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Original Article

An Exploratory Spatial Data Analysis of Health Indicators in Pakistan

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ABSTRACT

Pakistan exhibits significant spatial diversity in the distribution of its economic activities, accompanied by persistent regional disparities in various dimensions of health. This article aims to examine the distribution of health indices across 97 districts of Pakistan using exploratory spatial data analysis for the periods 2004-05 and 2014-15. To achieve this, an augmented health index was developed to measure health indicators across districts. The index comprises five key indicators, which were aggregated using Principal Component Analysis (PCA) to generate the final composite index. The findings reveal a positive global autocorrelation, indicating that districts with higher (or lower) health levels tend to be spatially clustered with neighboring districts exhibiting similar health outcomes. Scatterplot analyses of the health index reveal that districts in Punjab and Khyber Pakhtunkhwa (KP) predominantly fall in the High-High (HH) quadrant, while districts in Interior Sindh and Baluchistan are concentrated in the Low-Low (LL) quadrant for both study periods. These results underscore the dual structure of Pakistan's economic geography, consistent with findings from prior studies. Given the importance of geographic disparities in health outcomes, it is recommended to address inter-district inequalities by strengthening social and economic institutions and infrastructure, particularly in Baluchistan and Interior Sindh.

Introduction

The concept of spatial inequality refers to the dissimilarity in economic and social indicators of welfare across different spatial or geographical locations within a country (Kanbur, 2003). One area may have access to healthcare or clean water, whereas another area does not (Gajangi, 2016). The accurate measurement of spatial disparities and the analysis of their causes and consequences are of particular significance. Spatial imbalances are vital for at least two causes. First, inequality between regions of country is a constituent of overall inequality across individuals at national level. Secondly, disparity between regions frequently goes hand in hand with ethnic and political instability, which damage political stability and social structure (Kanbur & Venable, 2005).

Inequality among individuals and between different geographic areas remains a critical challenge for development in emerging countries today just as it was in early phases of development of developed countries (Williamson, 1965). Spatial disparities in education, health and health level pose key tests for developing economies and there is a growing fear in developing world about the regional and spatial inequality. It is believed that in developing and transition economies such as China, Mexico, Russia, South Africa and India, regional imbalances in economic activities, social indicators and incomes are growing (McCormick & Wahba, 2003: Kanbur & Zhang, 2005; Pose & Reaza, 2005; Friedman, 2005).

Growth and Development in Pakistan: An Overview

Despite numerous economic and political challenges at both national and international levels over the past two decades, Pakistan's GDP has grown significantly, increasing from $82.69 billion in 2000 to $346 billion in 2021—a nearly fourfold rise. Additionally, the country's per capita income has seen a threefold increase, rising from approximately $570 in 2000 to around $1,400 in 2021.

After the occurrence of economic growth in a state, then the question arises about the distribution of income from growth, either it assists all sections of the people equally or not. Pakistan is spatially a diverse state and its growth path has resulted in uneven social and economic development, particularly in terms of public service delivery (Easterly, 2003). With the passing of the eighteenth amendment in constitution, the seventh National Finance Commission Award (hereafter NFC)[1] has permitted the shift of further fiscal resources from the center to the provinces, which has now further influence over the provision of physical infrastructure, education and health services. This basic move toward the splitting up of power between the federation and the provinces conveys considerable long-term repercussions in the country for the policy planning, management, and implementation.

The majority of the current research studies on Pakistan economy has focused on provincial level, and overlooked the spatial disparity within the provinces among the districts. There are little facts regarding the trends in spatial disparities across districts over the previous two decades. Research at district level has become even more vital after 18th amendment passed in April 2010[2] as public and social services happen to be the lone sphere of provincial governments. The district level research better explains the geographical features of socio-economic facts and provides a comprehensive investigation of the effects spatially relative to studies undertaken in the country on a provincial level.

In light of the above-mentioned challenges, the major aim of this research is to investigate the spatial pattern of health level for 97 districts of Pakistan over the period of 2004 to 2015, by

[1] The NFC award is the allocation of fiscal assets by the federal government among the provinces of Pakistan annually. The award is constituted in 1973 Constitution of Pakistan under the Article 160.
[2] The eighteenth constitutional amendment to the 1973 constitution has raised the autonomy of provinces to great extent.

utilizing exploratory spatial data analysis techniques (hereafter ESDA). Thus, the study provides outcomes for clustering of socioeconomic features across Pakistani districts[3].

The paper is organized in the following mode: section 2 explains Literature review. Section 3 introduces Methodology. The section 4 presents our empirical findings and provides conclusions.

Literature Review

The role of geography has long been ignored by economist in their research, particularly in modern growth economics and macroeconomics until 1990s. However, for the last three decades, empirical studies are focusing on the association between geographical factors and territorial imbalances.

For developed world, studies on spatial disparities across regions found mixed results. In the case of the European Union, majority of research studies found that poor areas tend to fall behind while most well-off regions reveal unrelenting growth (Canova & Market, 1995; Magrini, 1999; Magrini, 2004). In the case of European Union and United States, it is recognized that innovation is highly concentrated in a very few regions (Carlino et al., 2001; Crescenzi et al., 2007) indicating that fundamental features for innovation to succeed are distributed highly unequally. In the same way, it has been found that the capability of European regions to translate knowledge into significant economic activities vary across space in accordance with different qualitative local social structures and innovation systems across regions (Rodriguez-Pose, 1999; Crescenzi & Rodriguez-Pose, 2008).

For developing countries, the localized nature of economic development and the role of social and institutional aspects emerge even more essential as favorable locality and contexts become less likely. Regional spatial disparity was widespread in some countries such as Brazil, but decreases over the period 1981-1997 (Azzoni et al., 2005). However, regional inequality remained steady at lower levels comparatively in other countries. While calculating inequality for Peru by using literacy and expenditure, Torero and Escobal, (2005) investigated that inequality was low across regions for the period 1972–93. Balisacan and Fuwa (2006) examined that the regional disparity in the Philippines and concluded that regional disparity condensed between 1985 and 2000. Similar findings were made for South Africa between 1990 and 2000 (Friedman, 2005), and Indonesia between 1984 and 1999 (Krugell & Naude, 2003). Meanwhile, in the case of China, it was recognized that geographic factors are significant statistically in revealing the spatial disparity largely between seashore and non- seashore (Chang, Bao, & Woo, 2002).

Currently, most of the studies focusing spatial disparity are based on a technique known as ESDA. A number of ESDA based analysis have been conducted on the subject of regional disparities (For instance, Battisti & Di Vaio, 2008; Ezcurra et al., 2007; Voss etal., 2006; Jensen et al., 2006; Magalhaes et al., 2005). There are few ESDA analysis performed on the Pakistan. For Pakistan, for the first time Ahmed (2011) studied the agglomeration of growth, income inequality, human development and education spatially across 98 districts. Ahmed found that

[3] The only other exceptions include (Burki *et al*. 2010) and (Ahmed, 2011) that have considered explicitly in their studies spatial dependencies.

bordering districts share growth and development levels of each other's, proving that economic topography does influence growth, development, and territorial disparities of Pakistan. The study further analyzed that the district wise distribution of growth, income inequality, human development and education, demonstrates a major trend for levels of development and socio-economic disparities to cluster in Pakistan.

Most of the research on socio-economy of Pakistan has focused on a provincial level (for example, Hamid & Hussain, 1992; Pasha et al, 1996; Khan & Jamal 2003; Aamir & Jamal 2003; Naqvi, 2007; Siddique, 2008; Burki et al., 2010; Arif, 2010). These studies overlook the significance of social interactions among the districts within the provinces[4]. The above empirical evidences clearly indicate that there is an abundance of work in assessing the issue of spatial inequality in the rest of the world over the past three decades; only limited studies have focused the issue for Pakistan. This not only draw attention towards investigating regional differences within the country in order to discover the most isolated subset of the people in terms of health, literacy and income, but in addition to support in the formulation of course of action that can eliminate these problems of dissimilarities in income and development. So, the study provides some of the first logical study on clustering of health indictors across districts of Pakistan.

Methodology

This section discusses research methodology and data base applied for analyzing data**.**

Model

The use of spatial econometric methods has achieved popularity with this bigger attention on issues of regional development and improvement of spatial data analysis (Arbia, 2006). There are several methods used to discover correlations in space. The commonly used technique is ESDA. This study utilizes technique ESDA.

Mapping the Distributions

Prior to estimation of models with data, GeoDa [5](one of diverse software packages for performing ESDA) is utilized to create scatter plots, box-plots and quartile maps. It maps the variables that are utilized in the study and examine spatial patterns visually through map.

Exploratory Spatial Data Analysis

A subgroup of exploratory data analysis is ESDA. When using EDA, the researcher gives the data a closer look and attempts to interpret it. During the year 1977, John Tukey created the EDA. The ESDA methodologies used in this work include investigation at the local level (LISA) and computation of global level indicators (Moran's *I* spatial autocorrelation). The creation of a spatial weight matrix is the initial stage in the spatial autocorrelation analysis process.

[4] Exception include Ahmed (2011)
[5]Geoda (short for Geographic Data Analysis) GeoDa is planned as a complement to current GIS purpose, not as an alternate. For example, GIS associated processes which are not applied within GeoDa comprises shape files/ merging/aggregating data, dissolving shape files, map projections, and changing shape files.

ESDA is a subgroup of Exploratory Data Analysis (hereafter EDA). In this study, the ESDA techniques employed comprise the computation of Global level indicators (Moran's *I* spatial autocorrelation) and analysis at local level (LISA). For spatial autocorrelation analysis, the first step is to define a spatial weight matrix.

Spatial Weight Matrix

For defining neighborhood in this study, two fundamental approaches utilized in this study are common borders (contiguity) and distance. Weights matrices based on contiguity consist of rook and queen. According to the rook criterion, districts are considered neighbors if they share a boundary, not a set of vertices. K nearest neighbors and distance bands make up weight matrices based on distance. Four weight matrices are developed based on the aforementioned two ideas in order to analyze the spatial distribution of the health index. The four weight matrices include; a rook contiguity matrix, k_7 nearest neighbor matrix, k_4nearest neighbor matrix, and W-150 miles matrix, which define neighbors as all the districts located inside a great circle distance with a cut-off of 150 miles. The matrices are finally row standardized, which is a suggested practice when the distribution of the factors under deliberation is probably biased because of errors in designing of sample or because of a forced aggregation method.

Because of space limit, we only discuss the k_7 nearest neighbor matrix:

$$w_{i\,j}(k) = 0 \;\; if \; i \; = \; j$$

$w_{i\,j}(k) = 1$ *if* $d_{i\,j} \leq D_i(k)$ *and* $w_{i\,j}(k) = w_{i\,j}(k) / \sum j \; w_{i\,j}(k)$ *for* $k = 7$ **(1)**

$w_{i\,j}(k) = 0$ *if* $d_{i\,j} > Di(k)$

From Equation (1), $d_{i\,j}$ is great circle distance between centroids of district i and j and $Di(k)$ is the 7^{th} order minimum distance between districts i and j, so that each district i has seven neighbors accurately.

After defining the weight matrix, next we estimate some spatial statistics that discuss the spatial distribution of health index.

Measures of Spatial Autocorrelation

Spatial autocorrelation basically refers to a methodical spatial dissimilarity in values across a map, or with the given locations patterns in values recorded at locations (Fingletonm & Upton, 1985). When features are alike in location, then it would be regarded as spatially positive autocorrelated. When features were different in location, then it would be considered as spatially autocorrelated negatively. When characteristics were not dependent on location, they are regarded as zero autocorrelation (Holt, 2007).

Global Spatial Autocorrelation

To discover the global spatial autocorrelation in the data, this study uses Moran's statistics. Originally, it was proposed by Moran in 1948, and the standard work by Ord and Cliff popularized it in 1973. Primarily, the Moran's *I* is the widespread employed measure due to its simplicity in understanding and its further splitting into a local statistic alongside presenting graphical data regarding presence or absence of spatial clustering. It is judged by mean of a null hypothesis test of random locality. Null hypothesis negative response advocates a spatial structure, which gives further insights into distribution of data. For the health index, it measures the strength of the linear relationship between its value at one location and the spatially weighted average (mean) of adjacent values and is formalized as:

$$I_t = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(k) x_{it} x_{jt}}{\sum_{i=1}^{n}\sum_{j=1}^{n} x_{it} x_{jt}} \qquad (2)$$

From Equation (2), w_{ij} is the degree of association between the districts i and j and the variable of interest in district i at year t is represented by x_{ij} (determined as a deviation from the mean value for that year). Positive spatial autocorrelation is pointed out, if values of I is bigger than the expected value $E(I) = -1/(n-1)$, while negative spatial autocorrelation is indicated, if values of I is lesser than the expected value.

Local Indicators of Spatial Association

The Moran's *I* is used to measures the presence of global spatial autocorrelation only; it does not give data on the accurate locations of spatial patterns (Holt, 2007). So, *local indicators of spatial association* (here after LISA) is essential to measure the magnitude and location of spatial autocorrelation (Anselin, 1995). Thus, this research employs LISA method. The technique displays the presence or absence of significant spatial outliers or clusters for each district. It also specifies local clusters that are significant (low–low or high–high) or spatial outliers locally (low–high or high–low). The mean of the Local Moran statistics is related to the value of Global Moran's *I* (Anselin et al., 2007).

$$I_i = \left(\frac{x_i}{m_o}\right) \sum_j W_{ij}\, x_j \quad \text{with} \quad m_o = \sum \frac{x_i^2}{n} \qquad (3)$$

From Equation (3), w_{ij} represents the elements of the weights matrix W (row-standardized) and x_i (x_j) is the observation in district i (j).

Variables Description and Data Source

Variables Description

The use of per capita output as a measure of living standard has been criticized by several economists, as it fails to explain the wider aspect of welfare (Sen, 1983; Stiglitz et al., 2009; Todaro & Smith, 2011; Roy & Bhattacharjee, 2009 Schepelmann et al., 2010). So, in this study, we attempt ESDA analysis for 97 districts by using health index for periods 2004-05 and 2014-15. The index is composed of five indicators. Principal Component Analysis (PCA) is employed to aggregate the weights obtained from these indicators (Basel et al., 2020).

Data Source

Data for the study is taken from PSLM Surveys covering the period 2004-05 and 2014-15. PSLM surveys cover data on socioeconomic indicators for 116 districts across four provinces of Pakistan.

Table 1: List of Indicators of Health Level

S. No	Health Index
1	Child affected by diarrhea in last thirty days (aged under 5)
2	Treatment of diarrhea in children (aged under 5)
3	Children that have been immunized (aged 12-23)
4	Health Consultation (number of individuals who consulted for treatment that is percentage of total individuals fallen sick during last two weeks**)**
5	Pre-natal Consultations

Data Limitations

PSLM surveys cover data for 116 districts across four provinces of Pakistan. Due to missing observations, 20 districts are dropped from the data for this study. The detail of the dropped districts is given in Table 2.

Table 2: List of districts dropped from data due to missing observation

	Provinces			
	Punjab	**KP**	**Sindh**	**Balochistan**
Districts	Chiniot, Nankana Sahib	Tor Ghar	Tando Allah Yar, Tando Muhammad Khan, Kashmore, Shahdadkot, Sujawal, Umerkot, Matiari, Jamshoro	Derabugti, Sheerani, Washuk, Ketch, Panjgur, Kohlu, Nushki, Harnai

Results and Discussion

Mapping the Distributions

The first step for our analysis is to map and examine the data. The mapping gives important information about outliers and the directions of spatial autocorrelation.

Quartile Maps

Quartile map is category of quantile map that sort values for a variable that are then grouped into four bins that each have the same number of observations. In quartile map, higher values are explained by darker colours, whereas lower values are illustrated by lighter coluors. Figure 1-2 comprises two quartile maps that display health index for period 2004-05 and 2014-15.

The quartile maps display the majority of Punjab's Eastern and Northern districts have the highest level of health level. Southern/South-Eastern Punjab districts are underdeveloped relative to the developed eastern and central districts of Punjab. In Khyber Pakhtunkhwa most of the districts belong to the category of high health level, whereas, districts of Northern and southern

Khyber Pakhtunkhwa are the least developed districts. With the exception of Quetta, Baluchistan's districts lies in the low health category. The distribution of districts in Sindh is heavily skewed toward low medium levels of health. With the exception of Karachi and Hyderabad, Southern Sindh is home to the least developed districts. Overall, the maps showed that there is slight improvement in spatial clustering of health level from 2004 to 2015.

Figure 1: Quartile Map for Health Index (2004-05)

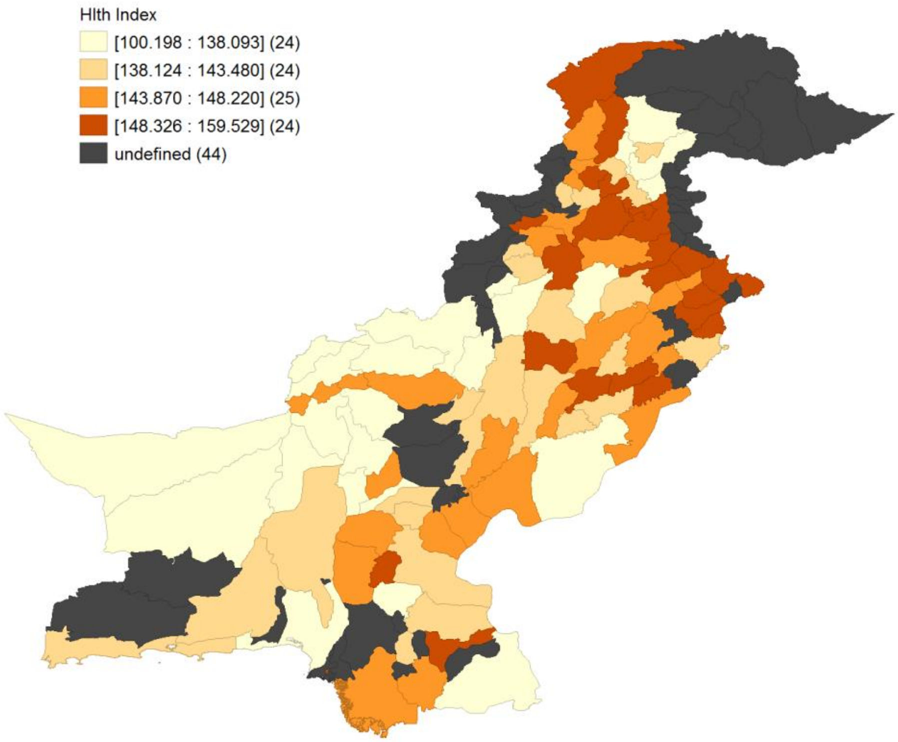
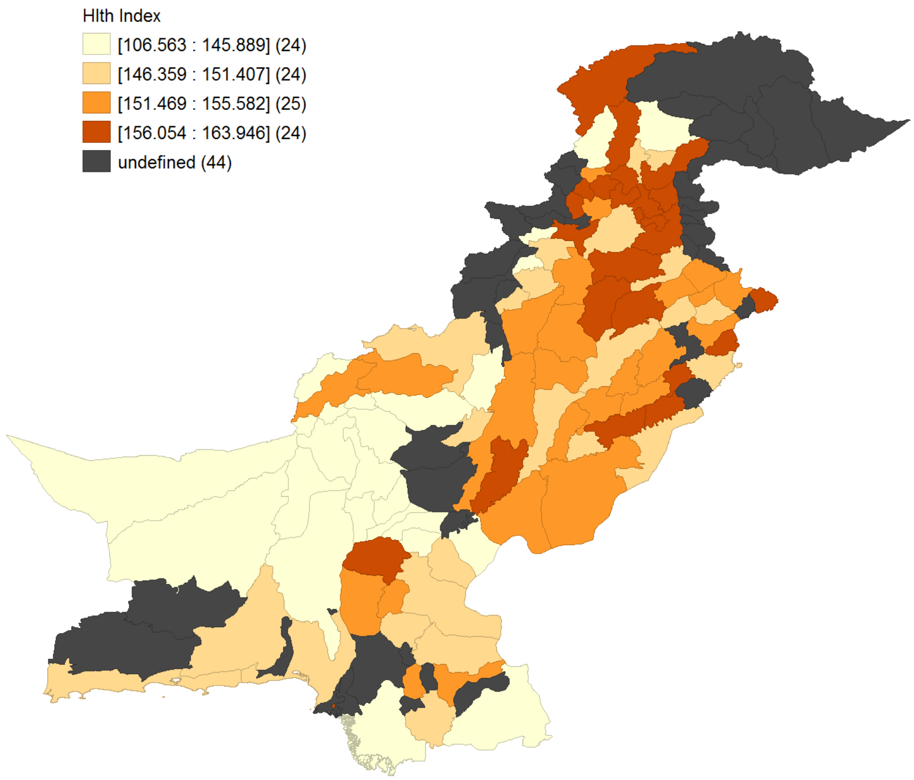


Figure 2: Quartile Map for Health Index (2014-15)



Box Plots

For mapping of data distribution, another necessary tool of ESDA is the box plot that presents five vital facts regarding a dataset: the lower quartile of the distribution expressed as Q1 representing 25 percent of the cumulative distribution, the Q2 representing median, the upper quartile expressed as Q3 represents 75 percent of the cumulative distribution, and Q4 representing topmost value. The main advantage of a box plot is to show the outliers, which are defined as values above or below a certain multiple of the difference between the first and third quartiles (randomly determined by GeoDa to 1.5). Such as, a lower outlier signifies a value below [Q1−1.5*(Q3−Q1)] and an upper outlier refer to the value over [Q3 + 1.5*(Q3 − Q1)]. The first quartile of the distribution is located in the lowest portion of the dark area. The median is indicated by the bar in the center of the dark region. The third quartile of the distribution is located in the upper section of the dark area.

The ‘‘box plots’’ listed in figures 3-4 give a first look of spatial distribution of health index across Pakistan’s districts. The box plot figures demonstrate the spatial pattern for the scores in 2004-05 and 2014-15. The box plot figures for 2004-05 revealed Islamabad, Lahore and Karachi as upper outlier for overall health. Whereas, for the year 2014-15, the box plots shows Bolan, JhalMagsi, Sibbi (Baluchistan) and Kohistan (KP) as the lower outlier for the period 20014-2015.

Figure 3: Box Plot for Health Index for the period 2004-05

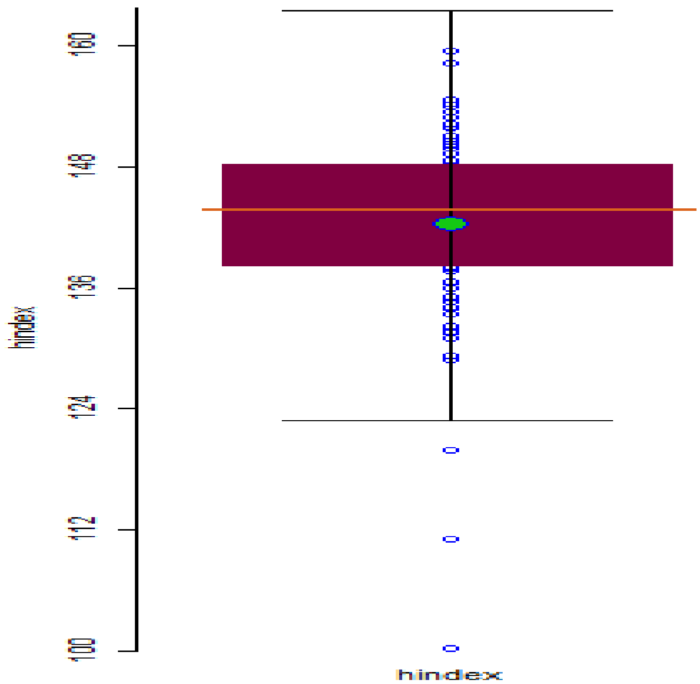
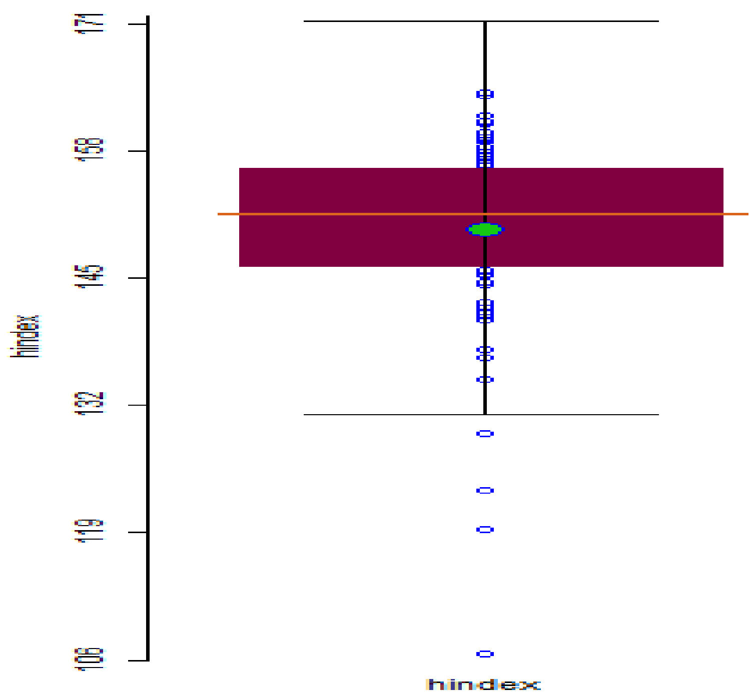


Figure 4: Box Plot for Health Index for the period 2014-15



Overall, the quartile maps and box plot revealed that overall districts from Balochistan and Interior Sindh have experienced the greatest stagnation in terms of health level over the period 2004-2015, as box plot revealed most of districts in lowest quartile belong to Sindh and Balochistan. Likewise, quartile maps also show that clusters of least developed districts belong to the provinces of Balochistan and Interior Sindh. On the other side, majority of districts of Punjab and KP are mapped as developed in both periods.

Spatial Autocorrelation

Box plots and quartile maps are useful tools for determining how the health index is distributed among districts. On the other hand, they do not adequately research whether a health index's spatial distribution is random or not. We believe that the health index may not be distributed evenly between districts for a number of reasons. For instance, the preceding data show that the distribution of the health index throughout Pakistan's districts is characterized by dissimilar clusters.

Global Spatial Autocorrelation

The concept of spatial autocorrelation or spatial association is essential to ESDA. Moran's *I* is the most common test for spatial autocorrelation (Cliff & Ord, 1981; Upton &Fingleton, 1985). It is judged through a test of a null hypothesis of random location. A spatial structure is suggested in case of rejection of this null hypothesis, which leads to more insights into data distribution.

Tables 3 and 4 below present the results of Global Moran's I for the years 2004–2005 and 2014–15, respectively. At the 1% level of significance, all four matrices support the existence of a significant positive global spatial autocorrelation. The district with a high (or low) level of development tends to be bordered by districts with a high (or low) level of development, as demonstrated by significant positive global spatial autocorrelation. We employ a weight matrix based on rook contiguity for the remainder of our study because all four weight matrices show a considerable positive global spatial autocorrelation.

Table 3: Moran's I and P-Value under Different Spatial Weights (2004-05)

Variables	Queen	Rook	K_4	K_7	W-150 miles
Health Index	0.191 (0.002)	0.191 (0.002)	0.191 (0.004)	0.211 (0.001)	0.141 (0.002)

Note: The values in parentheses are the p-values.

Table 4: Moran's I and P-Value under Different Spatial Weights (2014-15)

Variables	Queen	Rook	K_4	K_7	W-150 miles
Health Index	0.336 (0.001)	0.336 (0.001)	0.394 (0.001)	0.394 (0.001)	0.261 (0.001)

Note: The values in parentheses are the p-values

The Moran's *I* result for Health Index clearly indicate the increasing level of spatial dependence from 2004 to 20015, as given in Table 3 and Table 4.

Local Spatial Autocorrelation

Moran Scatter Plots

The global indicator "Moran's *I"* is helpful to identify global spatial autocorrelation, but it cannot detect local patterns of spatial association, for instance local spatial clusters or local spatial outliers of high values or low that are significant statistically. Moran scatter plot detect the groups of districts categorized in clustering of high or low values. Following the suggestion of Anselin (1996), it displays the distribution of health index for each district on the horizontal axis against the standardised spatial weighted average (spatial lag, which is the average of the neighbors' values) on the vertical axis. So, the Moran's scatter plot help us to investigate both local spatial association and global spatial association (as the slope of the line is the Moran's *I* coefficient).

According to the four types of local spatial relationships between a district and its neighbors, the Moran scatter plot is divided into four distinct quadrants:

1. Quadrant I (expressed as HH representing top right) explains that the health level of the district and "neighboring" districts are high and the spatial difference is not significant.
2. Quadrant II (expressed as LH representing top left) explains that the health level the district is low, whereas that of the "neighboring" districts is higher, with large spatial differences.
3. Quadrant III (expressed as LL representing bottom left) explains that the health level of the district and "bordering" districts are low and the spatial difference is not significant.
4. Quadrant IV (expressed as HL representing bottom right,) explains that the health level of the district are higher, whereas that of the "bordering" districts are low and the spatial difference is large.

Figure 5: Moran Scatter Plot of Health Index for the period 2004-05

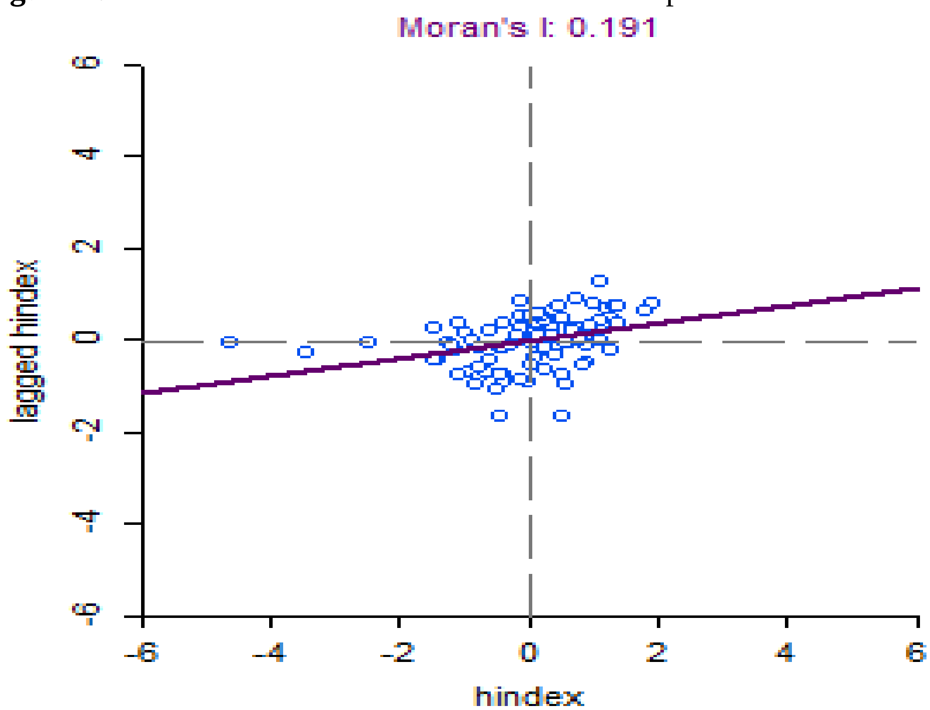
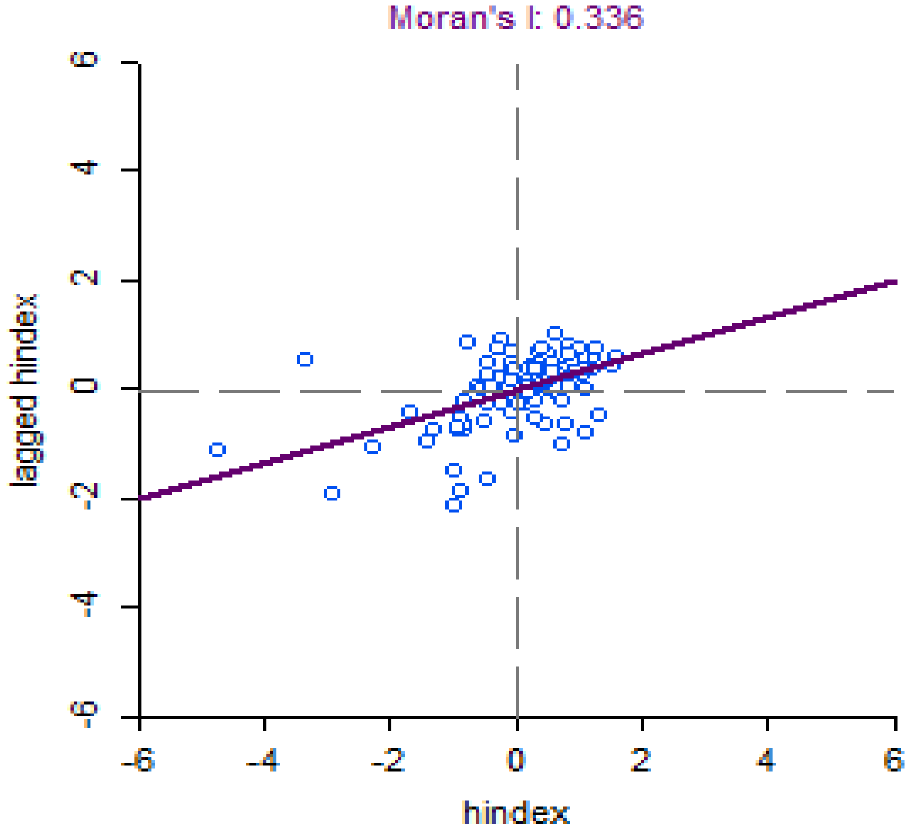


Figure 6: Moran Scatter Plot of Health Index for the period 2014-15



The presence of local spatial autocorrelation is proved by LISA findings and it show spatial heterogeneity in the shape of two distinct spatial clusters of high and low values of health level (see figure 5 & 6).

The Moran scatter plot serves as an exploratory tool for identifying clusters or outliers but does not indicate statistical significance. Figures 5 and 6 illustrate the Moran scatter plots of the health index for the periods 2004-05 and 2014-15. Districts in the first and third quadrants exhibit positive spatial autocorrelation, indicating clusters of similar values. Conversely, districts in the second and fourth quadrants show negative spatial autocorrelation, representing clusters of dissimilar values.

Both plots reveal positive global spatial autocorrelation, consistent with the earlier findings based on Moran's I. Most districts are concentrated in the first (High-High) and third (Low-Low) quadrants. The first quadrant (HH) primarily features districts from Punjab and KP, while the third quadrant (LL) predominantly includes districts from Interior Sindh and Balochistan..

Overall, the differences of health index across districts in Pakistan are caused mostly by the "HH" and "LL" agglomeration effects, while the "HL" and "LH" agglomeration effects are not evident. Moran Scatter plots also show that with the passage of time, "LL" and "HH" accumulation areas tend to expand. These findings reflect the twofold structure of Pakistan's districts.

Table 3: Distribution of spatial autocorrelation for Health Index (2004-05)

Var	HH (34)	LH (14)	LL (35)	HL (14)
Health Index	Abbottabad, Hafizabad, Bhakhar, Chakwal, Faisalabad, Gujrat, Attock, Gujranwala, Hangu, Islamabad, Haripur, Jehlum, Kasur, Khanewal, Kohat, Lahore, Mansehra, Mardan, Mianwali, Narowal, Naushahro Feroze, Nowshera, Pakpatten, Peshawar, Rawalpindi, Sargodha, Sahiwal, Toba Tek Sheikhupura, Sialkot, Sukkur, Swabi, Singh, Vehari	Buner, Charsada, Jhang, Karak, Khushab, LakkiMarwat, Lasbilla, Lodhran, Mithi, Muzaffagarh, Okara, Sanghar, Thatta, Upper Dir,	Awaran, Badin, Bannu, Barkhan, Batagram, Bolan, Chaghi, Dadu, Dera Ismail Khan, Dera Ghazi Khan, Gwadar, Jafarabad, Jakobabad, JhalMagsi, Kalat, Kharan, Khairpur, Khuzdar, Kohistan, Larkana, Loralai, Mastung, Mirpur Khas, MusaKhel, Nasirabad, Nawab Shah, Pashin, Qilla Abdullah, Qilla Saifullah, Rajanpur, Shangla, Sibbi, Tank, Zhob, Ziarat.	Bahawalnager, Bahawalpur, Chitral, Ghotki, Hyderabad, Karachi, Layyah, Lower Dir, Malakand, Multan, Quetta, RahimYarKhan, Shikarpur Swat.

Table 4: Distribution of spatial autocorrelation for Health Index (2014-15)

Var	HH (36)	LH (10)	LL (40)	HL (10)
Health Index	Islamabad, Abbottabad, Chakwal, Charsada, Faisalabad, Attock, Gujrat, Gujranwala, Hafizabad, Hangu, Haripur, Jehlum, Karak, Kasur, Khanewal, Khushab, Kohat, Lahore, Mansehra, Lakki Marwat, Malakand, Lower Dir, Mardan, Mianwali, Narowal, Naushahro Feroze, Nowshera, Okara, Peshawar, Sheikhupura, Rawalpindi, Sargodha, Sialkot, Swabi, Sahiwal, Toba Tek Singh	Bhakhar, Buner, Jhang, Kohistan, Lasbilla, Pakpatten, Sanghar, Thatta, Upper Dir, Vehari	Awaran, Badin, Bannu, Bahawalnager, Bahawalpur, Barkhan, Batagram, Bolan, Chaghi, Dadu, Dera Ghazi Khan, Gwadar, Jafarabad, Jakobabad, JhalMagsi, Kalat, Khairpur, Kharan, Khuzdar, Lodhran, Loralai, Mastung, Mirpur Khas, Mithi, MusaKhel, Muzaffargarh Nasirabad, Nawab Shah, Qilla Saifullah, Pashin, Qilla Abdullah, Rahim Yar Khan, Rajanpur, Shangla, Shikarpur, Sibbi, Tank, Zhob, Ziarat.	Chitral, D.I.Khan, Hyderabad, Karachi, Larkana, Layyah, Multan, Quetta, Sukkur, Swat.

The LISA findings confirm the presence of local spatial autocorrelation, revealing spatial heterogeneity in the form of two distinct clusters: one with high levels and the other with low levels of the health index (see Figures 5 and 6).

Conclusions and Recommendations

The study analyzed spatial distribution of health index for 97 districts of Pakistan for periods 2004-05 and 2015-15.

Conclusions

The main findings the study is given as under:

- Quartile maps clearly highlight a substantial development gap across Pakistan's districts.
- Moran's I indicates significant positive global autocorrelation, suggesting that districts with high (or low) development levels are spatially clustered with neighboring districts exhibiting similar levels of development.
- The Moran's scatterplots reveal that most districts in Punjab and Khyber Pakhtunkhwa (KP) fall in the High-High (HH) quadrant, while the Low-Low (LL) quadrant predominantly includes districts from Interior Sindh and Balochistan for both study periods.
- These findings underscore the dual structure of Pakistan's economic geography, as previously identified in the literature. In addition to spatial heterogeneity, the study also confirms spatial autocorrelation among districts.
- Overall, the results reaffirm the twofold nature of Pakistan's economic geography, consistent with earlier studies.

Recommendations

Following main recommendations come out from our results.

- The findings imply that studies using OLS to analyze socio-economic issues across districts may yield unreliable results. By ignoring spatial dependence, such analyses risk producing biased and overestimated estimates.
- The key policy implication is that development strategies should emphasize cluster-based development to address the needs of large population segments. Considering the importance of geographic disparities in development, it is recommended to reduce inter-district inequalities by increasing investments in education and workforce training in underdeveloped districts. Additionally, prioritizing the development of social and economic institutions, as well as infrastructure in Balochistan and Interior Sindh, should be a top priority for the government.

Future Research Possibilities

- Given the spatial dynamics highlighted in the study, further research can explore the factors contributing to the non-convergence of health and other indices across Pakistan's districts.
- Spatial econometric techniques can be extended to analyze economic, social, and environmental issues in Pakistan and other developing countries, following the examples set by studies in developed nations.

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Appendix

Figure 1: Provincial Administrative Map of Pakistan

Figure 1a: District Administrative Map of Pakistan

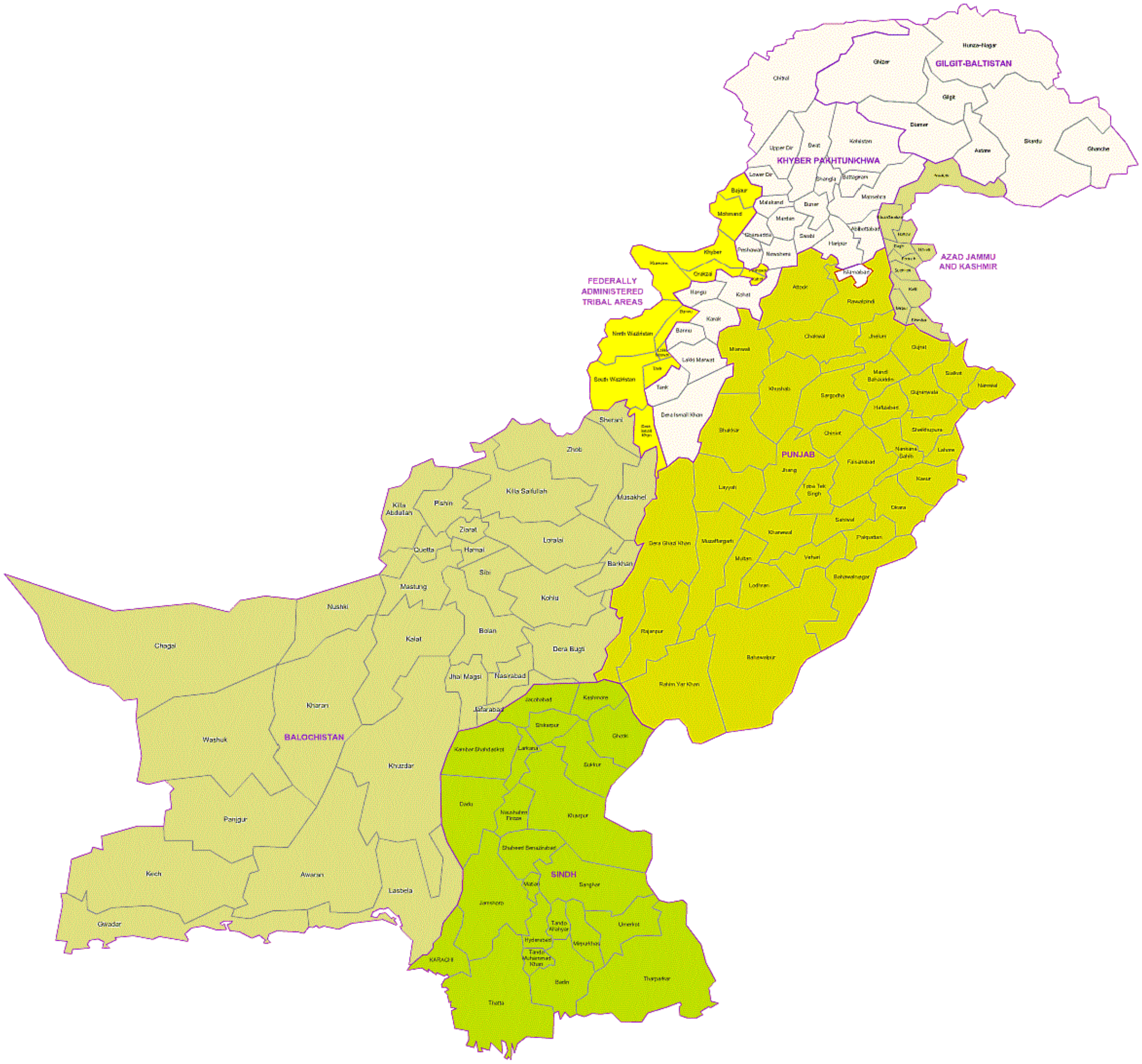

Table: Sample Binary Contiguity Weight Matrix

	Attock	Chakwal	Gujranwala	Gujrat	Hafizabad	Jhelum	Mandi Bahuddin	Rawalpindi	Sialkot
Attock	0	1	0	0	0	0	0	1	0
Chakwal	1	0	0	0	0	1	0	1	0
Gujranwala	0	0	0	1	1	0	1	0	1
Gujrat	0	0	1	0	0	1	1	0	1
Hafizabad	0	0	1	0	0	0	1	0	0
Jhelum	0	1	0	1	0	0	1	1	0
Mandi Bahuddin	0	0	1	1	1	1	0	0	0
Rawalpindi	1	1	0	0	0	1	0	0	0
Sialkot	0	0	1	1	0	0	0	0	0

*Full matrix is available in *GWT file format* from the author upon request.