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Local Spatial Autocorrelation and Local Spatial Heterogeneity Analyses of Subjective Poverty: A Study on the Provinces of Turkey *

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Abstract: In this study, we examined the spatial distribution of subjective poverty across Turkey's provinces. To accomplish this, we utilized the proportion of individuals who reported an inability to meet their basic needs, as reflected in the life index indicators computed by the Turkish Statistical Institute. After mapping the distribution of this variable by province, Moran's I statistic, which is the spatial interaction statistic, was calculated It has been determined that the spatial distribution of subjective poverty is not random. It has been observed that the subjective poverty or perception of poverty in the context of the provinces of Turkey is similar and has a cluster. The existence of local clusters belonging to this statistic was investigated with LISA statistic and Getis-0rd statistic. According to the findings, the provinces that are high spots are generally the ones in the southeast and eastern regions of Turkey. Low spot areas are generally seen in the provinces in the western part of the country. According to the local spatial heterogeneity statistic *Hi*, it is seen that the provinces in high and low spots are not different from their neighbors.

Keywords: Poverty, Subjective poverty, Spatial analysis of poverty, Poverty in Turkey, Spatial dependency, Local heterogeneity

JEL Codes: F43, R12, R15

1. INTRODUCTION

Poverty is an important social problem that all countries of the world are seeking solutions for and trying to reduce. The negative impact of this social problem can be reduced by developing and implementing people-oriented strategies. Economists try to reduce the severity of poverty with the strategies suggested by economic approaches. It is important to measure and reveal the extent of poverty in order to implement poverty reduction strategies.

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The World Bank has set the new international poverty line at $2.15 per person per day, using 2017 prices. In this context, according to the 2021 World Bank Development Report, there are more than 700 million people living in extreme poverty in the world (World Bank, 2021). In the same report, it was stated that the pandemic that occurred in 2020 pushed up to 150 million people into extreme poverty. Although global poverty has more recently returned to its pre-pandemic downward trend, between 75 million and 95 million people in 2022 are living in extreme poverty compared to pre-COVID-19 estimates due to the continued effects of the pandemic, the war in Ukraine and rising global inflation according to the (World Bank, 2022).

Policies to reduce poverty in Turkey have accelerated recently, yielding significant results. However, further measures are needed. Key policies include boosting economic growth, increasing public expenditures on essentials (food, health, education, housing), investing in rural infrastructure, supporting farmers, providing direct social assistance to disadvantaged groups, and protecting the natural environment. In Turkey, the income-based relative poverty rate, calculated as 50% of the equivalent household disposable median income, decreased by 0.6 percentage points from 15% in 2020 to 14.4% in 2021 (Turkish Statistical Institute-TurkStat, 2022). Although this decrease is important, more policies need to be developed and implemented to reduce poverty rates for social peace. According to relative poverty rates, the highest poverty levels among Level 2 regions in Turkey were in TR62 (Adana, Mersin) at 14.4%, followed by TRC3 (Mardin, Batman, Şırnak, Siirt) and TRA2 (Ağrı, Kars, Iğdır, Ardahan) both at 13.7%. Between 2006 and 2017, Turkey implemented ambitious reforms and experienced high growth rates, elevating the country to upper-middle-income status and reducing poverty (World Bank, 2023). The percentage of people living below the $6.85 per day poverty line nearly halved to 9.8% between 2006 and 2020. Despite significant policy interventions, Turkey's poverty rate remains high compared to many other countries. Several interventions target poverty reduction, including social assistance programs, employment initiatives, and expanded access to education and healthcare (Powell and Yörük, 2017). According to the World Bank analysis, Turkey exhibits a significantly high proportion of social assistance based on income level compared to other upper-middle-income countries, despite certain limitations in terms of generosity (Cuevas et al., 2020).

Poverty is a multidimensional concept. One of the solutions to be sought for poverty is to define it well. The magnitude of poverty can be revealed with a measurement method suitable for the definition of poverty. Thus, by looking at the statistics and indicators about the magnitude of poverty, policies and strategies for poverty can be developed. Poverty is generally defined through two approaches: subjective poverty and objective poverty. Objective poverty is an approach that is defined and measured in terms of income or expenditure (Mahmood et al., 2019). Objective poverty that is not based on happiness and taste is classified in two different ways (Foster, 1998): absolute poverty and relative (relative) poverty. Absolute poverty occurs when individuals do not have enough income to meet their minimum physiological material needs (food, shelter, clothing, etc.), regardless of place and time (Madden, 2000). Individuals who cannot meet these basic needs are considered poor. Relative poverty, measured by living standards in a given society, is measured by a given average income of the society and varies over time (Fritzell et al., 2015). Relative poverty is defined as those whose income is below 50% or 60% of the average or median income, which indicates the average welfare level of the society. It defines the average or median income of the society, which reflects the characteristics of family informatics, as the poverty line.

Subjective poverty is defined through people's assessments of who is poor according to their beliefs about their position in the system of inequalities (Siposné Nándori, 2011). The concept of subjective poverty measurement is introduced Van Praag (1968) and Vos and Garner (1991), which converts self-reported income adequacy into poverty lines. In this approach, poverty is measured through people's thoughts about whether they are poor or not. Subjective poverty indicates a very low level of satisfaction with certain life areas of the individual (Diener et al., 2009; Buttler, 2013). While some individuals who are not subjectively poor may feel poor, some who are objectively poor may not feel poor (Mahmood et al., 2019). Subjective poverty lines are determined by self-evaluations of the income statement that individuals need to meet their basic needs (Siposné Nándori, 2014). The subjective poverty line is determined by asking the question: "What is the minimum income required to meet basic needs?" (Goedhart et al., 1977). This question is referred to as the minimum income measurement question. The minimum income needed is calculated by taking into account the size and composition of the household.

Subjective methods used in poverty measurement may fall short in accurately reflecting the true extent of poverty, particularly when they fail to adequately correlate with various dimensions of household living standards. Such methods are often based on household per capita expenditure or income levels. However, the assumption that traditional poverty analyses sufficiently account for factors such as economies of scale and adult equivalence, while evaluating welfare solely through monetary indicators, may lead to significant shortcomings in poverty assessments. Moreover, the failure to consider differences in household size and composition, alongside the challenges in collecting reliable income and expenditure data, can result in findings that misrepresent or underrepresent the reality of poverty. Consequently, objective poverty measurements have emerged as an alternative approach.

This study adopts a subjective poverty measurement approach, an alternative method that captures household economic welfare based on subjective self-assessments. Individuals' perceptions of their welfare are influenced not only by demographic factors such as employment, health, marital status, and age but also by relative wealth perceptions shaped by comparisons with others in their region and intrinsic factors such as personality traits. According to Rojas (2008), subjective poverty provides a more robust and nuanced understanding of human experiences than objective poverty measures (e.g., monetary income). Furthermore, subjective measures excel in identifying the negative emotions associated with social comparisons, outperforming objective measures in this regard (Smith and Huo, 2014). By directly addressing individuals' perceptions, subjective measures offer a more accurate depiction of human experiences under the strain of stressful social comparisons (Shi et al., 2025).

It may be a more effective method to analyze poverty through people's tastes and preferences and to implement policies accordingly. Because poverty is a phenomenon that occurs on an individual basis. The development of a region or a province depends on the location of that region. Because Central Places developed by Christaller (1966) and development poles theories developed by Perroux (1950) reveal that the space of a region is effective in the development of that region. In this context, it has been evaluated that analyzing the spatial distribution of subjective poverty, which has been little studied, is important for solutions to poverty.

A region can gain wealth by taking advantage of the resources it has and the advantages around it. In this respect, it should be considered important to analyze the spatial distribution of poor individuals and to develop policies as a result of the analysis. The main purpose of this study is to analyze the spatial distributions of subjective poverty at the provincial level, which has not been investigated at the provincial level before, using spatial autocorrelation and spatial heterogeneity tests.

Existing efforts to understand and mitigate poverty often overlook the importance of spatial distribution. While national poverty rates provide valuable insights, they mask significant regional variations. This lack of spatial detail hinders the development of targeted and effective poverty reduction strategies. It is very important to examine the spatial distribution of poverty in many ways. i) Identifying poverty hotspots: By analyzing the spatial distribution of poverty, we can pinpoint areas with the highest concentrations of deprived individuals. This allows policymakers to prioritize interventions and allocate resources more efficiently. For instance, regions with high subjective poverty might require infrastructure projects, enhanced social services, or targeted job creation initiatives. ii) Understanding underlying factors: Spatial analysis can reveal correlations between poverty and other factors like geographic isolation, limited access to healthcare, or environmental degradation. By identifying these factors, policymakers can develop multi-faceted solutions that address the root causes of poverty in specific regions. iii) Monitoring progress: Tracking changes in the spatial distribution of poverty over time allows for a more nuanced evaluation of poverty reduction strategies. This can help policymakers identify what's working and adapt their approaches for greater impact. iv) Equitable Growth: Addressing spatial poverty traps contributes to more equitable growth. It ensures that development benefits reach all segments of society, reducing disparities (Bird, 2019). This study addresses this gap by analyzing the spatial distribution of subjective poverty at the provincial level in Turkey. This approach offers a deeper understanding of poverty variations across the country and can inform the development of more effective regional poverty reduction strategies.

The organization of the remaining parts of this study is as follows: In the second part, literature review was made, in the third part the methodology of the spatial analysis methods was explained, and in the fourth part, the analysis results and comments and discussions on these results. In the fifth chapter, there are the conclusions drawn from the research and policy recommendations regarding these results.

2. LITERATURE REVIEW

In most of the studies measuring poverty and investigating the factors affecting it, information about the objective (absolute and relative) approach has been taken into account (Loayza and Raddatz, 2010; Cervantes-Godoy and Dewbre, 2010; Lacour and Tissington, 2011; Cafri, 2018; Şengür and Sanjar, 2019). Compared to the objective approach, the number of studies on subjective poverty is quite limited (Goedhart et al., 1977; Kapteyn et al., 1985; Flik and Van Praag, 1991). Many studies have investigated the relationship between poverty and macro variables (Freeman, 2003; Gohou and Soumaré, 2012). A relatively limited number of studies have been conducted at the regional level.

Regions are not independent of each other and there is always an interaction between nearby regions (Gezici and Hewings, 2007). In addition, the advantages and disadvantages of a region's geographical location affect the interaction and economic performance of that region with other regions. In this context, there are studies conducted abroad (Crandall and Weber, 2004; Amarasinghe et al., 2005; Minot and Baulch, 2005; Voss et al., 2006; Chattopadhyay et al., 2014) and domestically on the spatial analysis of poverty (Özbilgin, 2016; Yıldırım et al., 2019). For example, Crandall and Weber (2004) found that job growth and social capital reduce poverty rates and these factors are also effective in reducing poverty in neighborhoods where poverty is high. Chattopadhyay et al. (2014) found that the socio-economic impact on poverty conditions is important and regional poverty differs depending on the place in their study in India using decomposition and spatial analysis methods. As a result of a study conducted in Vietnam by Minot and Baulch (2005) to analyze the geographical distribution of poverty, estimates of poverty at the provincial level showed that the poverty rate was highest in the far north and central highlands and lowest in the southeast and large urban centers. Anwar (2022), in his study of spatial analysis of regional poverty in Central Java, Indonesia, stated that poverty in neighboring regions has a positive effect and poverty in Central Java is caused by spatial factors. Davis et al. (2022) analyzed spatial changes in hunger and nutritional quality in a study on a city in Africa to make a spatial analysis of urban hunger. As a result of the analysis, significant differences were found both between urban neighborhoods and within neighborhoods.

There are two studies that deal with the spatial distribution of poverty in Turkey at the regional level using objective poverty (relative) rates (Özbilgin, 2016; Yıldırım et al., 2019). Yıldırım et al. (2019) conducted a spatial analysis of the distribution of poverty line values in Turkey over Level 2 regions, with the motive that relative poverty in a region is affected by the poverty in its neighbors. As a result of the analysis, it was determined that the relative poverty in many regions was affected by the neighboring regions. In another study conducted by Özbilgin (2016), economic factors affecting urban relative poverty in Turkey and spatial interaction between regions were analyzed for the period of 2008-2013. According to the analysis results, the increase in the population in the cities, the increase in the dependency ratio and the increase in the relative share of the wage earners/minimum wage earners affect the urban poverty. In addition, the increase in urban poverty, non-agricultural unemployment and inequality in income distribution in a region also affects neighboring regions. Tatlı et al. (2020) measured objective and subjective poverty for Bingöl and compared both poverty. Başaran and Çetinkaya (2013), on the other hand, calculated the subjective poverty rates for the whole of Turkey by considering some of the questions in the household budget survey and compared these poverty rates with the relative poverty rates. Işık Danışman (2018), on the other hand, measured subjective poverty in the central districts of Muğla and Mardin provinces with the data obtained by the survey technique. Also, Karakas and Akgis (2017) analyzed the subjective well-being levels of the provinces in Turkey and the geographical distribution of these levels. In the study, subjective well-being was analyzed using Principal Component Analysis (PCA) with data obtained from a total of 25 variables, including income, education, health, access to public services, and social networks, obtained from the 2013 Life Satisfaction Survey of the Turkish Statistical

Institute. As a result of the analysis, four main components were found that explained 76.6% of the total variance. The results of the study revealed that subjective well-being levels varied geographically throughout Turkey, and showed that the subjective well-being level, which was high in the western regions, was quite low in the eastern regions. In addition, it was determined that variables related to access to public services showed the highest relationship with subjective well-being levels. Unlike the study by Karakas and Akgis (2017), this study offers complementary insights into subjective poverty by approaching the subject from different perspectives and methodologies. In addition, this study examines subjective poverty, especially individuals' perceptions of not being able to meet their basic needs, as an indicator of poverty. The primary distinction between the studies lies in their conceptual focus and analytical techniques. By employing spatial interaction statistics such as Moran's I, Local Indicators of Spatial Association (LISA), and Getis-Ord statistics, this research identifies spatial clustering of subjective poverty, with high-poverty clusters concentrated in the southeastern and eastern provinces and low-poverty clusters in the western provinces. This methodological emphasis on spatial clustering and interaction provides granular insights into the geographic patterns of subjective poverty that the other study does not explore.

There is no study specific to Turkey that makes spatial analysis of poverty using the subjective poverty indicator. This study differs from other studies in that it focuses on the spatial analysis of the subjective poverty of 81 provinces. In addition, the equality of subjective poverty distribution across spatially defined clusters was assessed using spatial heterogeneity tests. There is no study investigating heterogeneity in the distribution of poverty with this test approach. In this context, a different structure related to poverty will be revealed.

This study uniquely examines whether subjective poverty is uniformly distributed within spatial clusters using spatial heterogeneity tests, providing a novel approach to understanding regional poverty dynamics. This paper contributes to the broader literature on the spatial analysis of poverty by: i) Introducing a comprehensive spatial analysis of subjective poverty across all provinces in Turkey, which has not been previously done. ii) Employing spatial heterogeneity tests to investigate the equality of subjective poverty distribution within spatial clusters, offering a new methodological perspective. iii) Enhancing understanding of how subjective poverty correlates with spatial factors and regional interactions, thereby enriching the discourse on poverty's geographical dimensions. These contributions provide valuable insights into the spatial dynamics of poverty, emphasizing the importance of subjective indicators and advancing methodological approaches in regional poverty analysis.

3. DATA AND EMPIRICAL METHODOLOGY

3.1. Data

Subjective poverty (SP) data is limited in Turkey as well as in the world. In the study of the life satisfaction indexes of the provinces, which was last done by TurkStat in 2015, individuals were asked whether they meet their basic needs for 81 provinces and the "proportion of households who declared that they could not meet their basic needs" was calculated based on the data obtained (TurkStat, 2015). The rate of households declaring that they cannot meet

Table 1: Descriptive Statistics of Subjective Poverty.

Variable	Obs	Std. Dev.	Mean	Min	Max	Skewness	Kurtosis
SP	81	50.96	10.19	32.80	75.00	0.731458	2.767801

their basic needs is a subjective poverty indicator. The most up-to-date data on subjective poverty (SP) belongs to 2015. There is no data measuring subjective poverty after this year. There are 32 provinces out of 81, while the proportion of households declaring that they cannot meet their basic needs is 50% and above, there are 49 provinces with a ratio below 50%. The proportion of households who declared that they could not meet their basic needs was evaluated as a subjective poverty measure because it was calculated based on the taste and evaluation of the people. The spatial distribution of subjective poverty was examined by using this ratio calculated by TurkStat for each province. The study of the TurkStat's is a research that aims to measure, compare and monitor the quality of life in provinces at the provincial level in terms of various life dimensions using objective and subjective indicators. TurkStat's study aims to measure, compare, and monitor the lives of individuals and households in the provinces of Turkey at the provincial level, using objective and subjective indicators, distinguishing between life dimensions (TurkStat, 2015). Descriptive statistics of subjective poverty are presented in Table 1. TurkStat's study aims to measure, compare, and monitor the lives of individuals and households in the provinces of Turkey at the provincial level, using objective and subjective indicators, distinguishing between life dimensions (TurkStat, 2015). Within the scope of the study, data were collected in 81 provinces in Turkey using the survey technique. Descriptive statistics of subjective poverty are presented in Table 1.

3.2. Empirical Methodology

In this study, which will be conducted on the regional distribution of subjective poverty, primarily spatial dependency statistics were used. Spatial dependency or spatial autocorrelation indices, which are the statistical projections of Tobler's (1970) law of geography, are the spatial or spatial correlations between the values of the same variable at different locations in space. This autocorrelation is when the observation values of a variable are positively or negatively correlated with itself due to their spatial location (Bouayad-Agha and De Bellefon, 2018). Spatial autocorrelation is positive when similar values of a variable constitute a geographical group. This autocorrelation is negative when the dissimilar values of a variable are clustered geographically. In such a case, geographically close locations are different from distant locations. This can happen when there is spatial competition. In the absence of spatial correlation, the spatial distribution of the observations is random. In order to measure this correlation, firstly, spatial proximity is measured and then spatial similarity or dissimilarity is investigated. The spatial autocorrelation index that measures geographical similarity is as follows.

$$\mathrm{Corr}(Y, WY) = \frac{\mathrm{Cov}(Y, WY)}{\sqrt{\mathrm{Var}(Y) \cdot \mathrm{Var}(WY)}} \tag{1}$$

Here, WY is the mean of the variable Y in the neighborhood of each spatial unit. This correlation formula is very general. Different indices have been developed to test spatial correlation: Some of these indices are global and thus provide a single value for the area under investigation. In addition to the global indexes, there are also local statistics examining the structure of each field in the study area.

In this study, global and local autocorrelation tests, which are among the spatial autocorrelation tests, will be discussed. The methodology of global Moran's I and local Moran's I statistics and G_i statistics, which is another local spatial autocorrelation statistics, will be explained. Then, the methodology of the H_i statistic, which is one of the tests investigating spatial heterogeneity in local cluster areas, will be explained.

3.2.1. Spatial Autocorrelation Tests

The most widely used index among the global indexes is the Moran's I statistic. The Moran's I statistic is based on the difference of each observation from the mean of all observations. The test statistic proposed by Moran (1948) is given in equation 2.

$$\mathrm{I} = \frac{\left(\sum_i \sum_j w_{ij} \cdot z_i \cdot z_j / S_0\right)}{\left(\frac{\sum_i z_i^2}{n}\right)} \tag{2}$$

Here, $z_i = x_i - \bar{x}$ is the variable with reduced slope; $\bar{x}$ is the mean of the x variable and w_{ij} are the elements of the spatial weight matrix. $S_0 = \sum_i \sum_j w_{ij}$ is the sum of the weight matrix observation values, and n is the number of observations. $S_0 = n$ when the weights are standardized at the row level. The numerator and the two values in the numerator in equation 2 cancel each other out.

There is a spatial random distribution in the null hypothesis of this statistic. *Under the alternative hypothesis, it is assumed that there is spatial clustering.* Moran's I statistic has a normal distribution. There is also an analytical distribution with a permutation approach based on a reference distribution.

A spatial structure can be read quickly through the scatter diagram of Moran's I statistics. This diagram is shown for subjective poverty in Figure 2 in the next section with application findings. Let x be the subjective poverty variable whose spatial scatter is examined. The values of this x variable are located on the horizontal axis of this scatterplot. On the y-axis, there is the mean (W_x) of the values of the x variable in the neighboring observations. If the observations of a variable are randomly distributed in space, it means that there is no relationship between x and W_x. The observations in the upper right part of the diagram are higher than the neighboring mean value of the values of the relevant variable. Therefore, positive spatial autocorrelation and high index value occur in this part. Here the structure is labeled H-H (high-high). In the lower left part, the observation values of the variable are lower than the mean. Here, there is similarity due to being neighbors and therefore there is positive spatial autocorrelation and low index value. The structure here is L-L (low-low). In the lower right, the observation values of the relevant variable are higher than the mean value in the dissimilar neighborhood, so there is negative autocorrelation and the index value is high, but the structure here is H-L (high–low). In the upper left part of the diagram, the observation values of the related variable are lower than the mean value in the dissimilar neighborhood. Therefore, there is negative autocorrelation and the index value is low. The structure here is L-H (low-high).

The Moran's I statistic is global since it is about the spatial structure in the studied area, but it does not provide information about the positions of the clusters. The LISA statistic developed by Anselin (1995) provides this information. This statistic, which is a local indicator of spatial association, provides a separate statistic for each location and this statistic is the local version of the Moran's I statistic. This statistic, which can detect local clusters or local outliers, is presented in equation 3.

$$\mathrm{I}_i = \frac{\sum_j w_{ij} \cdot z_i \cdot z_j}{\sum_i z_i^2} \tag{3}$$

The significance of this statistic is based on the conditional permutation approach. In the Moran diagram, classification is made based on the combination of the local Moran's I statistics of each observation and its significance. Significant location clusters H-H and L-L spatial clusters and H-L and L-H spatial extremes are determined. The first two clusters are also called high spot or high spot clusters and low spot or low spot clusters, respectively. Spatial outliers are the H-L and L-H fields.

Another statistic developed regarding the local or individual location of the spatial autocorrelation concept is presented by Getis and Ord (1992). This statistic is one of the first to be developed. This analysis, which serves to identify statistically significant high and low spots or locations, was later developed by Ord and Getis (1995). It is based on the logic of point pattern analysis. As originally formulated, the statistic was based on a ratio of observations within a given point range to all observations. A more general application of the statistic would be considering the values at neighboring locations as defined by the spatial weights. In this developed analysis, there are two types of measurement: With the G_i^* statistic, the value of a location and its neighbors is included in the calculation, and the other G_i statistic ignores the information of a location itself and only considers information from neighboring locations. These statistics are shown in equations 4 and 5.

$$\mathrm{G}_i = \frac{\sum_{i \neq j} w_{ij} \cdot x_j}{\sum_{j \neq i} x_j} \tag{4}$$

$$\mathrm{G}_i^* = \frac{\sum_j w_{ij} \cdot x_j}{\sum_j x_j} \tag{5}$$

The Getis-Ord statistic takes values between -1 and -1. Four values are obtained with the G test. First, the p-value is examined. The fact that the obtained p-value is statistically small and significant indicates that the observation values are spatially clustered. Getis-Ord statistics are evaluated as follows: $G_i > 0$ means that there is a grouping with values larger than the mean, and $G_i < 0$ means that values lower than the mean form a group. In the absence of local spatial dependence, this statistic has a normal distribution. Contrary to Local Moran statistics, Getis-Ord approach does not provide information about negative spatial correlation, that is, spatial outlier value collection. Distributions of these statistics can also be obtained with conditional random permutation approaches.

LISA defines local clusters and spatial outliers. Unlike the Local Moran statistic, the Getis-Ord method does not account for spatial outliers. Using these distinct statistical approaches, the spatial correlation of subjective poverty was analyzed. This enabled the measurement of the effects of different calculation methods on the results, facilitating a comparative analysis.

3.2.2. Local Spatial Heterogeneity (LOSH) Test: H_i Statistics

The local heterogeneity or locally varying variance statistic proposed by Ord and Getis (2012) is similar to the G_i statistic proposed by Ord and Getis. For example, when high crime rate clusters are detected in crime analysis, it determines whether these areas are equally dangerous. At the same time, it is revealed whether areas consisting of a mixture of safe and dangerous are equally safe-dangerous. A local mean of position i is defined as follows,

$$\bar{x}_i = \frac{\sum_j w_{ij} \cdot x_j}{\sum_j w_{ij}} \tag{6}$$

This average is calculated for each location and then local residuals are obtained as follows.

$$\mathrm{e}_j = x_j - \overline{x}_j, \quad j \in S_i \tag{7}$$

So, the H_i statistic is as follows.

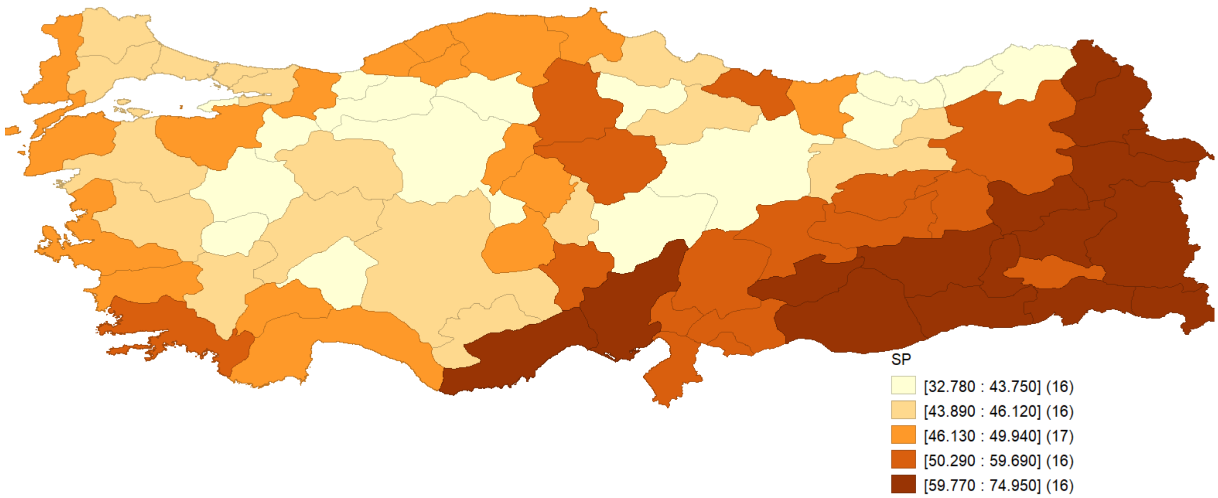
$$\mathrm{H}_i = \frac{\sum_j w_{ij} \cdot |e_j|^{\alpha}}{\sum_j w_{ij}} \tag{8}$$

Here, $a = 1$ means that deviation based on absolute measurement is obtained. If $a =$ 2, it is a measurement based on variance. The LOSH statistic determines the statistical significance of heterogeneity within a local area such as high spots. With this test, it is tested whether a local region is different from its neighbors (Chen and Tao, 2022).

4. EMPIRICAL FINDINGS

The use of quartile maps is quite common in spatial analysis applications. These maps divide a dataset into equal parts according to the determined number of quartiles. In this direction, the quartile map of the SP variable was examined. This map is given in Figure 1, the provinces with the highest subjective poverty rate are shown in the darkest colors. As the colors become brighter, the subjective poverty rates decrease. It is observed that the provinces in the Eastern and Southeastern Anatolia Regions affect each other positively and form clusters at a high rate. Therefore, it can be said that there is a spatial dependence visually.

Figure 1: Distribution of the SP Variable



It is seen that the subjective poverty rates decrease gradually as the color gets lighter on the map. In the provinces in yellow, this statement is at a lower level. The values of the variables are affected more by the observation values that are geographically close to each other, and thus a similarity occurs. Moran's I statistics was calculated in order to investigate whether there is a similarity between the provinces in terms of the SP variable. The spatial weight matrix to be used in the analysis was created according to the definition of queen neighborhood. The Moran's I scatter plot of this statistic is given in Figure 2.

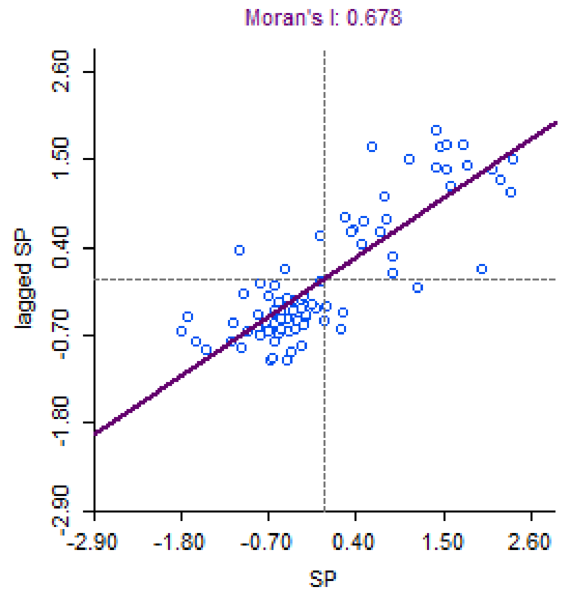
When this scatter diagram created for the SP variable is examined, it is seen that there is a significant a priori positive spatial autocorrelation in the variable. The p value of this statistic based on 999 permutations is 0.001. The hypotheses to test spatial autocorrelation are as follows;

$$\begin{aligned} H_0 &: \text{ There is no spatial autocorrelation.} \\ H_1 &: \text{ There is spatial autocorrelation.} \end{aligned}$$

Moran's I statistic takes values between 0 and 1. The estimated Moran's I statistic value of 0.678 for queen contiguity based spatial weights. According to this result, there is a moderate spatial relationship. This positive value indicates the presence of positive autocorrelation. The p value of this statistic based on 999 permutations is 0.001. In the context of the provinces of Turkey, it can be said that there is a similarity or clustering in terms of the SP variable. The equivalent of this similarity for each province was calculated with LISA statistics. The LISA clustering map is as in Figure 3.

As can be seen from the map given in Figure 3, the provinces with the highest subjective poverty rate low Turkey's average are generally southeastern provinces and the cluster formed

Figure 2: Univariate Moran's I Scatter Plot of SP (Queen Weight)



by these provinces are high spot regions. In other words, neighboring provinces with a high subjective poverty rate form a cluster together. The provinces in these high spot regions shown in red are as follows, in order of significance values: Adıyaman, Ağrı, Gaziantep, Kars and Şırnak are significant at the 1% level. Bingöl, Hakkari and Iğdır are significant at the 5% level. Batman, Bitlis, Diyarbakır, Mardin, Muş, Siirt, Şanlıurfa and Van are significant at the 10% level.

The subjective poverty rate is low in the provinces (blue colored ones) in the low spot cluster and these provinces form a cluster together. There is a similarity between these provinces due to spatial spread or spatial interaction. The distribution of these provinces and provinces according to their p values is as follows; Bursa, Eskişehir, Kütahya and Sakarya are significant at the 1% level. Ankara, Balıkesir, Bilecik, Bolu, Manisa, Uşak and Zonguldak are significant at the 5%level. Afyon is affected by its neighbors at the 10% significance level.

The cluster map of the local G^* statistic are as in Figure 4.

The provinces belonging to the low spot-areas are as follows, respectively, according to their p values; Bursa, Eskişehir, Kütahya and Sakarya are affected by their neighbors at 1%, Ankara, Balıkesir, Bilecik, Bolu, Manisa, Uşak and Zonguldak at 5% and Afyon at 10% significance level. These provinces have a higher level of income per capita and industrialization compared to other provinces in Turkey. According to the G* statistic, the provinces belonging to the high spot-areas are, respectively, Adıyaman, Ağrı, Gaziantep and Kars 1%, Bingöl, Hakkari and Iğdır 5%, Batman, Bitlis, Diyarbakır, Mardin, Muş, Şanlıurfa, Siirt, Şırnak and Van 1% from their neighbors is affected.

It has been observed that the provinces in the high spot area and the cities in the low spot area obtained by LISA statistics and Getis-Ord G_i^* statistics are the same. Subjective poverty values with outlier values do not have a significant effect on the LISA statistics.

Figure 3: Local Moran's I (LISA) Statistical Cluster Map

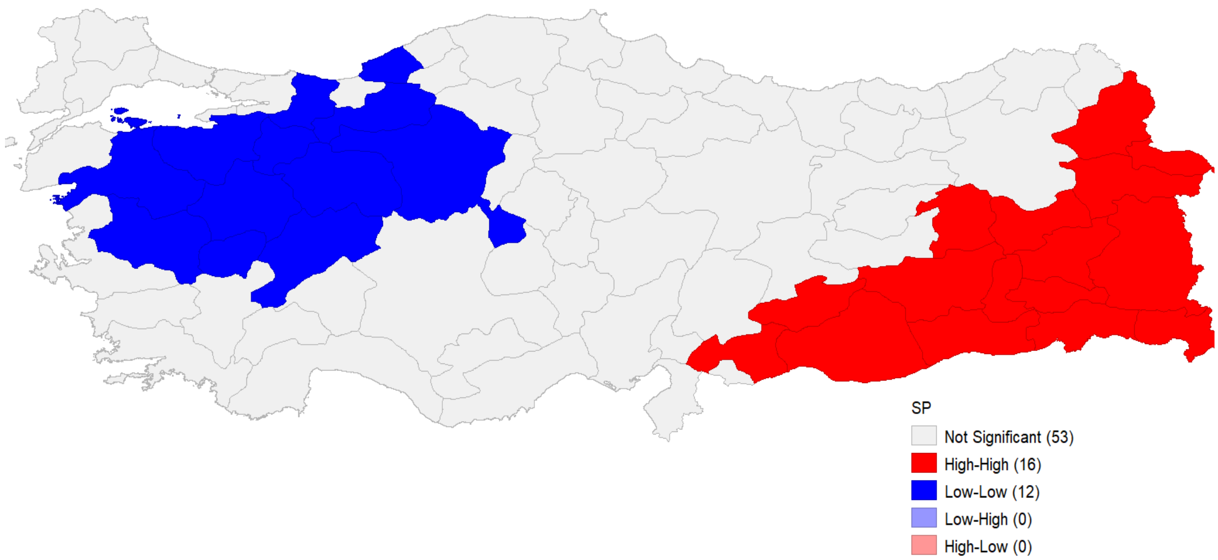
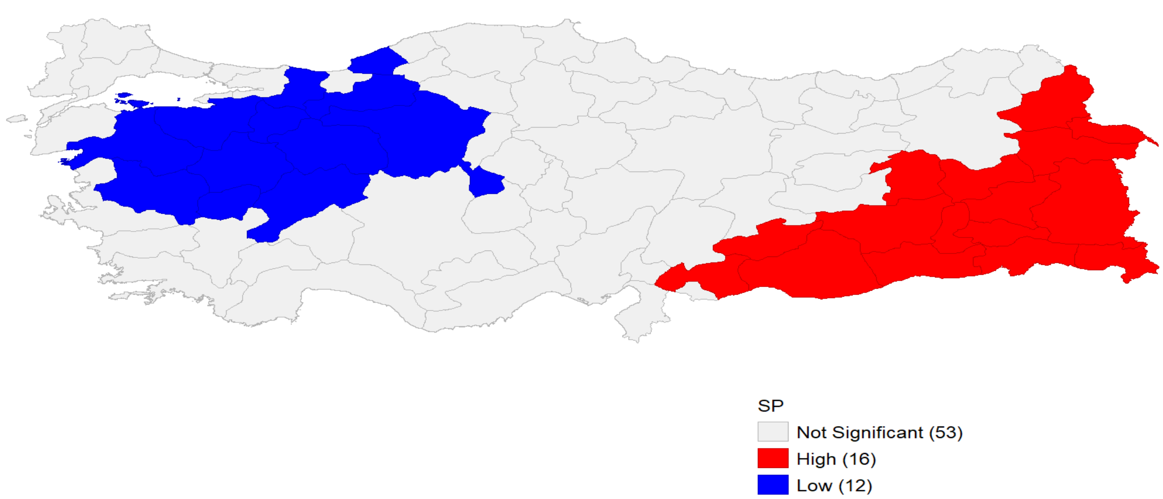


Figure 4: Clustering Map of Provinces by Local G^* Statistics



Therefore, the same results are obtained. The differences between these two statistical calculations are the differences in the confidence levels of the provinces as high spots or low spots. Yıldırım et al. (2019) obtained high and low spot regions and the provinces in these regions with LISA statistics are as follows. While TR10 (Istanbul), TR21 (Tekirdag, Edirne, Kırklareli), and TR42 (Kocaeli, Sakarya, Duzce, Bolu, Yalova) show those with high values surrounded by high values, TRB1 (Malatya, Elazig, Bingol, Tunceli) show those with low values surrounded by low values. According to the analysis conducted by Yıldırım et al. (2019), who investigated the local spatial correlation for objective poverty, high spot and low spot regions and the provinces included in these regions are different from the results found in this study. High spot provinces from this study are the provinces located in the northeast and south of the country. Low spot provinces are mostly located in the central and western regions of the country. According to the studies of Yıldırım et al. (2019), high spot regions are located in the northwest and low spot provinces are the provinces located in the east of the country. Only Bolu province is the province where spatial correlation was detected in both studies. However, according to Yıldırım's study, Bolu province in TR42, which is a high spot region, was detected as a low spot in this study. When both studies were evaluated together, it was found that the provinces with high and low objective poverty and subjective poverty were different. It is important to note that in contrast to this study, Yıldırım et al. (2019) included objective poverty data from provincial levels within the regions when analyzing spatial poverty.

The results of the spatial heterogeneity H_i statistics are given in Table 2. This statistic is a statistic that shows whether a region is different from its neighbors. As can be seen from the table, these statistical values are meaningless in the results of the provinces in general. In terms of subjective poverty rate, it can be said that the provinces have the same level as their neighbors. The provinces of Antalya and Ardahan are statistically significant at the level of 10%, while the provinces of Artvin, Erzurum and Karaman are statistically significant at the level of 5%. Among Turkey's 81 provinces, only these provinces' subjective perceptions of poverty differ from their neighbors. These provinces are not high and low spot provinces according to local spatial dependency statistics. According to Ord and Getis (2012), H_i and G_i statistics are usually evaluated together. Whether the subjective poverty rate is evenly distributed in the cluster obtained with the G_i statistic is revealed with H_i the insignificance of the H_i statistics for the provinces in the high and low spot areas means that these provinces are surrounded by similar neighborhoods in the context of subjective poverty.

Relative poverty rates for IBBS 2nd Level regions have been calculated by TurkStat with an objective poverty approach, based on 50 percent of the equivalent household disposable median income. According to the Regional Results of the Income and Living Conditions Survey of TurkStat for 2021, the regions with the highest relative poverty rates are TRC3 (Mardin, Batman, Şırnak, Siirt) and TRA2 (Ağrı, Kars, Iğdır, Ardahan) with 13.7% (Turkish Statistical Institute-TurkStat, 2022). In the same study, it was stated that the lowest annual average equivalent household disposable income was realized in TRB2 (Van, Muş, Bitlis, Hakkari) region with 18 thousand 278 TL. These relative regional poverty results reached by TurkStat with the objective poverty approach are similar to the spatial extent of subjective poverty reached in the study. In addition, Özbilgin (2016) and Yıldırım et al. (2019) exam-

Table 2: Spatial Heterogeneity Statistics

Provinces	H_i	Provinces	H_i	Provinces	H_i
Adana	1.304	Edirne	0.022	Malatya	1.717
Adıyaman	0.453	Elazığ	1.025	Manisa	0.641
Afyonkarahisar	1.284	Erzincan	0.706	Mardin	1.681
Ağrı	0.428	Erzurum	2.521**	Mersin	0.494
Aksaray	0.101	Eskişehir	0.583	Muğla	0.109
Amasya	0.654	Gaziantep	0.991	Muş	1.442
Ankara	0.234	Giresun	1.142	Nevşehir	0.590
Antalya	2.010*	Gümüşhane	0.371	Niğde	1.424
Ardahan	2.689*	Hakkari	0.312	Ordu	0.711
Artvin	4.124**	Hatay	0.461	Osmaniye	0.541
Aydın	0.179	Iğdır	1.534	Rize	2.079
Balıkesir	0.650	Isparta	0.156	Sakarya	1.123
Bartın	0.447	İstanbul	0.009	Samsun	0.902
Batman	1.218	İzmir	0.109	Şanlıurfa	1.796
Bayburt	0.498	Kahramanmaraş	1.549	Siirt	0.638
Bilecik	0.978	Karabük	0.431	Sinop	0.546
Bingöl	1.093	Karaman	1.733**	Şırnak	1.075
Bitlis	1.891	Kars	4.008	Sivas	0.806
Bolu	0.943	Kastamonu	0.456	Tekirdağ	0.045
Burdur	1.181	Kayseri	0.745	Tokat	1.259
Bursa	0.733	Kilis	0.273	Trabzon	0.072
Çanakkale	0.047	Kırıkkale	0.591	Tunceli	0.462
Çankırı	0.419	Kırklareli	0.058	Uşak	0.677
Çorum	0.346	Kırşehir	0.306	Van	1.603
Denizli	0.417	Kocaeli	0.721	Yalova	0.408
Diyarbakır	1.079	Konya	1.390	Yozgat	0.844
Düzce	0.837	Kütahya	0.415	Zonguldak	1.277

Note: ** and * indicate significance at the 5% and 10% level, respectively.

ined the spatial distribution of objective poverty rates (relative poverty) in Turkey. Although the spatial distribution of the subjective poverty in this study is similar to the distribution they obtained, there are differences for some provinces.

According to the GDP per capita calculations of TurkStat for the year 2021, Van is in the last three places for 81 provinces with 27 thousand 790 TL, Şanlıurfa with 27 thousand 48 TL and Ağrı with 26 thousand 837 TL. In addition to these, the per capita GDP values of other provinces (Adıyaman, Gaziantep, Kars, Bingöl, Hakkari, Iğdı, Batman, Bitlis, Diyarbakır, Mardin, Muş, Şanlıurfa, Siirt and Şırnak) that show the spatial neighborhood of subjective poverty are at the bottom of the 81 provinces ranking (TurkStat, 2022). The income and relative poverty findings of TUIK can be accepted as an answer to the question of why the subjective poverty reached in the study is clustered in some neighboring provinces.

In all of the analyzes above, it is seen that the majority of the provinces with high subjective poverty are in the South East Anatolia and East Anatolia regions. Turkey has been implementing the Southeastern Anatolia Project (GAP) in nine provinces (Adıyaman, Batman, Diyarbakır, Gaziantep, Kilis, Mardin, Siirt, Şanlıurfa and Şırnak) for the development of the Southeastern Anatolia region since the 1970s. Among the high spot provinces in this study, there are other GAP provinces except Kilis. It has also been confirmed that the continuation of remedial work towards this region with a high poverty cluster is an appropriate policy.

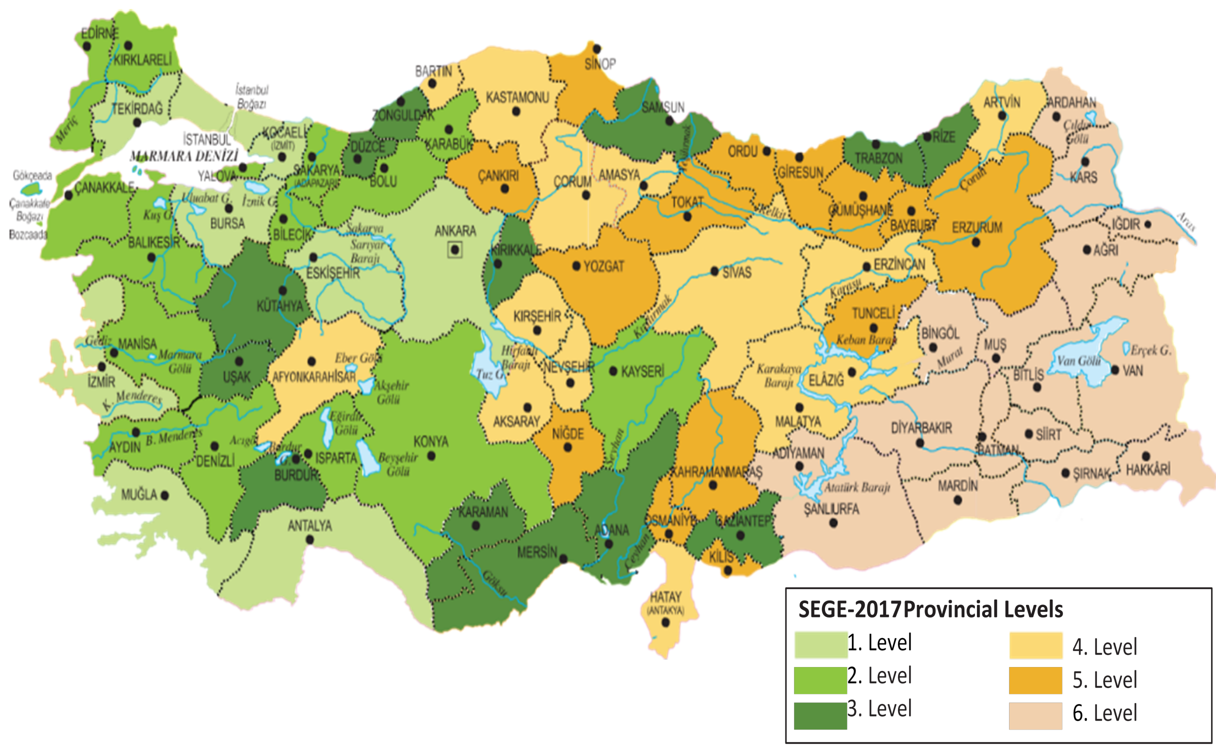
It can be said that the provinces in the southeast and east of Turkey experience more poverty than the provinces in other regions. In the Socio-Economic Development Ranking Survey (SEDI) conducted for all provinces by the Ministry of Industry and Technology in 2017, the highest level is 1 and the lowest level is 6 (Acar et al., 2017). According to the results of the study, high spot provinces and low spot provinces coincide with SEDI's 6th level provinces and 1st level provinces, respectively. In other words, the high level of subjective poverty showed a significant spatial distribution in the provinces in the 6th stage of the SEDI study. Low subjective poverty showed a significant spatial distribution in provinces in the 1st and 2nd stages of the SEDI study (Figure 5).

Demographic, labor market, education, health, competitive and innovative capacity, financial, accessibility and quality of life indicators in provinces where subjective poverty is spatially low are lower than in other provinces. It can be said that these factors lead to high subjective poverty. Because poverty is characterized by spatial patterns of social, economic, demographic, health, education, a developed infrastructure and political factors.

This study contributes to the existing scholarship on poverty in Turkey by employing a subjective poverty measure and analyzing it at the provincial level. i) Subjective measure: Traditionally, poverty is measured by income thresholds. However, this study utilizes the inability to meet basic needs as reported by individuals. This subjective approach captures the lived experience of poverty, potentially revealing areas where official income-based measures might miss crucial aspects. By including subjective experiences, we gain a more nuanced understanding of poverty across Turkish provinces. ii) Provincial-level data: Analyzing provincial data allows us to identify geographic clusters of subjective poverty. This can be particularly insightful for policymaking, enabling targeted interventions in regions with the highest concentrations of perceived deprivation.

The spatial clustering of subjective poverty, with high rates concentrated in the southeast and eastern regions and lower rates in the west, aligns with existing literature on income inequality in Turkey. However, this study goes beyond simply confirming existing patterns. By employing a subjective measure, we potentially capture additional dimensions of poverty not fully reflected in income data alone. For instance, subjective poverty might be higher in regions with limited access to essential services, even if income levels appear adequate on paper.

Figure 5: Levels of Socio-Economic Development by Socio-Economic Development Ranking Survey



5. CONCLUSION

In this study, the structure of subjective poverty in the spatial distribution of Turkey's provinces was investigated by spatial autocorrelation and spatial heterogeneity tests. Among the spatial autocorrelation tests, global and local Moran's I statistics and Getis-Ord G_i^* statistics were used. According to the findings obtained from these tests, it has been revealed that there is a similarity between the provinces in terms of subjective poverty due to locational similarity or proximity. The poverty of the neighbors of a province where poverty is high or low affects the poverty of that province. This situation was observed in the Moran's I scatterplot. With the local Moran's I or LISA, information on clusters, high spot areas and low spot areas and outliers related to subjective poverty was obtained. The subjective poverty level is high in high spot areas and the subjective poverty level is low in low spot areas. These two areas are areas of spatial positive autocorrelation. Negative spatial autocorrelation areas are outlier cluster areas. The Getis-Ord G_i^* local spatial autocorrelation statistics, which detects only the presence of positive autocorrelation, are similar to the LISA statistics. According to both statistics, the provinces in the high spot cluster are Adıyaman, Ağrı, Gaziantep, Kars, Bingöl, Hakkari, Iğdır, Batman, Bitlis, Diyarbakır, Mardin, Muş, Siirt, Şanlıurfa, Şırnak and Van. Subjective poverty levels are high in these provinces clustered in the high spot area. The reason for the clustering of high areas originating from the neighborhood is that these provinces are similar in terms of subjective poverty due to locational similarity. Provinces with low subjective poverty and in the low - low spot area; Bursa, Eskişehir, Kütahya, Sakarya, Ankara, Balıkesir, Bilecik, Bolu, Manisa, Uşak, Zonguldak and Afyon provinces. These provinces are the provinces located in the inner western region of Turkey, which are adjacent to each other. The heterogeneity statistic was obtained according to H_i, where the provinces in the high and low point clusters have equal subjective poverty with their neighbors. This statistic, known as the local variable variance statistic, measures whether the perception of poverty is equal within the clusters of low and high spots or whether a province in this cluster is different from its neighbors. The subjective poverty levels of the provinces in the high and low spot areas were found to be the same as their neighbors. Accordingly, provinces in high and low spot areas are surrounded by similar neighborhoods in the context of subjective poverty. Yıldırım et al. (2019) investigated the poverty line values for NUTS 2. Unlike Yıldırım et al. (2019), this study examined the NUTS 3 level. Thus, a more micro framework was examined. Thus, the spatial correlation for subjective poverty was revealed for each province in Turkey. In addition, another difference in this study was revealed with the H_i statistic whether high spot and low spot provinces were different from their neighbors. No other academic publication was found that used this statistic in studies on poverty. This is one of the main contributions of the study.

Most provinces clustered with high poverty rates have low levels of health, education, per capita income and quality of life. Poor health, low levels of education, and an underdeveloped infrastructure are key factors contributing to poverty. In essence, poverty is intricately linked to inadequate health, education, and income distribution. In this respect, it is recommended to increase policies aimed at improving these adverse conditions in the eastern and southeastern provinces clustered with high poverty. The GAP project, which was implemented to eliminate the development gap of Southeastern Anatolia with other regions, has not focused on the development of the infrastructure of the energy and agriculture sectors until today. The policies targeted by the GAP project can then be revised to focus on poverty-reducing structural reforms so that individuals in the region are not exposed to high poverty.

The policies targeted by the GAP project can then be revised to focus on poverty-reducing structural reforms so that individuals in the region are not exposed to high poverty. It is recommended to focus on projects that directly increase the income of the households within the scope of the Eastern Anatolia Development Program implemented in the Eastern Anatolia region, another region where subjective poverty is heavily clustered. In addition, it can be an effective tool for the development agencies established to make regional development effective, allocating resources to poverty-reducing practices that are inclusive of households. In Turkey, household heads in regions where subjective poverty is spatially concentrated should be trained so that they can be aware of their abilities, and industrial investments that will increase per capita income in these provinces should be increased.

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