.

7.Dos Santos, D. D. A., Lopes, T. R., Damaceno, F. M., & Duarte, S. N. (2024). Evaluation of deforestation, climate change and CO2 emissions in the Amazon biome using the Moran Index. Journal of South American Earth Sciences, 143, 105010.

8. Erdoğan, S., Dereli, M. A., & Yalçin, M. (2011). Spatial analysis of five crime statistics in Turkey. In FIG Working Week.

9. Ferreira, M. C. (2020). Spatial association between the incidence rate of COVID-19 and poverty in the SÃ£ o Paulo municipality, Brazil. Geospatial Health, 15(2).
10. Gan, L., Li, D. and Song, S. (2006). Is the Zipf law spurious in explaining city-size distributions? Economics Letters, 92(2), 256-262.
11. Geary, R.C. (1954). The contiguity ratio and statistical mapping. The Incorporated Statistician, 5(3), 115-145.
12. Getis, A., & Ord, J. K. (1992). The Analysis of Spatial Association by Use of Distance Statistics. Geographical Analysis, 24(3).
13. Goodchild, M.F. (1986). Spatial Autocorrelation. Catmog. 47, Geo Books, Norwich.
14. Griffith, D. A. (2009). Spatial filtering. In Handbook of Applied Spatial Analysis: Software Tools, Methods and Applications (pp. 301-318). Berlin, Heidelberg: Springer Berlin Heidelberg.
15. Griffith, D. A., & Chun, Y. (2022). Some useful details about the Moran coefficient, the Geary ratio, and the join count indices of spatial autocorrelation. Journal of Spatial Econometrics, 3(1), 12.
16. Guerin-Pace, F. (1995). Rank Size Distribution and the Process of Urban Growth. Urban Studies, 32(3), 551-562.
17. Kumar, G & Subbarayan, A. (2011). The Size Distribution of Cities and Towns in Andhra Pradesh (1951-2001). International Journal of Current Research, 3(1), 146-150.
18. Mills, Edwin S and Harmilton, Bruce W. 1994. Urban Economics, (5th Edition), Addison -Wesley.
19. Moran, P.A.P. (1950). Note on continuous stochastic phenomena. Biometrika, 37(1/2), 17-23.
20. Myint, S. W., Wentz, E. A., & Purkis, S. J. (2007). Employing spatial metrics in urban land-use/land-cover mapping. Photogrammetric Engineering & Remote Sensing, 73(12), 1403-1415.
21. Ratcliffe, J. H. (2010). The spatial dependency of crime increase dispersion. Security Journal, 23(1), 18-36.
22. Wywial, J.L. (2025). Generalised spatial autocorrelation coefficients. Statistics in Transition, 26(1), 1-8.
23. Zhang, C., Luo, L., Xu, W., & Ledwith, V. (2008). Use of local Moran's I and GIS to identify pollution hotspots of Pb in urban soils of Galway, Ireland. Science of the total environment, 398(1-3), 212-221.