



Spatial analysis of multidimensional poverty in Pakistan: Do income and poverty score of neighboring regions matter?

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Abstract Eradication of multidimensional poverty remains a significant issue for a number of low-income countries. It has significantly influenced economic development worldwide, and its abolition would improve human well-being and prosperity. In this study, a multidimensional poverty (MDP) index has been constructed by adopting the Alkire-Foster methodology and Geographic Information System application to (i) measure the multidimensional poverty in all districts of Pakistan, (ii) recognize the spatial patterns concerning MDP in Pakistan, (iii) examine the impact of per-capita income on MDP in Pakistan and, (iv) assess the spatial impact of neighbors' poverty scores on MDP. The findings of the study indicated that the magnitude of both headcount and MDP varies across provinces and was found to be higher and lower in Balochistan and Punjab, respectively. The spatial results revealed that in terms of both MDP and headcount poverty, the majority of Punjab districts were significantly clustered in low and very low quantiles (low-low quadrants) whereas districts from Balochistan were concentrated in high and very high quantiles (high-high quadrants).

Furthermore, the spatial regression showed that per capita income had substantially reduced the incidence of poverty both directly and indirectly. Most importantly, the poverty score of neighboring districts has significantly influenced the incidence of district own MDP. Based on the instant spatial results, Balochistan is considered the highly poverty-stricken province of Pakistan that needs government intervention and policy makers' prioritization towards the study indicators to eradicate the incidence of multidimensional poverty.

Keywords Living standard · Multidimensional poverty · Sociodemographic indicators · Spatial autocorrelation · Spatial error model · Spatial lag model

Introduction

Alleviation of extreme poverty is a complicated target as 10 percent of the world population (734 million people throughout in the year 2020) are still below 1.9 dollars per day (UNDP, 2015a; World Bank, 2020). Traditionally, improvement towards per capita income (unidimensional) had been deemed to be the key element to enhance economic development. This resulted in an unequal distribution of income among countries as well as among various regions within a country; thus, a larger portion of the income goes into the hands of a few people (Walker, 2007). The

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income inequality creates extreme poverty which, in turn, shrinks economic development and prosperity (Brueckner & Lederman, 2015; Gurgul & Lach, 2011; Manduca, 2019; Peach & Adkisson, 2020; Ray & Linden, 2018). Previous literature evidenced that significant regional income and wealth inequalities persist worldwide with the varied extent from country to country (Cörvers & Mayhew, 2021; Manduca, 2019; Panzera & Postiglione, 2020; Peach & Adkisson, 2020; Rey, 2004; Siddique & Khan, 2021; Walker, 2007).

In the modern era, the traditional unidimensional approach of poverty has been limited as (Sen, 1994) highlighted that poverty is a composite phenomenon, and no single factor is fully grasping its universal features. Poverty is a dynamic and multidimensional concept. In this context, researchers have adjusted the phenomenon from the traditionally unidimensional (monetary-based) poverty to a more advanced multidimensional view (Alkire & Foster, 2011a, 2011b; Alkire & Roche, 2013; Anand & Sen, 1997; Malik, 2013; Sen, 1994). Socioeconomic, health, housing, education, and other dimensions also play a crucial role in the comprehensive measurement of multidimensional poverty. For instance, (Alkire & Foster, 2011a, 2011b; Bourguignon & Chakravarty, 2019; Thomas et al., 2009) measured the multidimensional poverty by incorporating indicators from various domains, such as income, food, clothing, education, health, employment, housing and other variables.

Being a low- and middle-income country, Pakistan had practiced various poverty alleviations as well as various developmental programs such as “Ehsaas” to eradicate severe poverty (Government of Pakistan, 2020). As a result, over time, the multidimensional poverty (MPI), headcount poverty (H), and average deprivation share (A) declined significantly from the year 2004/05 to the year 2014/15. MPI, H, and A dropped from 29.2%, 55.2%, 52.9%, respectively, to 19.7%, 38.8%, 50.9%, respectively (Government of Pakistan, 2016). By adopting various developmental reforms, Pakistan is capable to capture the United Nations Development Programme (UNDP)’s Sustainable Development Goals (SGDs) of “No poverty” (UNDP, 2015b). Extensive literature on multidimensional poverty assessment has been found in Pakistan (Awan & Aslam, 2011; Idrees & Baig, 2017; Iqbal & Nawaz, 2017; Khan & Akram, 2018; Khan et al., 2014, 2016; Padda & Hameed, 2018) in

which the majority of the studies measured the multifaceted poverty at the geographical and provincial levels, and this resulted in the persistence of significant geographical inequalities (Khan et al., 2014). It is because the equitable access towards poverty-related socioeconomic, health, educations, housing, and other indicators/dimensions varies among various regions within a country. In the context of such drastic inequalities, the United Nations Development Program’s (UNDP) integrated Sustainable Development Goals (SDGs) Agenda of 2030 unanimously agrees on a need to reduce inequalities (SDG goal; 10 of reduced inequalities) between and within countries to enhance the human well-being (UNDP, 2015b). Therefore, the abolition of chronic poverty and reduction of inequalities among regions are the two key elements of economic development and a primary objective of nations throughout the world.

As for Pakistan, the growing population threatened people’s accessibility towards the multidimensional poverty-related indicators. As a result, significant disparities/inequalities in Pakistan concerning multidimensional poverty had been realized at geographical and provincial levels. In addition, it is also apparent that regions from one province are multidimensionally poorer than regions from other provinces (Iqbal & Nawaz, 2017; Khan et al., 2015; Khan et al., 2014; Khan & Akram, 2018). Given the latter, the researchers would investigate in depth the spatial patterns/clusters and dependence/correlations concerning multidimensional poverty.

Spatial analysis has a strong connection with Waldo Tobler’s first law of geography presented in 1970 that “everything is related to everything else, but near things are more related than distant things” (Miller, 2004; Tobler, 1970). The law became popular in 1990 when it became the foundation of spatial analysis (Dempsey, 2014). Considering the importance of spatial analysis, identification of atypical locations (presence of clusters or hotspots and cold spots) and outliers concerning multidimensional poverty has also become a new hot topic. Hot spot is a spatial cluster where a region with high value is surrounded by neighbors with high values, whereas cold spot is a cluster of regions where a region having low score is surrounded by neighbors who also have lower scores. Both hot spots and cold spots are considered positive spatial clusters. Contrast to positive clusters, a negative spatial cluster

is when a region with low (or high) value is surrounded by neighboring regions with high (or low) values (Anselin, 1995; Anselin et al., 2010). Previous studies utilized spatial econometric techniques to understand the spatial clusters and outliers concerning multifaceted poverty (Karahasan & Bilgel, 2021; Torres et al., 2011; Turriago-Hoyos et al., 2020; Wang & Wang, 2016; Wang et al., 2018). In Pakistan, spatial analysis of multidimensional poverty is rarely studied (Iqbal & Nawaz, 2017; Khan et al., 2014, 2015). For instance, recently Najam (2021) examined whether similar trends exist in poverty when the analysis is made either by using the conventional (unidimensional) income approach or the more advanced multidimensional approach to estimate the poverty measures. She did not focus on measuring the spatial impact of income and poverty scores of neighboring districts on the incidence of district of poverty.

To summarize, these studies have only focused on measuring the inequalities among provinces of Pakistan's multidimensional poverty, and no special consideration is given to investigate the spatial patterns (e.g., spatial clusters or outliers among various regions within the country). Considering the importance of multidimensional poverty and spatial analysis, the present study is the first attempt to address multidimensional poverty spatially. The contribution of this study to the existing literature is as follows:

- It measures poverty (by utilizing a multidimensional approach discussed in the methodology section in detail) in all districts of Pakistan.
- It recognizes the spatial clusters and/or spatial outliers concerning multidimensional poverty in Pakistan.
- It measures the spatial spillover impacts of income, a traditional measure used to recognize the impact on the multidimensional poverty, in Pakistan.
- Most importantly, this study is also designed to assess the impact of a neighbors' poverty score on multidimensional poverty by using the recent dataset of Pakistan Social and Living Standard Measurement (PSLM) survey, round-vii, 2019–20 (Pakistan Bureau of Statistics, 2020). Thus, the investigation of spatial clusters (hot spots and cold spots) and spatial outliers is momentous for policy planners in acknowledging the multidimensionally

poor/deprived areas to develop the appropriate policies.

Literature review

Literature review is the backbone of any significant research study. This section contains a detailed discussion on various socio-economic, demographic, health, housing, environment, etc., indicators that determine the multidimensional poverty. Most importantly, this section consists of a vast discussion on spatial patterns of MDP and regional inequalities concerning multidimensional poverty.

Khan et al., (2014) investigated multidimensional poverty across various regions of the Sindh province, Pakistan. For five time periods, data were collected from two sources: (1) Household Integrated Economic Survey (HIES) and (2) Pakistan Social and Living Standard Measurement Survey (PSLM). These surveys were conducted by the Pakistan Bureau of Statistics (PBS). The findings of the study showed that the magnitude of multidimensional poverty fluctuates significantly across various regions. They found that the substantial variations in MDP are mainly due to the disparities in the levels of deprivation of people's socioeconomic attributes. Moreover, from the study findings, it is also apparent that in comparison to urban areas, the magnitude of MDP is higher in rural areas across all regions of the province.

Similarly, Khan et al., (2015) conducted a study on spatial and temporal investigation of multidimensional poverty in rural areas of Pakistan. This study aimed to examine the variations in rural poverty across various regions of Pakistan with the application of a multifaceted poverty assessment framework. Multidimensional poverty was based on three main socio-economic domains: (1) Health, (2) Education, and (3) Housing. A total of 10 indicators were chosen from the dimensions mentioned earlier. Data on these critical dimensions were obtained from Households Integrated Economic Survey (HIES) and Pakistan Social and Living Standard Measurement Survey (PSLM) for different time periods. Their results revealed substantial disparities in the magnitude of rural poverty across various regions. An unpredictable declining trend of multidimensional poverty was apparent from one

time period to another. Further, the spatial–temporal analysis helped identify the areas where MDP was consistently high in all periods.

Wang and Wang (2016) conducted the following important study that proposed a multidimensional poverty methodology to measure the poverty-stricken counties and their significant determinants in China. The A-F methodology was used to construct the composite poverty index, and spatial analysis through Geographic Information System (GIS) evaluated the multidimensional poverty under different geographic and socioeconomic conditions. The findings of the study showed spatial patterns of poverty in the surrounding counties. Concerning poverty, the western areas showed significant aggregation effects, while the central and eastern regions showed the heterogeneous effects. Unsafe housing, family health and adult illiteracy, fuel type, and rate of the children's enrolment were significantly correlated. Moreover, all the three indices (H, A, and MPI) directly linked with the rocky desertification degree and topographic fragmentation degree.

Another study conducted by Iqbal and Nawaz (2017) estimated the spatial differences and socioeconomic determinants of health poverty in Pakistan by using the Alkire Foster (A-F) framework. This study mainly aimed to investigate the spatial inequalities in health poverty at the regional level and explore the socioeconomic determinants. The study outcomes revealed that the headcount of health poverty is higher in rural areas than in urban areas. Moreover, empirical analysis confirmed income, education, awareness, and regional variation as significant determinants of health poverty.

Vaziri et al. (2019) researched the spatial pattern of poverty in Malaysia. The main aim of the study was to illuminate the spatial configuration of poverty and examine the determinants of the spatial configuration of poverty by applying the hotspot as well as Geographically Weighted Regression (GWR) analysis. The study results revealed that the complexity of poverty is a serious issue in Malaysia as poverty demonstrated a clean and clear spatial cluster. Concerning poverty scores, most of the subdistricts located in the north-eastern states of Kelantan and Terengganu are significantly clustered as high poverty quadrants. Furthermore, they revealed these clusters worthy of consideration for the Malaysian Government to reduce/eradicate the incidence of poverty.

The next study was conducted by Salvacion (2020) to explore the spatial patterns and determinants of village-level poverty in the Philippines. To determine the spatial patterns and variables influencing poverty in study areas, this study applied the spatial analysis and Geographically Weighted Regression (GWR) model. According to the study results, high-high and low-high poverty incidence clusters were seen on the Marinduque Island, Philippines. Slope, annual rainfall, population growth rate, distance to ports, and distance to town centres were significant factors affecting the incidence of poverty. Also, the Geographically Weighted Regression (GWR) results showed that the effect of the above significant factors varies from village to village. Slope and annual rainfall had a higher effect on poverty incidence while the other variables had lower effects.

Like the previous study, Turriago-Hoyos et al., (2020) analysed spatially Colombia's multidimensional poverty with the Unsatisfied Basic Need (UBN) index approach. Data were taken from the available 2005 population census, and a spatial econometric technique was applied. The spatial analysis results confirmed the existence of spatial patterns (clusters and hot spots) in the Pacific Choco region, the Caribbean Coast, and the country's southern regions. The study also concluded that high levels of unemployment, a high proportion of ethnic minorities, low levels of urban population, and large size municipalities were seen in these spatial clusters and hot spots.

Li et al. (2020) explored the spatial determinants of rural poverty in the interprovincial border areas of the Loess Plateau in China. In this study, they examined the spatial heterogeneity of rural poverty patterns by using the Geographically Weighted Regression (GWR) technique. The results of the study exhibited significant association of county-level rural poverty to the county-level accessibility, water resource accessibility, and town-level accessibility. Furthermore, the effects of both county-level and town-level accessibility on rural poverty varied from border to border.

A similar study was conducted by Amaghous and Ibourk (2020) to analyse the regional inequalities in Morocco concerning multidimensional poverty. This study mainly focussed on two aspects. First, it analysed and described the patterns of multidimensional poverty, and second, it explored the convergence hypothesis. Data were extracted from HCP 2017 for

2004 and 2014, and analyses were conducted using spatial techniques. The study results depicted that multidimensional poverty is a regional concept that converges at slow speed. Moreover, this paper recommended some solutions for policymakers to reduce the spatial geographical disparities concerning multidimensional poverty.

Vasishtha and Mohanty (2021) attempted a study to examine the spatial association between multidimensional poverty and consumption poverty in India. Data were taken from the National Family Health Survey-4, 2015–16 and a multidimensional poverty index was constructed using Alkire-Foster methodology. To measure the spatial patterns of both multidimensional poverty and consumption poverty, Moran's I statistic, Local Indicators of Spatial Association (LISA), and cluster maps were used. The study revealed that 30.3 percent of the population is multidimensionally poor with an average intensity of 44.2 percent and MPI of 0.13. Variations in multidimensional poverty were found to be high from state to state. Moreover, the spatial regression results showed that multidimensional poverty is positively correlated with consumption poverty, and this association varied from one district to another district.

Recently, Das et al. (2021) examined the disparities in multidimensional poverty at the regional level in India. The study area was categorized in six regions: northern, eastern, north-eastern, central, western, and southern regions. This study also explored the multidimensional poverty across groups in each region. For this purpose, data were collected from the National Family and Health Survey for a decade (from 2005–2006 to 2015–2016), and regional variations were measured concerning multidimensional poverty. The results showed the highest and lowest MPI scores in eastern rural and northern regions, respectively. In addition, these regional variations increased by fourfold in 2015–2016 in comparison to 2005–2006. To reduce the inequalities, this study suggested that India's government adopt balanced regional policies.

Similarly, Ullah and Majeed (2022) measured the effect of institutional quality on multidimensional poverty and human development on the district-level by applying the spatial autoregressive technique and decomposing the total effect into direct and indirect effects. The results revealed that concerning multidimensional poverty, institutional quality, road length,

tertiary education, and demographic factors substantially influenced the multidimensional poverty directly as well as indirectly. Also, in terms of human development, institutional quality, road length, school infrastructure, health institutions, population density, and urbanization were found to be the significant spatial attributes of human development. In addition, the study outcomes also implied that the spillover effects of institutional quality substantially determined the wellbeing of neighbouring districts.

In a nutshell, this section provides extensive literature on spatial analysis of multidimensional poverty. It is apparent from these studies that spatial econometric models like Local Indicators of Spatial Association (LISA), Moran's I statistic, Spatial Lag Model (SLM), Spatial Error Model (SEM), and Geographically Weighted Regression (GWR) approaches are used extensively. These models confirmed that multidimensional poverty is a function of space or there is a spatial dimension.

The existing literature paid scarce attention to assessing the impact of income (traditionally used as a unidimensional poverty measurement approach) and a multidimensional poverty rate of neighboring regions on any specific region's own poverty score. While considering the literature, the present study has been designed to fill this gap that could be helpful for the government to reduce the inequalities in poverty incidence on regional levels.

Methodology

Research area

This study explored the spatial analysis of multidimensional poverty in all districts from four provinces of Pakistan. The current population of Pakistan is 231 million people, with a growth rate of 2 percent per year (United Nations, 2019). Also, there are 32.2 million households in Pakistan, with 20 million households in rural areas and 12.2 million households in urban areas. In general, the overall distribution of the population favours the male population, which is 51 percent, whereas the female population is 49 percent (Pakistan Bureau of Statistics, 2017).

In addition, there may be considerable spatial variations in the degree of multidimensional poverty across regions or provinces because the capital

districts of all provinces are better off than their surrounding districts. To the best of our information, earlier studies did not examine this issue. More importantly, Pakistan has been facing several natural catastrophes. For example, the 2005 earthquake in Kashmir collapsed many buildings, and the destruction reached a vast swathe of territory within 95 km of Kashmir (Tandon & Hasan, 2005). The province of Sindh remained in severe poverty when the summer monsoon failed in the year 2003 to irrigate the lands. Also, the flooding situation in 2005 led to massive destruction throughout Pakistan. These major hazards cause people and increase poverty which may vary across regions of Pakistan (Azeem et al., 2018). So, information on socioeconomic and demographic characteristics, housing, health, and water and sanitation attributes were gathered from four provinces of the country. However, due to law-and-order situations

at survey time as well as unavailability of data, districts from Gilgit Baltistan (GB) and Azad Jammu and Kashmir (AJK) were omitted from the study. Thus, districts from the remaining four provinces (Punjab, Sindh, Khyber Pakhtunkhwa (KP), and Baluchistan) were considered observations of the study (Fig. 1). Districts from these provinces were considered significant to explore the spatial analysis, primarily because the preceding studies did not measure the spatial clusters and/or spatial outliers in Pakistan concerning multidimensional poverty.

Data sources

Data were extracted from Pakistan Social and Living Standard Measurement (PSLM) survey, round-vii, 2019–20, recently collected by the organization of Pakistan Bureau of Statistics, Islamabad (Pakistan

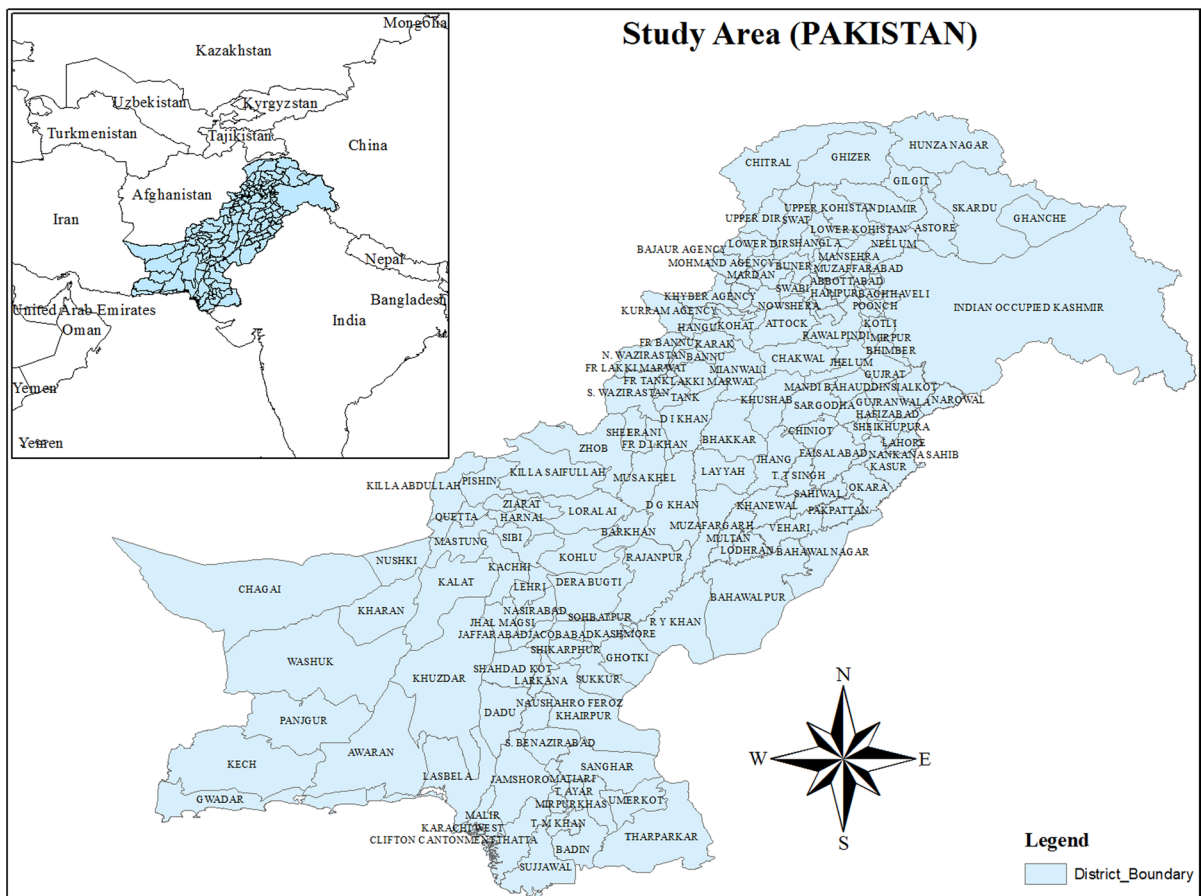


Fig. 1 Map displaying the study area (Pakistan) with district boundaries

Bureau of Statistics, 2020). Although this survey was not conducted for spatial analysis purposes, it does contain sufficient information to meet our study objectives. This survey contains rich data on multiple dimensions such as socioeconomic characteristics, demographics, education, health, housing, water, sanitation, environmental attributes, and so on. Data were collected from almost all districts on the household level.

Sample size and unit of analysis

PSLM survey adopted two stages stratified sampling method. Although the survey was conducted at the district level, information was collected at the household level. Therefore, each district was further managed into microlevel enumeration blocks, each covering 200–250 households. In this way, 6,334 enumerations blocks were found advantageous from which 83,234 households were surveyed. As this was a district-level survey, the district was considered a unit of analysis to investigate multidimensional poverty. Therefore, households from about all surveyed enumeration blocks were combined at the district level. By doing so, 124 out of 158 districts were determined and considered as the sample size. The remaining districts were excluded either because they have less information or due to law-and-order situations at survey time (as explained earlier).

Indicators of multidimensional poverty

To quantify the multidimensional poverty, based on the previous literature, this study selected nineteen indicators/variables from five different dimensions. All dimensions and indicators within each dimension were equally weighted as suggested by the experts (Karahasan & Bilgel, 2021; Khan et al., 2014, 2015, 2016; Wang & Wang, 2016). The selected dimensions and indicators are 1) Income: “*income of household (uni-dimensional)*”; 2) Education: “*years of schooling*”, “*school-aged children enrolment*”, “*distance to high school*”; 3) Health: “*immunization*”, “*prenatal care*”, “*post-natal care*”, “*distance to basic health unit*”; 4) Housing structure: “*room density*”, “*floor materials*”, “*roof materials*”, “*walls materials*”; 5) Living standard: “*cooking fuels*”, “*lighting fuels*”, “*safe drinking water*”, “*distance to safe drinking water*”, “*sanitation*”, “*broadcast facility*”, “*assets*

in possession”. The detailed explanation of these indicators, their deprivation cut-offs, and weights are summarized in Table 1.

Multidimensional poverty assessment

A multifaceted index was formulated to measure the complex poverty by taking the households from all districts as calculated inputs and districts as the outputs. For this purpose, the well-known and widely used Alkire-Foster (A-F) methodology of measuring Multidimensional Poverty Index (MPI) was used (Alkire & Foster, 2011a, 2011b; Khan et al., 2014, 2015, 2016; Wang & Wang, 2016). This framework was comprised of two stages: Identification Stage and Aggregation Stage.

Identification stage: “The dual cut-off”

Alkire and Foster (2011a) acknowledged a “dual cut-off” approach as a general foundation to measure multidimensional poverty. The first threshold was used to choose the indicators’ deprivation cut-off and assigned a weight to each indicator and dimension whereas the second threshold was used to choose the poverty cut-off to identify poor from non-poor. Both thresholds are described below.

First threshold: Deprivation cut-off and weight assignment to each indicator An individual or household i is considered to be deprived for indicator x_i , if its attainment in that indicator is below the cut-off, where the cut-off is symbolized by z_i , i.e., if $x_i < z_i$. Next, all study dimensions (and indicators within each dimension) were weighted equally, i.e., ($w_i = \frac{1}{\text{no.ofdimensions}} * \frac{1}{\text{no.ofindicators}}$), where, w_i is the weight assigned to i^{th} indicator. The cut-off z_i values and assignment of equal weights were determined by following previous studies on multidimensional poverty in Pakistan (Alkire & Foster, 2011a; Iqbal & Nawaz, 2017; Khan & Akram, 2018; Khan et al., 2014, 2015, 2016). The study indicators were weighted so their sum equals 1, i.e., $\sum_1^n w_i = 1$, where, n is the total number of indicators.

Second threshold: Poverty cut-off (identification of poor from non-poor) To identify poor from non-poor, a deprivation score was assigned to households according

Table 1 Study dimensions, indicators, deprivation cut-offs, and weights. Source: Author's own computations based on "Pakistan Social and Living Standard Measurement (PSLM) survey", 2019–20 (Pakistan Bureau of Statistics, 2020)

Dimension	Indicator	Deprivation cut-off	Weight
Income	Unidimensional	If household income is less than the national poverty line*, the assignment is 1, otherwise 0	1/5
Education	Years of schooling	If no man/woman in the household is primary pass, the assignment is 1, otherwise 0	1/15
	School-aged children enrolment	If any school-aged (6–16 years old) child the in household is not going to school, the assignment is 1, otherwise 0	1/15
	Distance to the high school	If distance of a household to high school is less than or equal to 1 km, the assignment is 0, otherwise 1	1/15
Health	Immunization	If all children of a household under 5 years of age are immunized, the assignment is 0, otherwise 1	1/20
	Pre-natal care	If a woman (pregnant) in the household received pre-natal consultation at least once, the assignment is 0, otherwise 1	1/20
	Post-natal care	If a woman received a post-natal check-up at least once within 6 weeks of delivery, the assignment is 0, otherwise 1	1/20
	Distance to Basic Health Unit (BHU)	If the distance of a household to the Basic Health Unit (BHU) is less than or equal to 1 km, the assignment is 0, otherwise 1	1/20
Housing structure	Room density	If a household has more than 3 members per room, the assignment is 1, otherwise 0	1/20
	Floor materials	If a household has used Cement or Bricks for the floor, the assignment is 0, otherwise 1	1/20
	Roof materials	If a household has used wood/bamboo in the roof, the assignment is 1, otherwise 0	1/20
	Wall materials	If a household has used burned bricks/blocks in walls, the assignment is 0, otherwise 1	1/20
Living standard	Cooking fuels	If a household uses Gas/LPG/Electricity/kerosene oil, the assignment is 0, otherwise 1	1/35
	Lighting fuels	If a household uses Electricity/solar energy for lighting, the assignment is 0, otherwise 1	1/35
	Safe drinking water	If a household (inside/outside of dwelling) uses piped water/bottled/filtered, the assignment is 0, otherwise, 1	1/35
	Distance to safe drinking water	If the distance to safe drinking water is less than or equal to 1 km, the assignment is 0, otherwise 1	1/35
	Sanitation	If flush of a household is connected to public sewerage/septic tank/open-drain/pit, the assignment is 0, otherwise 1	1/35
	Broadcast facility	If a household has no Television/LCD/LED, the assignment is 1, otherwise 0	1/35
	Assets in possession	If a household has no agricultural land/property/plot in possession, the assignment is 1, otherwise 0	1/35

1 and 0 denote deprived and non-deprived respectively.

*National poverty line = Rs. 3030.32 per adult equivalent using the HIES Survey, 2013–14

to their deprivations in component indicators. This score was calculated by taking the weighted sum of deprivations of a household, so it lies between 0 and 1. Mathematically,

$$c_i = \sum_1^n w_i ind_i \quad (1)$$

where c_i is the deprivation score of i^{th} household, w_i is the weight assigned to i^{th} indicator, and " ind_i " is the i^{th} indicator of a household. If a household is deprived in i^{th} indicator, i.e., if $x_i < z_i$ the $ind_i = 1$, otherwise $ind_i = 0$. The next task was to determine a cut-off to identify whether a household is multidimensionally poor or not. For this purpose, A-F (Alkire &

Foster, 2011a) methodology of poverty cut-off, k was adopted. According to this method, the i^{th} household is considered multidimensionally poor if its deprivation score is greater than or equal to the poverty cut-off k , i.e., if $c_i \geq k$. In contrast, if the deprivation score of i^{th} household is less than poverty cut-off k , it is non-poor, i.e., $c_i \leq k$. According to the A-F framework of censoring, the c_i of multidimensionally non-poor households were replaced as 0, even if their c_i is non-zero. As a result, by applying the censored deprivation score $c_i(k)$ method, if $c_i \geq k$, then $c_i(k) = c_i$, while if $c_i < k$, then $c_i(k) = "0"$.

Aggregation stage: multidimensional headcount ratio

Two key elements were required to compute the multidimensional headcount ratio. One was the incidence of households experiencing multiple deprivations denoted by H , and the other was the average proportion of households' weighted deprivations (intensity of deprivation) denoted by A (Alkire & Foster, 2011a). The mathematical derivation of both H and A is explained in Eq. (2) and (3), respectively.

$$H = \frac{q}{n} \tag{2}$$

where H denotes headcount ratio, q is the number of multidimensionally poor households, and n is the total number of households in a specific region.

$$A = \frac{\sum_i^n c_i(k)}{q} \tag{3}$$

where $c_i(k)$ is the censored deprivation score of i^{th} household, and q is the number of multidimensionally poor households. The multidimensional poverty, denoted by M_o , is equal to the product of both H and A . Mathematically, it can be shown as.

$$M_o = H \times A \tag{4}$$

Spatial analysis of multidimensional poverty

To identify the patterns of spatial dependencies (relationships) among the contiguous districts, spatial analysis was conducted. After measuring the multidimensional poverty in all study districts, two types of spatial analysis tests were used and explained in the next subsection.

Spatial autocorrelation (Moran's I) and local indicators of spatial association (LISA)

The spatial autocorrelation examines whether there exists a spatial association between the multidimensional poverty score of a district and its surrounding neighboring districts (Anselin, 1995). To test this spatial association, the two widely used test statistics (Global Moran's I and Local Moran's I) were used (Anselin, 1995; Getis, 2010; Ijumulana et al., 2020; Khan & Hussain, 2021; Lima et al., 2020; Yang et al., 2019). Statistically, the Global Moran's I is written as Eq. (5).

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n \sum_{j=1}^n w_{ij} \sum_{i=1}^n (x_i - \bar{x})^2}, i \neq j \tag{5}$$

where n denotes the number of districts; x_i and x_j are the multidimensional poverty scores of i^{th} and j^{th} districts, respectively; \bar{x} represents the mean score of multidimensional poverty of all districts; w_{ij} shows the weighted spatial matrix. When i^{th} and j^{th} districts share a joint boundary, $w_{ij} = 1$, otherwise $w_{ij} = 0$. I is the Global Moran's I statistic score ranges between +1 and -1, i.e., $-1 \leq I \leq 1$. If Moran's $I = 0$, it means that the multidimensional poverty (at district level) is randomly and/or irregularly distributed, when Moran's $I > 0$, it means that the multidimensional poverty scores are spatially agglomerated, and when Moran's $I < 0$, it means that the multidimensional poverty scores of neighboring districts are inversely associated. To test whether the score of Global Moran's I statistic, a null-hypothesis (H_0) of spatial randomness was tested against the alternative hypothesis (H_1) of spatial clusters/patterns.

To examine the significant spatial clusters and/or outliers among contiguous districts from four provinces of Pakistan, the Local Moran's I (also known as local indicators of spatial association) test was applied. The test statistic measures the degree of spatial correlation between a district and all its neighboring districts. Statistically, it is

$$I_i = \frac{n(x_i - \bar{x}) \sum_{i=1}^n w_{ij}(x_j - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2}, i \neq j \tag{6}$$

where n is the number of districts; x_i and x_j are the multidimensional poverty scores of i^{th} and j^{th} districts respectively; \bar{x} represents the mean score of

multidimensional poverty of all districts; w_{ij} is the spatial weight matrix. I_i is the extent of spatial association between each i^{th} and its surrounding districts. (Anselin, 1995) suggested to divide the LISA results into four quadrants, i.e., high-high (HH) also known as a hot spot, low-low (LL) also known as cold spot, high-low (HL) also known as an outlier, and low-high (LH) also known as the outlier. The (HH) and (LL) quadrants mean that the multidimensional poverty score of a district and its adjacent districts are significantly spatially consistent, whereas the quadrants of (HL) and (LH) mean that the contiguous districts are heterogeneous (Anselin, 1995).

Spatial regression

The spatial econometric analysis incorporates the spatial association between the contiguous districts because the general linear regression model does not incorporate the spatial association between the contiguous districts, which made the results of the general linear regression model biased and inconsistent. To make the regression output accurate, the spatial regression method has enhanced the ordinary least squares (OLS) regression model with the consideration of spatial correlation between exogenous and endogenous variables. The identification of appropriate spatial model is a major concern. Therefore, some of the widely used spatial regression models including (1) the spatially lagged X model (SLX), (2) spatial autoregressive model (SAR) and (3) spatial error model (SEM) was applied (Anselin, 1995; Lesage & Pace, 2009). The general specification of these models are as follows:

- (1) Spatially lagged X model (SLX model)

$$y = \beta X + \theta W_1 X + \varepsilon \quad (7)$$

- (2) Spatial autoregressive model (SAR model)

$$y = \rho W_2 y + \beta X + \varepsilon \quad (8)$$

- (3) Spatial error model (SEM model)

$$y = \beta X + \varepsilon, \varepsilon = \lambda W_3 \varepsilon + \mu \quad (9)$$

where y denotes district's multidimensional poverty and/or headcount poverty (dependent variable), X is the vector of explanatory variables, β is the

coefficient of explanatory variables, W_1 is the spatial weight matrix of the lagged values of independent variables, W_2 is the spatial weight matrix of the neighboring districts concerning the multidimensional poverty and/or the headcount poverty, ε is the random disturbance term, W_3 shows the spatial weight matrix of residuals and μ is the random error of normal distribution. θ , ρ and λ show the impact of neighbouring X 's, spatial agglomeration intensity of adjacent districts and regression residuals respectively.

As it is stated above that the selection of appropriate model is major concern, Anselin, (1995) suggested if $\rho \neq 0$, $\theta = 0$ and $\lambda = 0$ the spatial regression is the spatial lag model (SLM) or SAR model, which means a spatial agglomeration effect exists between the contiguous districts in terms of multidimensional poverty, but if $\rho = 0$, $\theta = 0$ and $\lambda \neq 0$, the spatial econometric model is the spatial error model (SEM) which means there is spatial agglomeration effect between the residuals of a regression model and finally if $\rho = 0$, $\lambda = 0$ and $\theta \neq 0$ the spatial regression is the lagged X model (SLX). To select the best model, (Anselin, 1995; Anselin & Rey, 2014) suggested to follow the criteria of Lagrange multiplier test. If the LM-lag (Lagrange multiplier test of spatial lag model) is statistically more significant compared to the LM-error (Lagrange multiplier test of spatial error model), then the SLM is best model to select and vice versa. In case, both the SLM and SEM models are insignificant means that the general regression model is the best fit (see Appendix 3, Fig. 8).

Analytical tools

Different statistical packages were used for the analysis in this paper. Statistical Package for Social Science (SPSS), version 20 was used to measure the multidimensional poverty. For the spatial econometric analysis, RStudio, version 4.1, Geographic Information System (GIS), version 10.5 and GEODA, version 1.18 were used (Anselin et al., 2010; Fischer & Getis, 2009).

Results

The measurement of multidimensional poverty (MDP) primarily depends upon the deprivation cut-off (k), as it is very complex and sensitive towards

MDP (see Appendix 2, Fig. 6, Fig. 7 and Table 7). Therefore, this study as well as earlier studies follows the United Nations Development Programme (UNDP’s) standard (Hu & Ou, 2013; Lu, 2013; Wang & Wang, 2016). According to the UNDP standard, if a household is deprived in 30 percent of indicators (i.e., in our study $k = 19/30\% = 5.7$ or ≈ 6), it is considered multidimensionally poor.

Province-based incidence of headcount (H) and multidimensional poverty (MDP)

The incidence of headcount (H), average intensity (A) and MDP—for overall country as well as for all provinces of Pakistan—at poverty cut-off $k=6$ is shown in Fig. 2. The results revealed that absolute poverty (Headcount ratio) and MDP is about 41 percent and 23 percent respectively across the country. However, considerable variations exist among all the provinces concerning both headcount poverty and MDP. Both headcount and MDP of Punjab province are relatively lower than other provinces. In contrast, these ratios are higher in Balochistan in comparison to other provinces; this result indicates that Balochistan is the poverty-stricken province of the country.

Furthermore, the average intensity (A) of deprivation differs slightly among all provinces, and is higher in Sindh province.

District-based headcount (H) and multidimensional poverty (MDP)

Panels (a) and (b) of Fig. 3 visualized the headcount ratio and multidimensional poverty (MDP) scores of all study districts of Pakistan. Districts were categorized into five quantiles concerning their headcount and MDP scores (i.e., very low, low, moderate, high and very high). The details of H, A, and MDP scores of each study district are shown in Appendix 1, Table 6. Both maps showed about the similar pattern of poverty prevalence but varied patterns across all provinces. From both panels of the figure, it is apparent that almost all districts from Punjab province lie in the “low” and “very low” quantiles. In contrast, districts from Balochistan province lies in the “high” and “very high” quantiles. Both H and MDP are severe in almost all districts of Balochistan. In other words, the incidence of H and MDP is lower in Punjab districts in comparison to the districts from other provinces of Pakistan. Moreover, the incidence of

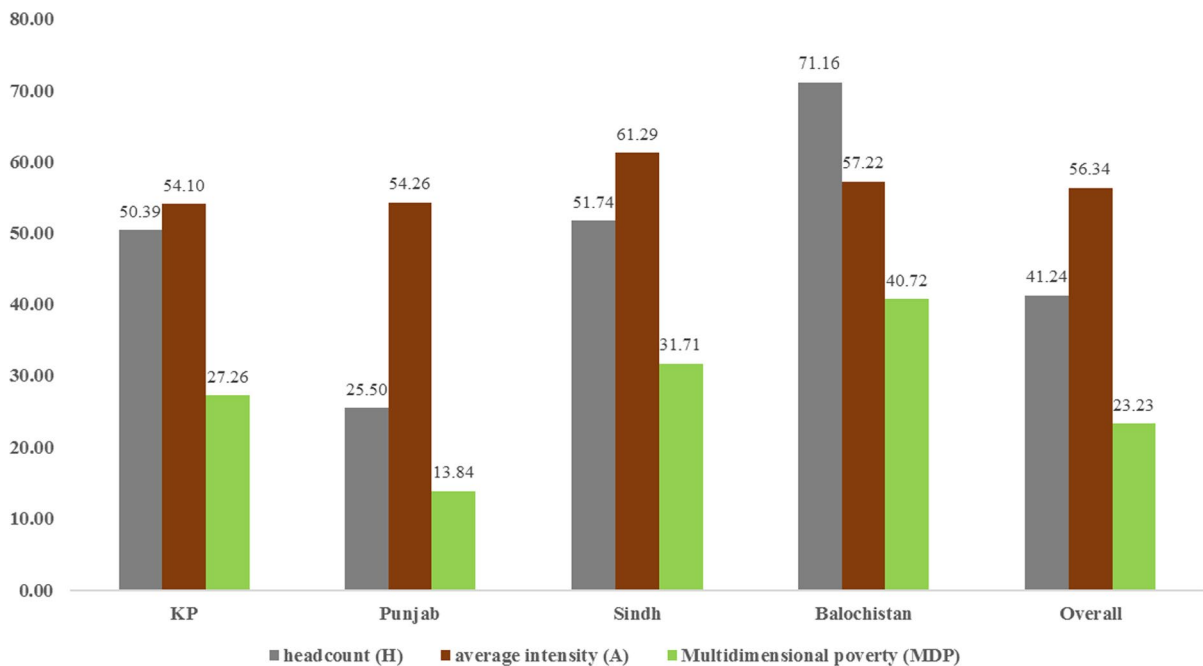


Fig. 2 Province-wise headcount, average intensity and multidimensional poverty

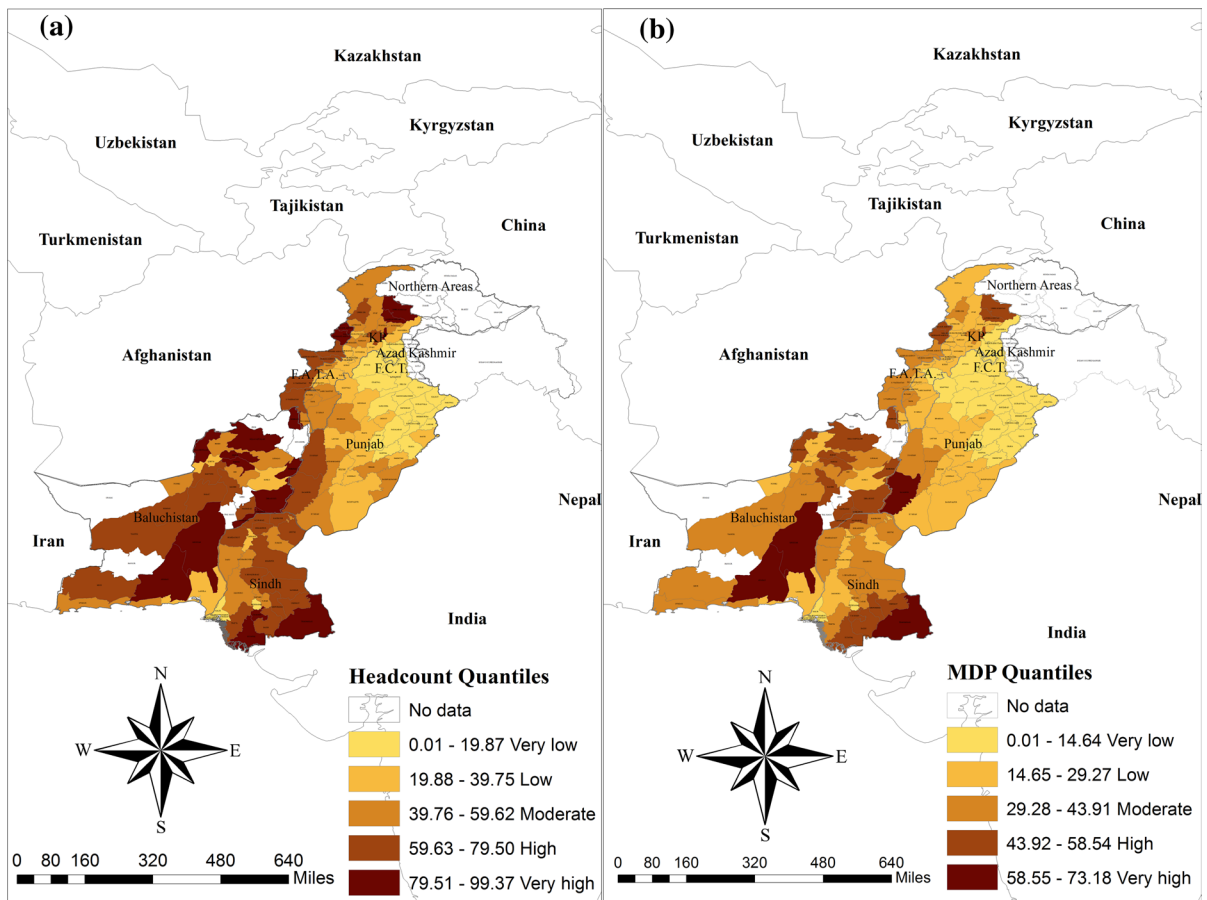


Fig. 3 Map displaying the spatial representation of Pakistan’s district **a** Headcount scores and **b** Multidimensional poverty (MDP) scores. These representations are the author’s own

computations based on “Pakistan Social and Living Standard Measurement (PSLM) survey”, 2019–20 (Pakistan Bureau of Statistics, 2020)

MDP and headcount varied across districts from KP and Sindh provinces. Most of the districts from these two provinces lies in moderate “quantile”. However, the newly merged districts of KP – previously known as FATA – have made a cluster of “high” and “very high” quantiles concerning both MDP and headcount ratio.

Spatial autocorrelation (Moran’s I) and the local indicators of spatial autocorrelation (LISA) analysis of headcount ratio (H) and multidimensional poverty (MDP)

As it is apparent from both panels of Fig. 3 that majority of the districts (especially from Punjab and Balochistan) have made some sorts of spatial clusters of “low,” “very low,” “high,” and “very high”

quantiles concerning headcount ratio and MDP, spatial analysis was conducted to assess whether these spatial clusters are significant or not.

Table 2 shows the results of Global Moran’s I test for both headcount and MDP indices. The test score of “H” showed that the incidence of headcount poverty of a district is 61 percent spatially correlated with its surrounding districts with a z score of 11.12 and pseudo p-value of 0.001. Similar to headcount, the test score of multidimensional poverty scores also confirmed that the neighboring districts are 59 percent spatially associated with one another.

Figure 4 presents the local indicators of spatial autocorrelation (LISA) analysis through Moran’s scatterplots. The Moran scatterplot analysis was conducted to check the spatial clusters (e.g., hotspots and cold spots and spatial outliers). The results showed

Table 2 Test of Significance for Spatial Clusters and Outliers. Source: Author’s own computations based on “Pakistan Social and Living Standard Measurement (PSLM) survey”, 2019–20 (Pakistan Bureau of Statistics, 2020)

Index	Moran’s I	E(I)	Sd(I)	z-scores	Pseudo <i>p</i> -value
Headcount ratio (H)	0.61	−0.0078	0.0558	11.12	0.001
Multidimensional poverty (MDP)	0.59	−0.0078	0.0544	10.75	0.001

Used 999 random permutations in the calculation of these estimates

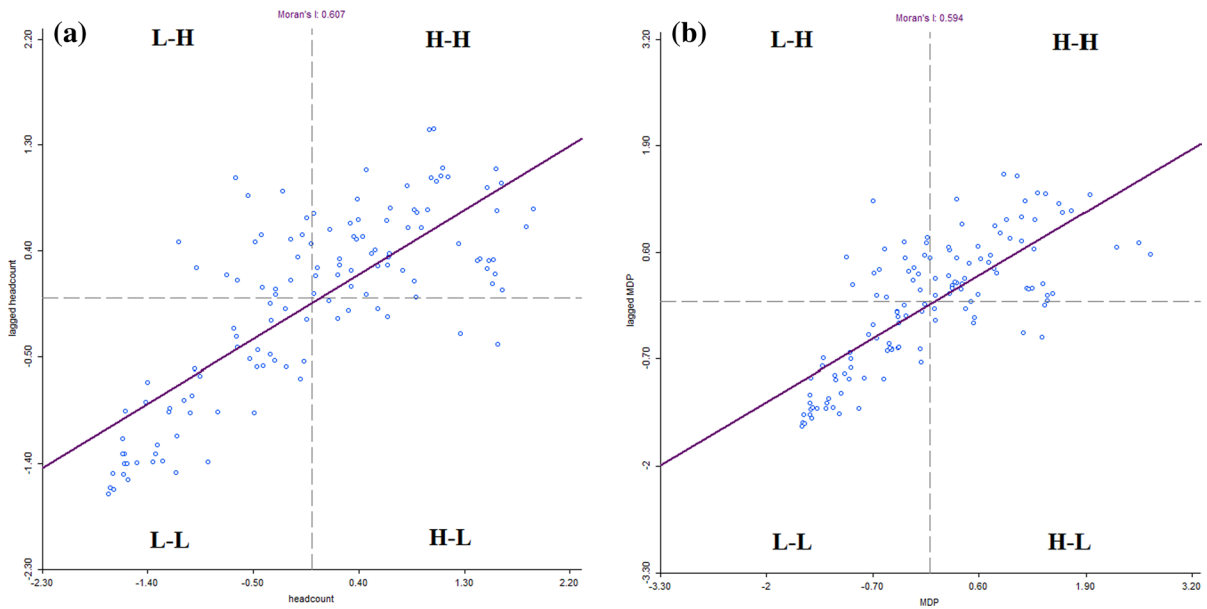


Fig. 4 Moran scatter plots of Pakistan’s district (a) Headcount scores and (b) Multidimensional poverty (MDP) scores. L–H, H–H, L–L, and H–L denote Low–High, High–High, Low–Low, and High–Low quadrants respectively

that both headcount poverty (Fig. 4a) and MDP (Fig. 4b) scores of most of the districts were spatially clustered among one another and concentrated in high-high, H–H (hotspot) and low-low, L–L (cold spot) quadrants. Less districts were concentrated in low–high, L–H (outlier) and high-low, H–L (outlier) quadrants which means that these districts are spatially heterogenous. However, the frequency of the districts in these quadrants vary both for headcount (H) and multidimensional poverty.

As evident from Moran scatterplots, the spatial clusters of headcounts and MDP exist, and Fig. 5 visualized the local indicators of spatial association (LISA) results to mark the locations of these spatial clusters as well as determined whether these clusters are statistically significant or not. The first two quadrants of HH and LL embodies districts with high

(low) scores of headcounts poverty/MDP surrounded by high (low) neighboring districts, whereas the last two quadrants (LH and HL) signify the districts with high (low) values of headcount poverty/MDP covered by low (high) neighbors. From the results of Figs. 5a and 5b, it is apparent that districts from Punjab province have made significant cluster of low-low (LL) districts which means that these districts have lower headcount poverty and/or MDP surrounded by districts with low headcount and/or MDP scores. In contrast, most districts from Balochistan and some from Sindh province have made a substantial pattern of high-high (HH) regions which means that these high headcounts and/or MDP districts are amalgamated with high headcount poverty and/or MDP districts. Moreover, some of the districts from Balochistan have made a heterogenous pattern of low–high (LH)

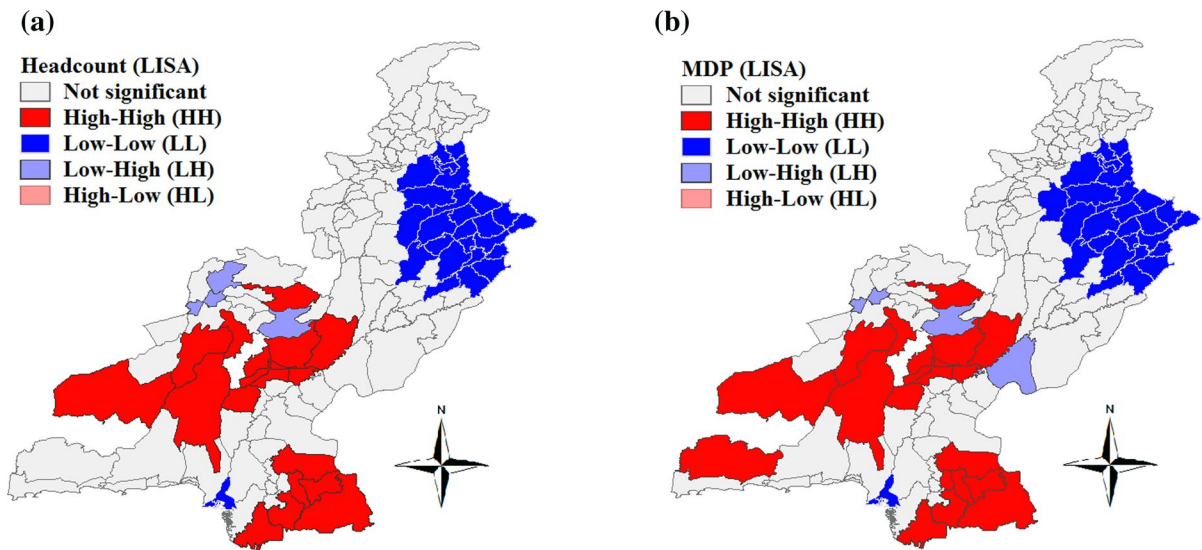


Fig. 5 Map displaying Local Indicators of Spatial Autocorrelation (LISA) agglomeration of Pakistan’s district **a** Headcount scores and **b** Multidimensional poverty (MDP) scores. HH, LL, LH, and HL denote High-High, Low-Low, Low-High, and High-Low respectively

LL, LH, and HL denote High-High, Low-Low, Low-High, and High-Low respectively

districts which means that the headcount poverty and/or MDP score of these districts are low, but their surrounding/neighbors districts have high headcount and/or MDP scores.

Spatial regression analysis

Before measuring the impact of neighbors (poverty scores) on incidence of district own poverty, diagnostic tests of spatial dependence for both headcount and MDP were applied (Table 3). The results showed that in both (headcount and MDP) cases,

the Lagrange Multiplier test of spatial lag as well as spatial error is significant which means that exists spatial dependence among the districts in terms of headcount and MDP poverty. The choice of appropriate spatial model is a major concern because the Lagrange Multiplier score of both lag and error models are significant. Therefore, following (Anselin, 1995), the spatial lag model was considered appropriate because the Robust LM (lag) is highly significant compared to the Robust LM (error) model both for headcount and MDP. However, it is not clear whether SLM is the best one or SLX.

Table 3 Diagnostic Tests for Spatial Dependence of Headcount (H) and Multidimensional Poverty (MDP). Source: Author’s own computations based on “Pakistan Social and

Living Standard Measurement (PSLM) survey”, 2019–20 (Pakistan Bureau of Statistics, 2020)

Test statistic	Headcount poverty (H)			Multidimensional poverty (MDP)		
	DF	Value	P-value	DF	Value	P-value
Moran’s <i>I</i> (error)	0.4707	8.67	0.0000	0.4339	8.0099	0.0000
Lagrange Multiplier (Lag)	1	83.72	0.0000	1	74.16	0.0000
Robust LM (Lag)	1	11.79	0.0006	1	13.49	0.0021
Lagrange Multiplier (error)	1	76.71	0.0000	1	64.89	0.0000
Robust LM (error)	1	3.77	0.0528	1	4.16	0.0413
SARMA	2	88.47	0.0000	2	78.33	0.0000

DF denotes degree of freedom

Therefore, the regression results of SLX model were also explained in Table 4.

Table 4 presents the results of both general linear regression (OLS) and all the spatial Lag models. By looking at OLS results, the coefficient of determination (R^2) showed that 48 percent and 49 percent variations in headcount and MDP are explained by the explanatory variables, respectively. It is shown that one percent increase in income per capita – a unidimensional indicator that is traditionally used to measure poverty—has significantly reduced both

headcount and MDP by 0.63 percentage points and 0.43 percentage points, respectively. However, the general linear regression model does not capture the spatial dependences, which made our regression results biased. Therefore, spatial regression models results were obtained. In comparison with the OLS, the slightly higher R^2 scores of SLX model concerning both headcount and MDP confirmed that the results of spatially lagged X (SLX) model are unbiased and efficient. The significance of F-test also confirmed that SLX model is fitted best. From the results

Table 4 Spatial Regression Analysis of Headcount (H) and Multidimensional Poverty (MDP). Source: Author’s own computations based on “Pakistan Social and Living Standard Measurement (PSLM) survey”, 2019–20 (Pakistan Bureau of Statistics, 2020)

Dependent variable: Headcount poverty (H)				
	OLS (Nonspatial)	Spatially lagged X (SLX)	Spatial lag (SAR)	Spatial error (SEM)
Variables	Coefficient	Coefficient	Coefficient	Coefficient
Intercept	581.22 (56.28) {10.33} ***	688.744 (78.43) {8.782} ***	346.38 (51.14) {6.77} ***	485.18 (53.42) {9.08} ***
Per capita Income (Ln)	−63.60 (6.71) {−9.48} ***	−51.12 (9.23) {−5.54} ***	−39.06 (5.87) {−6.65} ***	−51.77 (6.34) {−8.16} ***
Lag coefficient (lag x for SLX, rho for SAR, lambda for SEM)	−	−25.30 (12.99) {−1.97} **	0.62 (0.07) {9.23} ***	0.75 (0.06) {11.79} ***
R-squared	0.48	0.49	−	−
F-statistic	89.94	47.85	−	−
P-value of (F-statistic)	0.000	0.000	−	−
Wald-statistic	−	−	85.17	139.16
P-value of (Wald-statistic)	−	−	0.000	0.000
Dependent variable: Multidimensional poverty (MDP)				
	OLS (Nonspatial)	Spatially lagged X (SLX)	Spatial lag (SAR)	Spatial error (SEM)
Variables	Coefficient	Coefficient	Coefficient	Coefficient
Intercept	393.87 (32.79) {12.01} ***	459.74 (45.62) {10.08} ***	255.02 (32.28) {7.90} ***	338.20 (32.20) {10.50} ***
Per capita Income (Ln)	−43.72 (3.91) {11.19} ***	−36.08 (5.37) {−6.72} ***	−28.94 (3.71) {−7.80} ***	−36.93 (3.83) {−9.65} ***
Lag coefficient (lag x for SLX, rho for SAR, lambda for SEM)	−	−15.50 (7.56) {−2.05} **	0.56 (0.07) {7.96} ***	0.72 (0.07) {10.71} ***
R-squared	0.49	0.51	−	−
F-statistic	125.2	66.28	−	−
P-value of (F-statistic)	0.000	0.000	−	−
Wald-statistic	−	−	63.4	114.72
P-value of (Wald-statistic)	−	−	0.000	0.000

“()”, “{ }”, “[]”, “***”, “**”, and “*” denotes “standard error”, “t-value”, “z-value”, “level of significance at 10%”, “5%”, and “1%” respectively

of SLX, it is obvious that both the income per capita and neighbours per capita income remained highly significant and mitigated both headcount poverty and MDP. The rho coefficients (in SAR model) confirmed that headcount and MDP are not randomly distributed but rather spatially distributed which means that neighboring districts have significantly influenced the districts own poverty incidence. Both headcount and MDP of surrounding/neighboring districts have significantly determined the districts own headcount and MDP poverty by 0.62 percentage points and 0.56 percentage points, respectively. The lambda (λ) coefficient (of SEM model) is also significant which means that the residuals are spatially agglomerated. The Wald-statistic is significant for both the SAR and SEM models which confirmed that these models are best fitted.

Table 5 shows the spillover (direct and indirect) effects of SLX model both for headcount and MDP. From these results it is obvious that the own district's per capita income (direct effect) substantially decreased respectively the headcount incidence and MDP by 0.51 percentage points and 0.36 percentage points. On average, one percent increase in the neighbors' per capita income (indirect effects) has also significantly mitigated the headcount and MDP by 0.25 and 0.15 percentage points respectively. Moreover, the total effects of both headcount and MDP are significant at 1% level of significance which clearly indicates that per capital income is sensitive towards poverty.

Discussion

The traditional measurement of poverty through a monetary (a unidimensional income) approach had

been criticized as (Sen, 1994) stated that poverty is a multidimensional phenomenon. Therefore, Pakistan has considerably focused measuring multidimensional poverty from period to period and found a considerable declining trend from 2004 to 2015. The incidence of headcount (41.2%) and MDP (23.23%) scores in our study are slightly higher than national headcount (38.8%) and MDP (19.7%) score previously measured in 2015 (Government of Pakistan, 2016). The latter results seem plausible because the government is trying to alleviate the poverty, but on the other hand, a growing population and rapid urbanization have become major obstacles to prevent people's accessibility towards the study indicators, which ultimately increased both headcount and MDP. One possible reason may be the differences in the selection of study indicators.

Substantial variations exist among the four provinces of Pakistan concerning headcount and MDP as shown in Fig. 2. Among these provinces relatively, Punjab was declared as the lowest poverty-stricken province in terms of both headcount and MDP scores. In contrast, Balochistan is acknowledged as the highest poverty-stricken province concerning headcount and MDP scores. These results were found consistent with the previously measured multidimensional poverty in Pakistan (Khan & Akram, 2018). Furthermore, when these results were compared with the national headcount and MDP scores, except for Punjab, the incidence of headcount poverty and MDP are higher than the national levels. The latter results may be true because of the good governance, low corruption, and political stability in Punjab provincial government in comparison to other provinces of Pakistan. However, this is not the fairly accurate reason. Again, we must emphasize that these results may occur because of the selection

Table 5 Spatial spillover (Direct and Indirect) income effects for spatially lagged X (SLX) model. Source: Author's own computations based on "Pakistan Social and Living Standard Measurement (PSLM) survey", 2019–20 (Pakistan Bureau of Statistics, 2020)

	Dependent variable: Headcount poverty (H)			Dependent variable: Multidimensional poverty (MDP)		
	Direct	Indirect	Total	Direct	Indirect	Total
Income (ln)	− 51.12	− 25.29	− 76.41	− 36.08	− 15.49	− 51.57
St. Err	9.22	12.99	9.34	5.37	7.56	5.44
z-value	− 5.54	− 1.97	− 8.17	− 6.72	− 2.05	− 9.48
p-value	0.000	0.049	0.000	0.000	0.040	0.000

of the indicators for the multidimensional poverty index.

The headcount and MDP estimates of each district are visually displayed on the map and properly categorized in five quantiles to recognize its spatial characteristics (Fig. 3). Almost all districts from the Punjab province displayed a cluster/pattern of districts ranked in low and very low quantiles. Our results, which are similar to earlier research, have confirmed that the incidence of headcount and MDP in the Punjab province is low in comparison to other provinces (Khan et al., 2015). In other words, multidimensional accessibility towards the study indicators is relatively more than other provinces. Some of the low and moderate quantile districts are found in KP provinces; however, the newly merged districts of KP—previously known as the Federally Administered Tribal Areas (FATA)—have made a cluster of high and very high quantile districts as shown in Fig. 2. The latter may be true because FATA regions faced several disputes, since this government of Pakistan could not facilitate them in almost all study indicators. In contrast, the incidence of headcount and MDP is higher in districts of the Balochistan and Sindh province. Most districts from these two provinces have made a cluster/pattern of high and very high quantile districts. This pattern is slightly heterogenous concerning MDP scores than the patterns in terms of headcount poverty. These patterns confirmed the districts of Balochistan and Sindh provinces as worst poverty-stricken areas of Pakistan, which showed either the government failure of capturing multidimensional poverty or unequal distribution of the infrastructure development budget.

The spatial analysis (Moran's I) confirmed that both the severe poverty-stricken districts and low poverty-stricken districts have spatial dependence among their surrounding neighbors poverty (Table 2 and Fig. 4). Moran's I statistic showed that the headcount poverty in districts is about 61 percent spatially associated with one another. Similarly, by considering the multidimensional poverty, districts have 59 percent significant spatial relationship among each other. Moreover, the Moran's scatterplots equally divided both the headcount and MDP scores of the districts in to four equal quadrants (high-high, H-H (hotspots), low-low, L-L (cold spots), low-high, L-H (outliers), and high-low, H-L (outliers)). By looking at both headcount and MDP, most of the districts are

found in H-H and L-L quadrants, which confirmed spatial autocorrelation among contiguous/adjacent districts as shown in Fig. 2. In other words, most of the districts with higher (lower) headcount poverty and/or MDP scores are surrounded by their neighboring districts who also have higher (lower) headcount and/or MDP scores. In contrast to these results, fewer districts of Pakistan are bunched in the L-H and H-L (outliers) quadrants. Considering headcount poverty and/or MDP scores, these districts are heterogeneously associated among each other. In other words, districts having lower (higher) incidence of headcount and/or MDP scores are surrounded by the districts who have higher (lower) headcount and/or multidimensional poverty as shown in Fig. 4.

The local indicators of spatial autocorrelation (LISA) analysis as revealed in Fig. 5 have performed a substantial role in pointing out the exact locations of the districts in terms of headcount and MDP in the hotspots, cold spots, and outlier (the four quadrants). The high-high, HH aggregated districts in terms of both MDP and headcount poverty are mainly distributed in the south and south-eastern part (Sindh and Balochistan) of the country. These districts have higher MDP and headcount poverty incidence and are surrounded by the neighboring districts that also have higher headcount and MDP scores. In contrast, the low-low, LL amalgamated districts are primarily concentrated in the north-eastern (Punjab), and there are very few in the south (Sindh) portion of the country. These less multidimensionally poor districts (in terms of both headcount and MDP) are surrounded by districts which belong to the low and very low quantiles. In addition, very few districts from the western part of the country (mainly from Balochistan) are spatially (but heterogeneously) clustered in low-high, LH quadrants. These districts have lower headcount and MDP scores, but their adjacent districts have higher headcount and MDP scores. In other words, these districts are multidimensionally better off, but their surrounding districts are deprived/worse off.

The significant spatial associations of districts with their surrounding/neighbors districts in terms of headcount and MDP indicated the researchers to measure the extent of these influences. Both the SLX and SAR model results concluded that per capita income, per capita income of neighbors, especially the neighboring districts poverty incidence, substantially impacted the districts own poverty score

(Table 4). The districts poverty incidence (headcount/MDP) is significantly mitigated by these factors. Per capita income directly and indirectly mitigated the incidence of headcount and MDP. However, in both cases the direct effects were found to be higher than indirect effects. Moreover, the neighbors' poverty positively influenced the own poverty incidence. On average, a unit increase in the incidence of neighbors' poverty has substantially increased the districts own poverty by 0.62 percent and 0.56 percent, respectively, for headcount and MDP.

This study is limited based on the various considerable grounds. First, a large number of indicators may also contribute in measurement of multidimensional poverty, but we have used only 19 indicators because the utilized dataset did not contain sufficient information on poverty related indicators. Second, the spatial analysis was performed at the district level because at the union council level, the useful respondents were insufficient to capture the exact picture of poverty incidence. Third, the number of districts was reduced up to 124. The remaining districts were ignored either due to the law-and-order situation or had less information about its multidimensional poverty.

Conclusion and policy implications

Multidimensional poverty is a global concern and is measured in almost all nations, especially in low- and middle-income countries. This study focussed on three different aspects of poverty. First, it examined multidimensional poverty using spatial methods by including some additional indicators that were previously not incorporated. Second, using spatial analysis, this study also investigated whether some sort of spatial relationship exists among neighboring/contiguous districts concerning both headcount and MDP scores. Third, this study also examined the impact of the neighbors' poverty scores and per capita income (traditionally used to measure poverty) on the district's own poverty.

From these results, it is concluded that both the incidence of headcount poverty and MDP remained consistent and did not mitigate from previously measured governmental headcount and MPI scores that may show the government's failure to capture the poverty. Both headcount and MDP incidences were found to be higher in Balochistan in

comparison to other provinces. Similarly, Punjab was concluded as the low poverty-stricken province of the country. Almost all districts from Balochistan were found in the high and very high quantile districts. In contrast, about all districts from Punjab province are in the cluster of low and very low quantile districts. This province-based comparison concluded that the government has unequally allocated the infrastructure development budget.

The district-based spatial analysis concluded spatial associations among the neighboring/contiguous districts concerning both headcount and MDP incidence. A significant cluster of low–low, LL districts (ranked in low and very low quantiles) quadrants concerning headcount and multidimensional poverty was found in Punjab which concluded that the government of Pakistan is either concentrating mainly towards Punjab districts in terms of poverty alleviation or there is an unequal distribution of budget allocation. In contrast, a significant cluster of high-high, HH districts (ranked in high and very high quantiles) quadrants were seen in both Sindh and Balochistan. The spatial regressions showed that the per capita income has substantially reduced the incidence of poverty in two different ways i.e., directly and indirectly. More importantly, the poverty score of neighboring districts has significantly influenced the districts own poverty incidence concerning both headcount and MDP scores.

Although considerable inequalities/disparities exist in multidimensional poverty at the national as well as provincial levels, the spatial analysis of multidimensional poverty at the district level recognizes the patterns of weaker (poverty-stricken) areas of Pakistan. The findings of the study may help the government and policymakers to achieve the SDG's (No poverty; Goal 1 and Reduced inequalities; Goal 10) by suggesting some policy implications.

- There is a dire need to develop and improve the people's accessibility towards the study indicators to reduce and/or eliminate the severity multidimensional poverty, especially in poverty-stricken districts.
- It is necessary for policymakers to give relatively more preferences to the poverty-stricken districts (mostly from Baluchistan province) to reduce the inequalities in terms of multidimensional poverty.

- Keeping in view the importance of spatial regression, it is necessary to improve the financial positions of people residing in districts making the cluster of high-high quadrants because of spatial spillover effects. This would reduce the spatial dependence of districts on one another and ultimately will reduce the disparities concerning multidimensional poverty.
- Government must focus not only on the district’s own poverty severity; neighboring districts are also important to consider. It is necessary to improve people’s financial statuses as well as their accessibility towards study indicators to control the incidence of multidimensional poverty.

Author contribution SUK designed the study, performed data analysis, generated maps and tables and wrote the first draft of the manuscript. BWS guided in writing the manuscript and grammatically polished the final draft. All authors have read and approved the final manuscript.

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Declarations

Competing interests The authors have declared they have no financial interests.

Appendix 1

See Table 6

Table 6 District based percentage scores of Headcounts, Average intensity and Multidimensional poverty of Pakistan

District	H	A	MDP	District	H	A	MDP
Khyber Pakhtunkhwa (KP)				Sahiwal	18.01	51.53	9.25
Abbottabad	11.24	48.03	5.40	Sargodha	19.42	52.37	10.17
Bajur	88.87	57.28	50.90	Sheikhupura	10.65	50.19	5.35
Bannu	39.27	51.56	20.25	Sialkot	4.11	51.62	2.12
Batagram	45.45	52.14	23.70	T.T. Singh	19.84	52.86	10.50
Bunair	65.31	55.56	36.28	Vehari	41.76	45.92	19.18
Charsada	51.69	54.22	28.02	Sindh			
Chitral	48.66	51.67	25.14	Badin	78.29	65.72	51.45
D. I. Khan	48.13	54.14	26.06	Dadu	56.85	54.64	31.07
Hangu	42.72	50.83	21.72	Ghotki	63.10	54.65	34.49
Haripur	9.39	51.27	4.81	Hyderabad	16.72	56.85	9.50
Karak	30.23	49.31	14.91	Jacobabad	72.10	60.90	43.91
Khyber	61.68	52.56	32.41	Jamshoro	46.50	54.78	25.47
Kohat	38.11	53.69	20.46	Karachi Central	0.79	55.00	0.44
Kohistan	89.86	57.59	51.75	Karachi East	1.55	49.60	0.77
Kurrām	59.64	54.93	32.76	Karachi Malir	9.00	50.44	4.54
Lakki Marwat	53.85	52.31	28.17	Karachi South	0.41	54.00	0.22
Lower Dir	44.36	52.99	23.51	Karachi West	4.72	53.20	2.51
Malakand	34.41	47.83	16.46	Kashmore	71.49	60.47	43.24
Mansehra	20.79	52.64	10.94	Khairpur	68.82	59.63	41.04
Mardan	41.63	53.06	22.09	Larkana	35.94	61.17	21.98
Mohmand	90.51	58.38	52.84	Matiari	56.93	59.37	33.80
North Waziristan	71.62	49.97	35.79	Mir Pur Khas	69.84	67.56	47.19
Nowshera	39.02	53.01	20.68	Nowshero Feroze	49.08	57.39	28.17
Orakzai	72.08	47.89	34.52	Sanghar	65.11	64.19	41.79
Peshawar	30.46	52.43	15.97	Shahdadkot	65.96	51.19	33.77
Shangla	56.60	47.97	27.15	Shaheed Banazir Abad	65.57	61.87	40.57
South Waziristan	65.35	51.58	33.70	Shikarpur	62.38	63.14	39.39
Swabi	36.42	52.38	19.08	Sujawal	88.54	62.14	55.01

Table 6 (continued)

District	H	A	MDP	District	H	A	MDP
Swat	42.86	52.92	22.68	Sukkur	46.46	56.62	26.31
Tank	54.24	58.56	31.76	Tando Allah Yar	58.15	63.84	37.13
Tor Garh	82.39	56.70	46.72	Tando Muhammad Khan	81.90	59.86	49.03
Upper Dir	63.02	57.80	36.43	Tharparkar	91.93	65.85	60.53
Punjab				Thatta	60.40	61.54	37.17
Attock	4.29	48.40	2.07	Umer Kot	75.58	65.82	49.74
Bahawalnagar	44.99	56.23	25.29	Balochistan			
Bahawalpur	38.32	53.61	20.54	Awaran	97.74	67.59	66.07
Bhakhar	45.93	54.68	25.11	Barkhan	86.88	53.38	46.38
Chakwal	4.04	46.25	1.87	Dera Bugti	90.83	62.55	56.82
Chiniot	34.33	50.96	17.49	Duki	78.46	42.12	33.05
D. G. Khan	65.85	60.43	39.79	Gwadar	57.43	54.47	31.28
Faisalabad	14.32	51.59	7.39	Harnai	86.24	56.29	48.54
Gujranwala	6.97	49.69	3.46	Jaffarabad	79.53	61.90	49.23
Gujrat	3.75	52.53	1.97	Kachhi/ Bolan	77.71	59.76	46.44
Hafizabad	16.28	52.00	8.47	Kalat	76.67	53.09	40.70
Islamabad	1.38	51.75	0.71	Kech/Turbat	60.47	54.03	32.67
Jehlum	3.57	53.00	1.89	Kharan	74.62	50.66	37.80
Jhang	34.93	51.82	18.10	Khuzdar	99.37	71.15	70.71
Kasur	23.44	52.01	12.19	Kohlu	30.00	50.33	15.10
Khanewal	33.16	56.57	18.76	Lasbela	27.91	54.83	15.30
Khushab	25.84	51.81	13.39	Loralai	58.28	53.41	31.13
Lahore	3.56	52.33	1.86	Mastung	70.19	50.27	35.29
Layyah	36.22	49.79	18.04	Nasirabad/ Tamboo	75.00	60.53	45.40
Lodhran	35.15	52.53	18.47	Nushki	52.00	47.38	24.64
Mandi Bahauddin	12.97	51.65	6.70	Pishin	40.83	53.31	21.77
Mianwali	20.42	50.45	10.30	Qilla Abdullah	91.10	55.64	50.69
Multan	29.45	51.40	15.14	Qilla Saifullah	91.98	55.60	51.14
Muzaffar Garh	56.35	55.49	31.27	Quetta	32.94	53.52	17.63
Nankana Sahib	11.65	50.00	5.83	Shaheed Sikandar Abad	91.49	53.47	48.91
Narowal	16.14	50.31	8.12	Sherani	90.01	52.70	47.43
Okara	14.53	49.04	7.13	Sibbi	58.62	55.96	32.81
Pakpattan	21.74	48.58	10.56	Sohbatpur	90.63	59.74	54.14
Rahim Yar Khan	47.49	56.08	26.63	Washuk	76.03	56.17	42.71
Rajanpur	73.18	62.46	45.71	Ziarat	88.54	53.94	47.76
Rawalpindi	4.79	48.11	2.31	–	–	–	–

Appendix 2

See Fig. 6, Fig. 7 and Table 7

Fig. 6 Headcount at district level at different cut-off (k) score

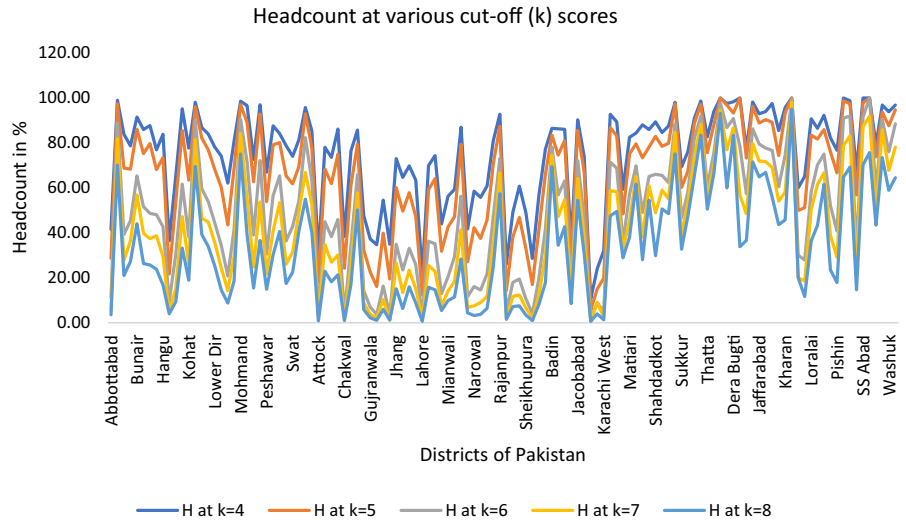


Fig. 7 MDP at district level scores at different cut-off (k)

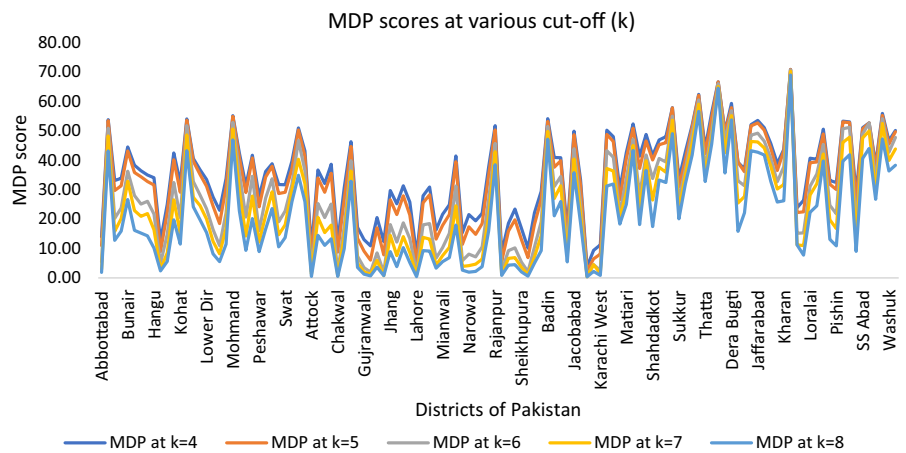


Table 7 District based Headcount and MDP scores at different cut-off (k) values

District	Cut-off (k)=4		Cut-off (k)=5		Cut-off (k)=6		Cut-off (k)=7		Cut-off (k)=8	
	H	MDP	H	MDP	H	MDP	H	MDP	H	MDP
Khyber Pakhtunkhwa (KP) province										
Abbottabad	41.47	13.92	28.68	10.95	11.24	5.40	5.43	2.90	3.49	1.88
Bajur	99.03	53.79	97.42	53.47	88.87	50.90	81.77	48.29	70.16	43.16
Bannu	83.81	33.11	68.83	29.66	39.27	20.25	27.94	15.83	21.05	12.73
Batagram	78.66	33.87	68.38	31.28	45.45	23.70	36.36	20.16	27.27	15.95
Bunair	91.55	44.49	86.01	43.19	65.31	36.28	56.85	32.83	44.02	26.66
Charsada	85.96	38.25	75.28	35.86	51.69	28.02	39.89	22.91	26.40	16.16
Chitral	87.70	36.43	79.68	34.40	48.66	25.14	37.43	20.89	25.67	15.26
D. I. Khan	76.88	34.99	68.13	32.79	48.13	26.06	38.75	21.84	23.75	14.32
Hangu	83.86	34.06	73.42	31.59	42.72	21.72	29.43	16.30	16.77	10.08
Haripur	36.46	12.61	21.66	8.94	9.39	4.81	5.05	2.93	3.97	2.42
Karak	65.12	24.98	53.49	22.28	30.23	14.91	15.12	8.49	9.30	5.60
Khyber	95.18	42.50	85.53	40.18	61.68	32.41	47.21	26.56	33.25	19.71
Kohat	77.74	32.32	63.40	29.10	38.11	20.46	26.04	15.01	18.87	11.44
Kohistan	98.04	54.07	96.09	53.58	89.86	51.75	81.49	48.60	69.57	43.22
Kurram	86.79	40.62	82.14	39.62	59.64	32.76	46.43	27.41	39.29	24.21
Lakki Marwat	83.97	36.73	76.92	35.12	53.85	28.17	44.87	24.58	33.97	19.77
Lower Dir	78.20	33.45	68.12	31.11	44.36	23.51	35.64	20.04	25.26	15.39
Malakand	74.19	27.52	60.22	24.40	34.41	16.46	24.19	12.41	14.52	8.17
Mansehra	62.08	23.01	43.54	18.49	20.79	10.94	14.33	8.20	8.71	5.54
Mardan	80.81	33.80	68.62	30.82	41.63	22.09	29.59	16.96	18.54	11.48
Mohmand	98.54	55.19	97.08	54.89	90.51	52.84	84.31	50.62	75.18	46.92
N Waziristan	96.62	42.48	89.19	40.86	71.62	35.79	55.41	29.93	39.19	22.76
Nowshera	72.66	31.41	62.62	28.99	39.02	20.68	24.77	14.21	15.42	9.37
Orakzai	96.95	41.67	92.89	40.78	72.08	34.52	53.81	27.82	36.55	20.14
Peshawar	66.98	27.67	53.83	24.14	30.46	15.97	21.76	12.14	14.85	8.90
Shangla	87.66	36.14	79.15	34.26	56.60	27.15	40.85	21.23	30.21	16.59
S Waziristan	84.16	38.77	80.20	37.92	65.35	33.70	53.47	29.24	40.59	23.58
Swabi	78.81	31.71	65.34	28.67	36.42	19.08	26.05	14.65	17.44	10.51
Swat	74.00	31.62	61.83	29.06	42.86	22.68	31.38	18.07	22.48	13.68
Tank	81.36	39.66	69.49	37.03	54.24	31.76	49.15	29.97	40.68	25.86
Tor Garh	95.77	50.99	92.96	50.26	82.39	46.72	66.90	40.35	54.93	34.85
Upper Dir	85.29	43.17	77.73	41.31	63.02	36.43	52.49	31.98	39.96	25.86
Punjab Province										
Attock	30.29	9.76	18.00	6.74	4.29	2.07	2.29	1.25	0.86	0.51
Bahawalnagar	78.08	36.65	68.34	33.99	44.99	25.29	34.67	20.58	22.92	14.48
Bahawalpur	73.57	32.08	61.89	29.06	38.32	20.54	26.95	15.42	18.24	11.03
Bhakhar	86.12	38.65	74.88	35.57	45.93	25.11	30.14	17.93	21.29	13.28
Chakwal	38.38	12.19	24.24	8.76	4.04	1.87	1.35	0.65	1.01	0.52
Chiniot	76.42	30.61	61.19	26.65	34.33	17.49	25.67	14.00	17.01	9.93
D. G. Khan	85.71	46.28	79.47	44.66	65.85	39.79	57.80	36.33	50.25	32.89
Faisalabad	47.72	17.22	32.51	13.47	14.32	7.39	8.96	5.05	5.89	3.55
Gujranwala	37.29	13.00	22.58	9.14	6.97	3.46	3.74	2.00	2.19	1.25
Gujrat	34.66	10.86	16.11	6.07	3.75	1.97	2.21	1.23	1.10	0.70
Hafizabad	54.49	20.50	39.87	16.97	16.28	8.47	10.30	5.92	5.98	3.67

Table 7 (continued)

District	Cut-off (k)=4		Cut-off (k)=5		Cut-off (k)=6		Cut-off (k)=7		Cut-off (k)=8	
	H	MDP	H	MDP	H	MDP	H	MDP	H	MDP
Jhelum	34.92	12.31	19.44	7.83	3.57	1.89	1.19	0.73	1.19	0.73
Jhang	72.98	29.70	60.13	26.57	34.93	18.10	26.52	14.44	15.16	8.95
Kasur	64.65	25.18	49.61	21.53	23.44	12.19	13.48	7.53	6.25	3.79
Khanewal	69.82	31.35	57.89	27.89	33.16	18.76	23.33	14.05	15.96	10.27
Khushab	63.42	25.77	47.32	21.36	25.84	13.39	15.10	8.60	8.72	5.22
Lahore	21.86	7.81	12.29	5.07	3.56	1.86	1.78	1.03	0.68	0.44
Layyah	69.90	27.93	59.18	25.56	36.22	18.04	25.51	13.79	15.82	9.23
Lodhran	74.40	30.87	64.16	28.23	35.15	18.47	22.87	13.14	14.68	9.09
M Bahauddin	43.93	16.34	31.80	13.20	12.97	6.70	7.53	4.32	5.44	3.27
Mianwali	56.34	21.65	42.61	17.89	20.42	10.30	14.08	7.53	9.86	5.50
Multan	59.27	24.82	47.15	21.55	29.45	15.14	18.30	10.35	11.39	6.91
Muzaffar Garh	86.96	41.40	79.37	39.48	56.35	31.27	41.38	24.49	28.34	17.92
Nankana Sahib	41.75	15.38	27.18	11.41	11.65	5.83	6.80	3.87	4.37	2.65
Narowal	58.57	21.56	42.23	17.35	16.14	8.12	7.57	4.18	3.19	1.94
Okara	55.81	19.38	37.50	14.78	14.53	7.13	9.01	4.70	3.78	2.22
Pakpattan	60.87	21.97	45.77	18.46	21.74	10.56	11.67	6.35	6.41	3.86
R Y Khan	81.17	37.71	70.88	34.89	47.49	26.63	35.32	21.05	25.03	16.01
Rajanpur	92.72	51.71	87.36	50.34	73.18	45.71	66.67	42.88	57.47	38.43
Rawalpindi	26.09	8.60	14.27	5.57	4.79	2.31	1.92	1.06	1.49	0.87
Sahiwal	49.19	18.58	38.11	15.95	18.01	9.25	11.78	6.60	7.16	4.30
Sargodha	60.72	23.39	46.81	19.76	19.42	10.17	12.32	6.86	7.54	4.52
Sheikhupura	48.97	16.83	33.08	13.01	10.65	5.35	6.54	3.53	3.36	2.02
Sialkot	28.57	10.13	17.03	6.90	4.11	2.12	1.96	1.10	0.98	0.59
T.T. Singh	56.70	22.12	41.39	18.19	19.86	10.50	12.20	7.11	8.13	5.04
Vehari	77.26	29.46	66.13	26.69	41.76	19.18	29.93	14.42	17.87	9.26
Sindh Province										
Badin	86.54	54.09	83.49	53.23	78.29	51.45	74.62	49.83	69.42	47.15
Dadu	86.29	40.89	74.62	37.65	56.85	31.07	47.21	26.98	34.52	21.11
Ghotki	86.10	40.87	81.02	39.81	63.10	34.49	54.81	31.31	42.78	25.96
Hyderabad	35.87	16.15	27.66	13.50	16.72	9.50	12.77	7.61	8.51	5.45
Jacobabad	90.28	49.90	85.58	48.72	72.10	43.91	64.26	40.43	54.55	35.74
Jamshoro	73.89	33.32	66.88	31.51	46.50	25.47	38.22	22.23	30.57	18.73
Karachi East	10.53	3.72	5.57	2.34	1.55	0.77	0.62	0.36	0.62	0.36
Karachi Malir	24.00	9.39	15.00	6.45	9.00	4.54	9.00	4.54	4.00	2.21
Karachi West	32.08	11.19	19.81	8.06	4.72	2.51	2.52	1.54	1.26	0.86
Kashmore	92.76	50.24	86.88	48.75	71.49	43.24	58.82	37.15	47.51	31.23
Khairpur	89.37	47.98	83.19	46.36	68.82	41.04	58.33	36.37	49.57	31.93
Larkana	59.38	30.12	48.44	26.52	35.94	21.98	32.81	20.48	28.91	18.26
Matiari	82.48	42.61	75.18	40.58	56.93	33.80	45.26	28.89	37.96	25.00
MP Khas	84.39	52.36	79.63	50.90	69.84	47.19	65.08	45.01	61.64	43.30
N Feroze	88.07	41.37	73.39	37.20	49.08	28.17	38.07	23.37	27.98	18.12
Sanghar	86.00	48.80	78.13	46.58	65.11	41.79	60.93	39.80	54.55	36.52
Shahdadt	89.36	41.64	82.98	40.07	65.96	33.77	48.94	26.46	29.79	17.47
SB Abad	84.56	46.91	78.48	45.24	65.57	40.57	58.99	37.62	50.63	33.30

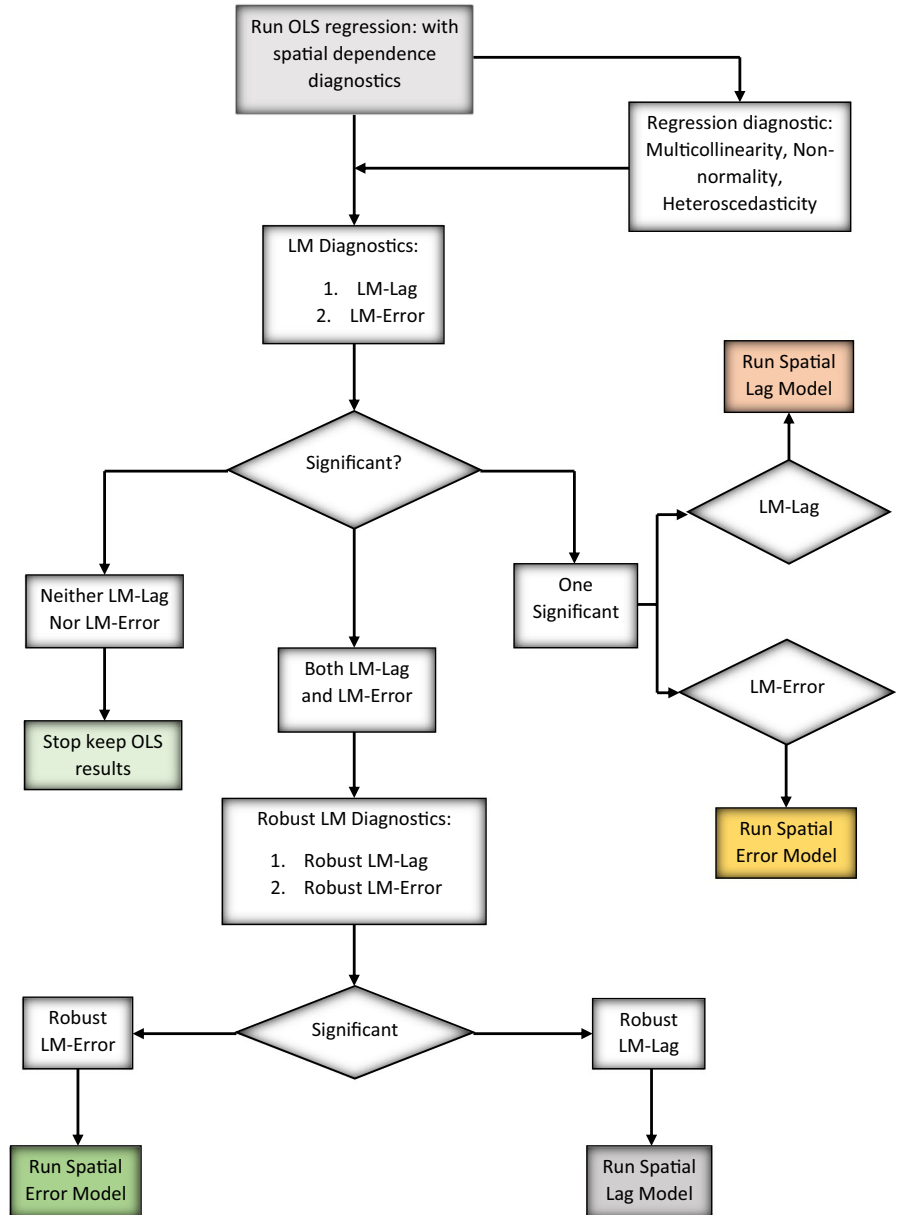
Table 7 (continued)

District	Cut-off (k)=4		Cut-off (k)=5		Cut-off (k)=6		Cut-off (k)=7		Cut-off (k)=8	
	H	MDP	H	MDP	H	MDP	H	MDP	H	MDP
Shikarpur	87.46	48.04	79.87	45.92	62.38	39.39	55.12	35.94	48.51	32.46
Sujawal	98.09	57.92	97.45	57.82	88.54	55.01	84.71	53.63	75.16	49.06
Sukkur	69.36	33.59	60.27	30.92	46.46	26.31	38.72	23.15	32.66	20.06
TA Yar	76.09	42.89	67.39	40.45	58.15	37.13	53.26	34.95	47.28	32.02
TM Khan	90.95	51.94	88.57	51.22	81.90	49.03	73.81	45.91	65.24	41.80
Tharparkar	98.60	62.39	97.19	62.06	91.93	60.53	88.42	59.03	83.51	56.57
Thatta	82.67	44.10	75.74	42.24	60.40	37.17	55.45	35.30	50.50	32.79
Umer Kot	94.01	56.18	88.02	54.45	75.58	49.74	70.51	47.45	66.36	45.55
Baluchistan Province										
Awaran	100.00	66.67	100.00	66.67	97.74	66.07	94.74	65.10	93.23	64.56
Barkhan	97.50	49.68	96.88	49.44	86.88	46.38	76.88	42.54	60.00	35.66
Dera Bugti	98.33	59.29	93.33	57.89	90.83	56.82	86.67	55.13	83.33	53.68
Duki	100.00	39.35	100.00	39.35	78.46	33.05	56.92	25.45	33.85	15.78
Gwadar	77.23	37.06	73.27	36.09	57.43	31.28	48.51	27.63	36.63	22.15
Harnai	98.17	52.05	96.33	51.65	86.24	48.54	79.82	46.38	71.56	43.23
Jaffarabad	92.98	53.49	88.89	52.67	79.53	49.23	71.93	46.18	64.91	42.72
Kachhi/ Bolan	93.98	51.02	90.36	50.20	77.71	46.44	71.69	44.16	66.87	41.80
Kalat	97.50	45.74	89.17	44.08	76.67	40.70	69.17	37.95	55.83	32.88
Kech/Turbat	85.47	38.87	74.42	36.53	60.47	32.67	54.07	30.20	43.60	25.80
Kharan	95.77	43.65	93.46	43.20	74.62	37.80	58.08	31.73	45.77	26.22
Khuzdar	100.00	70.88	100.00	70.88	99.37	70.71	98.12	70.25	94.98	68.97
Kohlu	60.00	23.80	50.00	22.20	30.00	15.10	20.00	11.20	20.00	11.20
Lasbela	65.12	26.40	51.16	22.49	27.91	15.30	18.60	11.00	11.63	7.72
Loralai	90.73	40.67	83.44	39.11	58.28	31.13	50.33	28.15	36.42	22.33
Mastung	86.54	40.34	81.73	39.41	70.19	35.29	61.54	32.03	43.27	24.54
Nasirabad	92.31	50.58	85.90	48.94	75.00	45.40	66.67	42.13	61.54	39.74
Nushki	82.29	33.11	76.00	31.81	52.00	24.64	38.86	19.71	23.43	13.09
Pishin	76.67	32.44	66.67	30.02	40.83	21.77	29.17	16.79	17.92	10.93
Qilla Abdullah	100.00	53.28	98.73	52.98	91.10	50.69	78.81	46.07	64.83	39.64
Qilla Saifullah	98.73	52.99	97.47	52.74	91.98	51.14	83.12	47.79	69.20	41.91
Quetta	67.45	28.70	56.86	25.87	32.94	17.63	23.73	13.46	14.71	9.02
SS Abad	100.00	51.09	97.87	50.64	91.49	48.91	87.23	47.55	70.21	40.55
Sherani	100.00	52.70	100.00	52.70	100.00	52.70	91.89	50.00	75.68	44.00
Sibbi	79.31	38.61	73.79	37.42	58.62	32.81	49.66	29.34	43.45	26.76
Sohbatpur	96.88	55.91	93.75	55.27	90.63	54.14	85.94	52.50	73.44	47.25
Washuk	93.84	46.61	87.67	45.45	76.03	42.71	67.81	39.95	58.90	36.36
Ziarat	96.88	50.11	94.79	49.71	88.54	47.76	78.13	43.80	64.58	38.29

Appendix 3

See Fig. 8

Fig. 8 Spatial regression model decision process suggested by Luc Anselin & Rey



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