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Spatial spillover effect of multi-dimensional poverty in Malawi

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High and persistent levels of multidimensional poverty pose a significant challenge in Malawi. Finding effective methods to eradicate poverty in all its forms remains a key policy concern. Economic and human geographical theories suggest that poverty persists due to spatial dependence and the resulting neighbourhood or spillover effects; the level of multi-dimensional poverty in one area is affected by that in neighbouring areas. This study investigated the spatial patterns of multidimensional poverty in Malawi using data from the 2019 Integrated Household Survey. Using the Alkire-Foster method, a local multidimensional poverty index was constructed based on the needs and characteristics of Malawi. This research employs a spatial lag model to determine whether poverty levels in a cluster influence neighbouring areas. Results show that as of 2019/2020, 61% of individuals in Malawi lived in multidimensional poverty. On average, those affected experienced deprivation in 51% of the weighted indicators. The Multidimensional Poverty Index (MPI) was lower in urban areas (0.148) compared to rural areas (0.342). Key findings reveal the significant spatial dependence of multidimensional poverty, indicating that poverty clusters geographically. Importantly, increased education in one area is correlated with reduced poverty in surrounding areas. Additionally, climate shocks do not only increase multidimensional poverty in the directly impacted clusters but they have ripple effects on neibhouring clusters. These results suggest that targeted anti-poverty interventions, particularly educational investments in poverty hotspots, could effectively reduce poverty in Malawi.

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Introduction

Goal No. 1 of the United Nations' Sustainable Development Goals (SDGs), adopted in 2015, aims to end poverty in all its forms by the year 2030. It includes addressing multidimensional poverty, which goes beyond a lack of income to encompass various deprivations such as poor health, lack of education, inadequate living standards, limited access to quality work, and a poor environment (UNDP and OPHI, 2023). The concept of multidimensional poverty was a key gap identified during the previous Millennium Development Goals (MDGs) era, between 2000 and 2015, where poverty reduction focused primarily on income, leaving out other critical aspects of poverty (United Nations, 2015). The SDGs aim to fill this gap by addressing a broader spectrum of human deprivation.

As of 2023, more than half of the SDGs' implementation period has elapsed, but a substantial portion of the global population remains multidimensionally poor. According to the 2023 Global Multidimensional Poverty Index (MPI) Report by UNDP and OPHI, 1.1 billion people—approximately 18% of the world's 6.1 billion people—are considered multidimensionally poor. The situation remains particularly dire in many developing regions of Africa, Asia, and Latin America, where people continue to experience various forms of deprivation despite the adoption of social protection schemes aimed at addressing extreme poverty, inequality, risk, and vulnerability (Borga and D'Ambrosio, 2021).

Approximately five out of six poor people live in the sub-Saharan region or South Asia (UNDP and OPHI, 2023). Despite tremendous progress in economic growth, with many developing nations moving from low-income to middle-income, multidimensional poverty remains a major concern, as approximately 65% of the poor live in middle-income countries (I.b.d). Considering the enduring prevalence of poverty in low-and middle-income nations, the elimination of multidimensional poverty continues to pose a formidable challenge.

Like many developing nations, Malawi endures high levels of multidimensional poverty. According to the 2022 Malawi multidimensional poverty index report by the National Statistical Office of Malawi, about 59 out of every 100 individuals suffer from various forms of poverty, and on average, poor people lack about 54% of the possible deprivations (National Statistical Office, 2022).

A pivotal step in the literature's endeavour to eradicate poverty in all its forms has been the shift from solely monetary measurements to a multidimensional approach. Sen, (1985) argued that poverty should not only be defined or measured in monetary terms, as it is multidimensional in nature. He contended that poverty is a complex concept that must consider people's diverse characteristics and circumstances. The poor generally lack not only income but also education, health, justice, credit, and other productive resources and opportunities. Thus, poverty should be viewed as a deprivation of capabilities that limits what people can achieve, rather than merely a lack of income. Scholars and policymakers have also praised the multidimensional measurement of poverty for its ability to adequately capture the various deprivations people experience and provide a more comprehensive understanding of deprivation (Alkire and Foster, 2011; Martinez and Perales, 2017).

Prior to 2021, Malawi had solely relied on the income or monetary measure of poverty. However, to complement the monetary measure and to get a more comprehensive understanding of deprivation, the Malawi Multidimensional Poverty Index (M-MPI) was developed by incorporating various dimensions of poverty beyond income, such as health, education, work, and environment.

In the effort to eradicate poverty, Malawi has, since its independence in 1964, implemented various growth and poverty medium-term strategies, namely the Malawi Poverty Reduction Strategy Paper (2002–2005), Malawi Growth and Development Strategies I-III (2006, 2011, 2018), and currently, the Malawi 2063 first 10-year implementation plan (National Planning Commission, 2020). These include aspects such as the Agricultural Input Subsidy Programme and social protection schemes such as the social cash transfer programme and public works programmes. Despite evidence that these programmes reduce monetary poverty in Malawi, multidimensional poverty remains high in the country (National Statistical Office, 2022).

According to the Malawi Poverty Report for 2020, using an absolute poverty line of MWK 165,879 per person per year, 51.7% of the population is considered poor (National Statistical Office of Malawi, 2021). This figure is significantly lower than the multidimensional poverty headcount ratio of 59% reported in the same year. This discrepancy suggests that the monetary measure of poverty does not adequately capture the complexity of poverty in Malawi, as it tends to underestimate the extent of deprivation in the country. This implies that the Malawi Multidimensional Poverty Index (M-MPI), by incorporating various dimensions of poverty beyond income—such as health, education, work, and environment—provides a richer and more nuanced picture of poverty in Malawi.

The sluggish decline and persistence of high levels of multidimensional poverty in Malawi raises concerns over the well-being of Malawians and cast doubt on realising the 2030 Agenda for Sustainable Development (SDG), especially Goal No. 1 of eradicating poverty in all its forms. Not only that, the realisation of the Malawi agenda 2063's medium-term goal to raise the country's income status to a lower-middle level by 2030 and to meet most of the Sustainable Development Goals (SDGs) looks gloomy. Hence, sparks interest in the search for other reasons why multidimensional poverty persists and factors that may hamper the effectiveness of anti-poverty interventions in reducing it.

Economic and human geographical theories suggest that poverty persists due to spatial dependence and the resulting neighbourhood or spillover effects (Galvis and Roca, 2010). Thus, multidimensional poverty in one geographical area may be correlated with multidimensional poverty in nearby areas. This argument is supported by Tobler's first law, which states that "everything is related to everything else, but near things are more related to each other than distant things" (Tobler, 1970). Spatial clustering of multidimensional poverty may also be explained by economic interdependencies among neighbourhoods highlighted by the economic agglomeration theory.

Economic agglomeration theory explains the clustering of similar industrial firms and how their proximity attracts supportive services and markets, thereby attracting more firms (Krugman, 1991; Venables, 1996). Similarly, areas that share similar multidimensional poverty levels or conditions that contribute to poverty tend to concentrate together, resulting in a higher prevalence of poverty. This may be attributed to the existence of economic interdependencies among clusters or areas that are in close proximity to each other (Fujita and Thisse, 2013). For instance, neighbouring areas rely on each other for trade, infrastructure, and social services such as education and healthcare, which may directly affect multidimensional poverty. Consequently, any changes in these factors in one area may not only affect the levels of multidimensional poverty in that area but also in the surrounding areas that depend on it. Thus, poverty spillovers are not simply a matter of geographical proximity but of systemic constraints that extend beyond individual communities. Without targeted investments in human capital, infrastructure, and economic diversification, poverty can perpetuate itself, creating a reinforcing cycle.

Studies on multidimensional poverty reveal significant spatial spillover effects, where poverty in one area influences neighbouring regions. In Colombia, Turriago-Hoyos et al. (2020) found clusters of poverty linked to unemployment and low urbanization. Khan and Sloboda, (2023) identified poverty hotspots in Balochistan, Pakistan, influenced by neighbouring districts' income levels. Similarly, Peng et al. (2018) demonstrated that financial development in China reduced rural poverty through direct and spillover effects. Urbanization in rural China negatively affected economic poverty but showed a limited impact on health and education poverty (Wang et al. 2023). In Ecuador, financial inclusion reduced poverty significantly (Álvarez-Gamboa et al. 2021), while property tax revenues in Colombia had notable spillovers (Ramírez et al. 2017).

In Morocco, Amaghouss and Ibourk, (2020) analysed multidimensional poverty using a spatial analysis approach. By examining data from 75 provinces between 2004 and 2014, the study found that poverty is a geographical phenomenon characterised by significant spatial inequalities, although there is a slow rate of convergence between wealthier "centre" and poorer "periphery" provinces. The authors propose that disparities in education and healthcare access are major contributors to this spatial inequality.

Oteng-Abayie et al. (2023) investigate the spatial effects of microfinance on poverty and inequality across districts in Ghana, using data from national living standards surveys. The study employed spatial econometric techniques to determine the relationship between microfinance intensity and spatial disparities, finding that microfinance has a statistically significant negative impact on both spatial inequality and poverty. These effects include both direct benefits within a district and spillover effects on neighbouring districts.

The pure theory of public expenditure by posits that education has external benefits. The advantages of improved education are not only experienced by the target communities but also by nearby communities. Nevertheless, studies on multidimensional poverty globally have often overlooked its spatial spillover effects.

However, studies on spatial determinants of multidimensional poverty including those discussed above, have focused on economic factors such as employment, urbanization, income, financial development, property tax revenue, and financial inclusion. Our empirical literature review did not identify any studies globally that have specifically examined the spatial spillover effects of education on multidimensional poverty. While studies on education and poverty exist, including those exploring spillover effects, they only focused on income or monetary poverty and not multimesional poverty (Abramitzky, 2021; Hofmarcher, 2021; Mussa, 2017; Niazi and Ullah Khan, 2012; Qiu et al. 2023). Additionally, these studies have not explored the spillover effect of education across geographical space. Given this gap, our study provides a novel contribution by considering the influence of geography and space in examining multidimensional poverty in Malawi while exploring the spatial spillover effects of education.

Additionally, previous studies on poverty in Malawi have mainly focused on the monetary or income poverty (Kaluwa and Kunyenje, (2019); Mccarthy et al. 2016; Mussa, 2011, 2014; Mwale et al. 2022; National Statistical Office of Malawi, 2022) and the few studies on multidimensional poverty have ignored the influence of geography and space (Mtocha et al. 2024). Therefore this paper also fills the gap in Malawian literature on multimensional poverty.

More importantly, this paper contributes to the literature on multidimensional poverty by using a country-specific index, the Malawi multidimensional poverty index (M-MPI), which was recently launched in 2021. This index is different from the global MPI and other country-specific indices because it is customised to suit the specific needs and priorities of Malawi and reflects the national understanding of poverty as well as the country's policy priorities. The dimensions and indicators of Malawi's Multidimensional Poverty Index (MPI) were carefully selected to align with the country's specific needs and policy priorities, ensuring that they accurately reflect the national understanding of poverty (National Statistical Office of Malawi, 2022). For instance, food security deprivation is included in Malawi's MPI but is not part of the global MPI. This distinction is crucial because food security remains a major challenge in Malawi, making it essential for poverty measurement and policy intervention. Similarly, child labour, a significant issue in many developing contexts, is not considered in the global MPI, but it remains a pressing concern for Malawi. The selection of these indicators was guided by the Malawi Growth and Development Strategy (MGDS) III, which served as a blueprint for achieving sustainable growth and poverty reduction. Therefore, using this index helps to understand poverty in the country well.

Methods

Data sources and sampling design. The study utilized data sourced from Malawi's fifth Integrated Household Survey (IHS V) (2019/2020). IHS is a multi-topic survey implemented by the government of Malawi through the National Statistical Office (NSO). It collects data on household consumption (both food and non-food), demographic characteristics, health, education, labour force participation, credit and loans, household enterprises, agriculture, housing infrastructure and asset ownership, and food security indicators.

The IHS V sampling frame is derived from the listing information and cartography provided by the 2018 Malawi Population and Housing Census (PHC). It encompasses the three major regions of Malawi: the North, Centre, and South, and is stratified into rural and urban strata. The urban strata consist of the four main areas: Lilongwe City, Blantyre City, Mzuzu City, and the city of Zomba. All other areas are classified as rural. Each of the 28 districts is treated as a separate sub-stratum within the broader rural stratum. Additionally, the sampling frame excludes populations residing in institutions such as hospitals, prisons, and military barracks.

A stratified two-stage sampling design is employed for the IHS. At the first sampling stage, the sample enumeration areas (EAs) for IHS V were selected within each stratum (district) systematically with PPS from the geographically ordered list of EAs in the sampling frame. Each EA represents the smallest operational area established for the census, characterised by well-defined boundaries on maps, and corresponds to the workload of a single census enumerator. The size for each EA is based on the total number of households in the 2018 Malawi Census frame. On average, each EA contains approximately 215 households, which is an ideal size for conducting a new household listing in each sampled EA. The sampling frame of census EAs for each district was sorted by rural/urban classification, TA and EA codes. Using systematic sampling, this ordering of the sample EAs provided a high level of geographic implicit stratification.

Following the selection of sample EAs, a listing of households was conducted in each sample EA to provide the sampling frame for the second-stage selection of households. A total of 12,288 households from 768 Enumeration Areas were selected. However, due to COVID-19, 51 Enumeration Areas could not be visited by the end of the 12-month fieldwork period, resulting in a final total of 11,434 households in 717 Enumeration Areas or clusters.

The spatial units of analysis for the study are the Enumeration Areas or the clusters.

Spatial modelling

Spatial weight matrix. Before performing any spatial analysis, it is necessary to define and construct a spatial weight matrix. Identifying the presence of spatial dependence and analysing its effect on multidimensional poverty can only be accomplished by incorporating a spatial weight matrix denoted as W. A spatial weight matrix is a square matrix that defines the adjacency of geographical units under study and is specified as follows:

$$W = \begin{bmatrix} w_{11} & \cdots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{n1} & \cdots & w_{nn} \end{bmatrix}$$

Where n is the number of observed enumeration areas or clusters (EAs) and w_{ij} is ij^{th} the element of the spatial weight matrix indicating the geographical proximity between clusters i and j.

The design of the spatial weight matrix is a crucial and challenging task in spatial econometrics. Various spatial matrices have been used in previous studies, including the queen contiguity matrix, the inverse distance matrix (with or without a cut-off point), and the economic distance matrix (Ramírez et al. 2017; Wang et al. 2023). With the queen contiguity matrix, geographical units are considered neighbours if they share common borders. On the other hand, the inverse distance matrix utilises geographic distance to determine neighbours. According to geographic distance, the theory suggests that spatial dependence should be stronger among units that are closer to each other compared to those that are more distant. However, both the queen contiguity and inverse distance matrices do not take into account the economic and social relations among geographical units. Hence, the economic distance matrix was developed to account for the level of economic interdependence among geographical areas.

However, it should be noted that no spatial weight matrix is superior over the other; it depends on the context of the analysis, the nature of data, and research objectives. Different spatial weight matrices are specified depending on the spatial structure of the data or how neigbhourhood is defined. For areal data, the most common criteria include contiguity or inverse distance, while for point data typically rely on neighbourhood definitions based on a fixed radius or k-nearest neighbours (Anselin, 2022).

Due to the sampling design for the IHS and the use of enumeration areas as the unit of analysis, it is impractical to use the queen contiguity matrix. Systematic sampling of enumeration areas makes it very unlikely to sample contiguous clusters; therefore, many clusters will end up without neighbours because the contiguous clusters were not sampled. Additionally, it is challenging to use the economic distance matrix because it relies on the cluster's economic outcomes, such as per capita income, trade, and cost of living, to compute economic distance. The multidimensionality of the economic indicators complicates their definition. Furthermore, the unavailability of data on other economic outcomes in the IHS prevents the construction of an economic indicator that reflects all economic factors, making this a more subjective spatial weight matrix.

Nevertheless, the IHS provides GPS coordinates for central points within clusters, enabling the calculation of geographic distances between clusters. Therefore, the inverse distance matrix was used to consider the impact of space. Furthermore, LeSage and Pace, (2010) have argued that the choice of a spatial matrix does not significantly affect the findings, as its sensitivity to W is not as strong as commonly believed. This, therefore, justifies the use of the inverse distance matrix.

Spatial autocorrelation analysis. In order to examine whether there exists a spatial association between the multidimensional poverty score of a particular geographical unit and poverty scores of neighbouring areas, the global Moran's I and Geary's C tests for spatial autocorrelation were utilized. The Global Moran's I is used to test the existence of global spillovers. Global spillovers arise when changes in a characteristic of one region impact all regions' outcomes. In our case, multidimensional poverty in one area impacts the immediate neighbours, and the neighbours affect their neighbours, and so on. The global spillovers may also have feedback effects since impacts can be passed on to neighbours and back to the area of origin. Geary's C is a global measure of spatial autocorrelation, similar to Global Moran's I, but more sensitive to local differences between neighboring units.

Spatial Lag regression model. This study employs the Spatial Lag (SAR) regression model. SAR incorporates the spatial lag of the dependent variable, permitting examination of the influence of multidimensional poverty in neighbouring areas on the corresponding poverty in the particular area. Furthermore, it allows disaggregation of the effects of the explanatory variables into direct and indirect (spillover) effects, allowing exploration of the spillover effect of education levels in a particular area on the multidimensional poverty of neighbouring areas.

Therefore, following Anselin, (2022), SAR is expressed as follows:

$$Y = \alpha\iota_N + \rho WY + X\beta + \varepsilon \tag{1}$$

Direct and indirect (spillover) effects. Rearranging Eq. 1, the Spatial Lag Model can be expressed as follows:

$$Y = (I - \rho W)^{-1}(\alpha\iota_N + X\beta) + (I - \rho W)^{-1}\varepsilon \tag{2}$$

When $|\rho| < 1$ this expression can be expressed as an infinite series, the Leontief expansion involves the explanatory variables and the error terms:

$$\begin{aligned} Y = {} & (I_N + \rho W + \rho^2 W^2 + \cdots)(\alpha\iota_N + X\beta) \\ & + (I_N + \rho W + \rho^2 W^2 + \cdots)\varepsilon \end{aligned} \tag{3}$$

The Leontief expansion allows for defining two effects: a multiplier effect involving the explanatory variables and a spatial diffusion effect involving the error terms (Le Gallo, 2021). The multiplier effect shows the influence of explanatory variables from neighbouring areas on multidimensional poverty for a particular area, while the diffusion effect shows the influence of a random shock in one area on multidimensional poverty levels in neighbouring areas. However, both of these effects diminish with distance (Le Gallo, 2021).

LeSage and Pace (2021) caution against directly interpreting the coefficients from the spatial lag model as marginal effects for two reasons. First, the model, in its reduced form (see Eq. 2), is nonlinear. Therefore, the coefficients cannot be interpreted directly, but rather the calculated marginal effects, as is the case with other nonlinear models. Second, multiplier effects arising in spatial lag models cause the marginal effects to be different from the coefficients form a standard regression model.

To calculate the marginal effects, we obtain partial and cross-partial derivatives from Eq. (2) in the following way:

$$\begin{bmatrix} \frac{\partial E(y_1|x_i')}{\partial x_{1k}} & \cdots & \frac{\partial E(y_1|x_i')}{\partial x_{nk}} \\ \vdots & \ddots & \vdots \\ \frac{\partial E(y_n|x_i')}{\partial x_{1k}} & \cdots & \frac{\partial E(y_n|x_i')}{\partial x_{nk}} \end{bmatrix} = (I - \rho W)^{-1}\beta_k \tag{4}$$

The resulting matrix of partial and cross-partial derivatives provides both direct and indirect effects. The direct effects are represented by the diagonal elements of the matrix, while the indirect (spillover) effects are represented by the off-diagonal elements.

Construction of the Multidimensional Poverty Index

Alkire-Foster (AF) methodology. The study uses the Alkire-Foster methodology developed by Alkire and Foster (2011) to construct the multidimensional poverty index.

The use of the Alkire-Foster (AF) method for calculating the Multidimensional Poverty Index (MPI) demonstrates a commendable recognition of the complexity inherent in the phenomenon of poverty. In contrast to traditional income-based measures, the AF method delves deeper by identifying deprivations across multiple dimensions of life, including but not limited to health, education, housing, work and many others. This multidimensional approach facilitates a more comprehensive understanding of the ways in which poverty affects individuals and households (Mtocha et al. 2024).

AF methodology involves two main stages; the identification stage and the aggregation stage. The identification stage involves identifying individuals or households that are considered multidimensionally poor. In the multidimensional measurement setting, where there are multiple variables, identification is a substantially more challenging exercise, and there are various approaches that can be used in this regard. A key strength of the AF method is its use of the dual cut-off approach. The AF approach first identifies individuals or households that are deprived in each dimension or indicator by comparing the person's achievement against the corresponding predetermined deprivation threshold. This ensures that individuals facing significant deprivation in a specific area are not overlooked, even if they meet the minimum requirements in other areas (Mtocha et al. 2024).

Given a set of d dimensions with r indicators, a vector of d deprivation cut-offs are denoted by $z = (z_1, \cdots, z_d)$. Denoting households' achievement in an indicator j by x_j, a household i said to be deprived of an indicator j if $x_{ij} < z_j$. For each indicator, a deprivation dummy variable g_{ij}^0 is generated such that:

$$g_{ij}^0 = \begin{cases} 1, if\, x_{ij} < z_j \\ 0, otherwise \end{cases}, \text{for all}\, j = 1, 2 \cdots, r \,\text{and}\, i = 1, 2 \cdots, n$$

The deprivation in each of the dimensions may not have the same relative importance. Thus, different weights w_j may be attached to different dimensions depending on their relative importance. To determine a household's deprivation level in each dimension, a deprivation score (c_i) is calculated as the summation of the weighted deprivation values:

$$c_i = \sum_{j=1}^{d} w_j g_{ij}^0.$$

The score increases as the number of deprivations a household experiences increases, and reaches its maximum when the person is deprived in all dimensions (Alkire et al. 2021). A person who is not deprived in any dimension has a deprivation score equal to 0. In addition to the deprivation cut-offs z_j, the AF methodology uses a second cut-off to identify multidimensionally poor households, referred to as the poverty cut off (k). A household is considered poor when the proportion of the weighted deprivations it experiences exceeds the threshold k. Thus, the poverty identification function is given by

$$\rho_k(x_i; Z) = \begin{cases} 1, & if\, \frac{c_i}{n_d} > k \\ 0, & otherwise \end{cases},$$

where n_d is the number of dimensions.

Upon identification, the deprivations of non-poor persons are censored or replaced with zero values in the censored deprivation matrix.

The computation of the MPI requires aggregating two components: the MP incidence or headcount ratio and MP intensity. The headcount ratio or incidence is the proportion of the population that is multidimensionally poor. This involves counting poor households or individuals identified using the poverty cut-off and dividing the total by the total number of households or individuals. The multidimensional poverty incidence is given by: $H = \frac{q}{n} = \frac{1}{n}\sum_{i=1}^{n} \rho_k(x_i; Z)$, where q is the number of poor households. Intensity of multidimensional poverty is the average share of weighted indicators in which poor people are deprived. It is calculated as the sum of deprivation scores of the poor and divided them by the total number of poor people. Mathematically, $A = \sum_{i=1}^{q} \frac{C_i(k)}{q}$, where $c_i(k) = \sum_{j=1}^{d} w_j g_{ij}^0(k)$. The intensity of multidimensional poverty (A) is also sometimes known as the breadth of poverty.

The Multidimensional Poverty Index, also known as the adjusted headcount ratio, is then derived by the product of the MP incidence (H) and the intensity (A).

$$M_0 = H \times A = \frac{q}{n} \times \sum_{i=1}^{q} \frac{c_i(k)}{q}$$

$$MPI(M_0) = \frac{1}{n}\sum_{i=1}^{n} c_i(k) = \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{d} w_j g_{ij}^0(k)$$

An important property of MPI computed using the AF methodology is that the MPI can be decomposed by population subgroup. This means that overall poverty is a population-share weighted sum of subgroup poverty levels. This property is useful in analysing poverty by geographical area, which is the focus of our study.

The Malawi Multidimensional Poverty Index (M-MPI). The study uses the 2022 Malawi multidimensional poverty index (M-MPI) as the dependent variable. The M-MPI was created using the multidimensional measurement method of Alkire and Foster (AF). The multidimensional poverty index encompasses the deprivation of individuals or households in various other dimensions of life, other than income. M-MPI consists of four dimensions: health and population, education, environment, and work. Within the four dimensions, 13 indicators were identified, and these are given in Fig. 1. Each dimension is equally weighted, and each indicator within a dimension is also equally weighted. Table 1 presents the dimensions, weights and deprivation cut-offs for the Malawi Multidimensional Poverty Index.

The choice of dimensions and a set of indicators to be considered in the multidimensional poverty measure was preliminarily key. The dimensions and their respective indicators were selected to align with Malawi's specific needs and priorities, ensuring they reflect the national understanding of poverty and the country's policy objectives (National Statistical Office of Malawi, 2022). For instance, the Malawi multidimensional poverty index has a food security deprivation indicator, which is not part of the global MPI. This is because in Malawi, food security is a major problem that still needs to be addressed. In addition to that, child labour is also a major challenge in a developing context like Malawi; however, this was not taken into account in the global MPI computation. Furthermore, the selection process was guided by the Malawi Growth and Development Strategy (MGDS) III, which was a blueprint for Malawi to achieve growth and graduate out of poverty. Additionally, future iterations of the Multidimensional Poverty

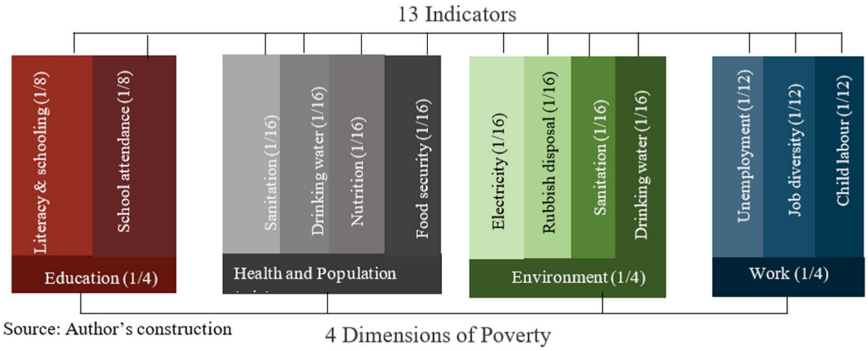

Fig. 1 Structure of the Malawi Multidimensional Poverty Index. The figure illustrates the structure of the Malawi Multidimensional Poverty Index, which is organized around four core dimensions of deprivation. Each dimension is represented horizontally, with vertical bars rising from them to denote the specific indicators used to measure poverty within that dimension. Each indicator represents a distinct aspect of well-being and is aligned with its corresponding dimension. The fractions shown in brackets next to each dimension and indicator indicate the weights assigned to them in the construction of the MPI. These weights reflect the relative importance of each dimension and indicator in the overall poverty measurement.

Table 1 Dimensions, indicators, weights and deprivation cut-offs for Malawi Multidimensional Poverty Index.

Dimension	Indicator	Deprivation cut-offs
Education (1/4)	Literacy and schooling (1/8)	A household is deprived if all members aged 15+ have less than 8 years of schooling, OR cannot read or write in any language.
	School Attendance (1/8)	A household is deprived if at least one child aged 6-14 is not attending school
Health and population (1/4)	Sanitation (1/16)	A household is deprived if the sanitation facility is not a flush or a VIP latrine or a latrine with a roof OR if it is shared with other households
	Drinking Water (1/16)	A household is deprived if its main source of water is unimproved OR it takes 30 minutes or more (round trip) to collect it
	Nutrition (1/16)	A household is deprived if there is at least one child under 5 who is either underweight, stunted or wasted
	Food Security (1/16)	A household is deprived if, in the past 12 months, they were hungry but did not eat AND went without eating for a whole day because there was not enough money or other resources for food
Environment (1/4)	Electricity (1/16)	A household is deprived if they do not have access to electricity
	Rubbish Disposal (1/16)	A household is deprived if rubbish is disposed of on a public heap, is burnt, disposed of by other means or there is no disposal
	Housing (1/16)	A household is deprived if at least two of the following dwelling structural components are of poor quality: -Walls (grass, mud, compacted earth, unfired mud bricks, wood, iron sheets or other materials) -Roof (grass, plastic sheeting or other materials) -Floor (sand, smoothed mud, wood or other materials)
	Asset Ownership (1/16)	A household is deprived if they do not own more than two of the following basic livelihood items: radio, television, telephone, computer, animal cart, bicycle, motorbike or refrigerator AND does not own a car or truck
Work (1/4)	Unemployment (1/12)	A household is deprived if at least one member aged 18-64 has not been working but has been looking for a job during the past four weeks
	Job diversity (1/12)	A household is deprived if all working members are only engaged in farm activities, household livestock activities or casual part-time work (ganyu)
	Child Labour (1/12)	A household is deprived if any child aged 5-17 is engaged in any economic activities in or outside of the household

Author's construction.

Index (MPI) will be shaped by the first 10-year implementation plan (MIP-1) of Malawi's Vision 2063.

The poverty cut-off for the Malawi multidimensional poverty index (M-MPI) is set at 38%. Thus, a household that is deprived of one and a half of the four dimensions is considered multidimensionally poor. Similarly, a household that is deprived of 38% of the 13 indicators is considered poor.

Independent variables

Education. It is inherently difficult to measure education and is endogenous in multiple ways. In the literature, years of schooling is commonly used as a proxy for education (Hofmarcher, 2021b). However, Malawi's Integrated Household Surveys (IHS) do not directly collect data on years of schooling. Instead, respondents report the highest class level they have ever attended.To estimate years of schooling, we assigned a numerical equivalent to each education level. For instance, completing Secondary Form 1 was considered equivalent to nine years of schooling. However, this method is prone to measurement errors as it does not account for class repetition. For example, an individual who repeated Standard 8 due to selection constraints but later attained Form 4 would be

Table 2 Variable definitions and their expected signs.

Variable	Definition and measurement	Expected sign
Household size	A continuous variable capturing the number of individuals within a household	−/+
Residence	Location of the cluster (rura l = 1, urban=0)	+
Age	A continuous variable capturing the average age of household heads in a cluster	−/+
Male-headed	Percentage of male-headed households in a cluster	+
Dependency ratio	Dependents, both young (under 18 years old) and elderly (65 years and older) as a percentage of the working age group (18–64)	+
Climate shock	The number of households that were affected by a climate shock in a cluster	+
Market access	A dummy variable capturing the availability of a market (daily or weekly) in the cluster	−
Health centre	A dummy variable indicating availability of a clinic or hospital in the cluster (yes = 1)	−
Schools	A dummy variable indicating the availability of schools, public or private in a cluster (yes = 1)	−

Author's construction.

Table 3 Multidimensional poverty in Malawi.

Area	M0	H	A
National	0.312	60.83%	51.25%
Urban	0.148	30.90%	47.91%
Rural	0.342	66.37%	51.54%
Northern region	0.269	53.66%	50.15%
Central region	0.322	62.56%	51.52%
Southern region	0.314	61.24%	51.26%

Author's construction based on IHS V data, 2019/20.

considered to have completed 12 years of schooling, even though their actual schooling duration was longer. Similar distortions arise for individuals who repeated Form 4 due to university selection constraints.

These measurement inaccuracies introduce further endogeneity. To test for endogeneity, we conducted a Wu-Hausman test, using school availability within a cluster as an instrument for education (years of schooling). The results confirmed that education was endogenous, but school availability proved to be a weak instrument.

According to Andrews et al. (2019), weak instruments undermine the reliability of instrumental variable (IV) estimators, leading to biased estimates, improperly controlled t-tests, and invalid confidence intervals. Consequently, relying on conventional IV regression with a weak instrument could lead to misleading conclusions.

To address this, we explored alternative estimation methods, such as Lewbel, (2018), which allow for identification even in cases of weak or nonexistent instruments. Unfortunately, Lewbel's approach has not yet been adapted for spatial econometrics, making its application infeasible in our study.

As a result, years of schooling were dropped, and school availability within a cluster was used as a proxy. This decision aligns with the nature of spatial analysis, where using cluster-level variables helps mitigate measurement inconsistencies. If years of schooling had been used, aggregating it at the cluster level would have smoothed out variability and inequality, potentially distorting the underlying patterns of educational attainment. Moreover, in spatial econometric models, averaging individual-level data within clusters can exaggerate spatial correlation, leading to potential bias in estimation. By contrast, school availability is inherently a cluster-level variable, making it a more appropriate choice for this type of analysis.

While we acknowledge that school availability is an imperfect proxy for education, this limitation is primarily due to data constraints rather than a methodological shortcoming.

Control variables. The control variables that were utilized in the study include household size, climate shocks, area of residence, percentage of male-headed households, dependency ratio, and the age of the household head and other cluster characteristics such as the availability of a health care centre and a community market. Table 2 provides the definitions of all independent variables that were used in the study, including their a priori expectations.

Empirical results and discussion

Descriptive statistics. Table 3 summarises multidimensional poverty levels in Malawi, categorized by area. At the national level, the results show that in 2019/2020, approximately 61% of Malawian individuals lived in multidimensional poverty. On average, a person experiencing poverty faced deprivation in 51% of the weighted indicators. The multidimensional poverty index of 0.312 indicates that if all Malawians were poor, they would be deprived of 31% of the weighted indicators.

In relation to multidimensional poverty by area of residence, the findings reveal that rural residents face greater deprivation compared to urban residents. Specifically, around 66% of individuals in rural areas live in multidimensional poverty, while the figure is 30% in urban areas. However, regarding the intensity of poverty, the results indicate that a poor individual in a rural area experiences the same level of deprivation as a poor individual in an urban area. The urban MPI (0.148) is lower than the MPI for rural individuals (0.342).

At the regional level, the results indicate that the central region had the highest percentage of individuals experiencing multidimensional poverty (62.56%), followed by the southern region (61.24%). Conversely, the region with the lowest percentage of individuals suffering from various forms of poverty was the northern region (53.66%). Additionally, the northern region exhibited the lowest MPI score (0.269) compared to the southern (0.314) and central regions (0.322). Regarding the intensity of multidimensional poverty, the results demonstrate that an average poor individual from the northern region faces the same level of deprivation in terms of weighted indicators as an average individual from either the south or the central region, albeit slightly lower in intensity for the former.

Table 4 presents the summary statistics for the clusters. The subsequent analyses utilise the most recent data from Malawi's living standards measurement survey, specifically the fifth Malawi integrated household survey (IHS V). The IHSV collected data from 717 clusters or enumeration areas, which provided geographical coordinates for the households. To ensure the security and de-identification of respondents, these coordinates were offset within a 5-km radius. Consequently, this study examines the characteristics of all households at the cluster level. However, it is important to note that the geographical coordinates

Table 4 Cluster average values for the variables used in the estimations.

Variable	Mean/percentage	Standard deviation	Minimum	Maximum
Household size	4.42	0.63	2.81	6.94
Climate shock (%)	61.43	26.91	0.00	100.00
Male headed households (%)	69.52	15.18	12.50	100.00
Age of household head	43.20	4.85	30.94	58.13
Dependency ratio (%)	60.19	26.62	2.38	181.82
Rural = 1 (%)	81.73			
School = 1 (%)	46.86			
Health clinic = 1 (%)	25.10			
Market access = 1 (%)	51.05			
Number of clusters	708			

Author's calculations based on IHS V data.

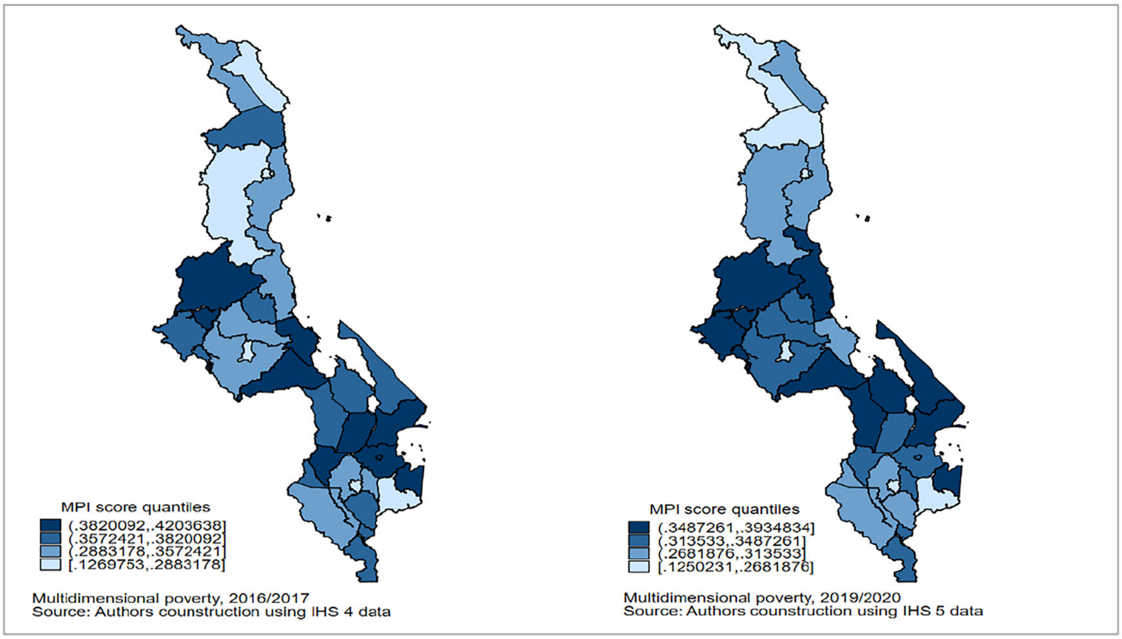

Fig. 2 Spatial distribution of Multidimensional poverty in Malawi, by districts (2016/2017 and 2019/2020). This figure compares the spatial distribution of the Multidimensional Poverty Index (MPI) across Malawi's districts in two time periods: 2016/17 (left map) and 2019/20 (right map), using data from the Fourth and Fifth rounds of the Integrated Household Survey (IHS4 and IHS5), respectively. Districts are shaded according to MPI score quantiles, with darker shades representing higher levels of multidimensional poverty. The legend indicates the MPI score ranges (quantiles) used to classify districts.

for 9 clusters were not recorded, and as a result, these clusters were not included in the spatial analysis of multidimensional poverty.

On average, each cluster comprised 16 sampled households, with approximately 70% of them headed by males. Household sizes ranged from 3 to 7 members, and the typical household head was 43 years old. The average dependency ratio across clusters stood at 60%, varying widely from a minimum of 2% to a maximum of 182%. Climate shocks affected around 61% of households, highlighting the widespread impact of environmental challenges. In terms of location, 82% of the clusters were situated in rural areas, reflecting the country's urbanization status.

Access to essential services varied across clusters. Only 25% of clusters had a health facility, while 46% had a school. Additionally, 51% of clusters had access to a community market, either operating on a weekly or daily basis.

Spatial analysis of multidimensional poverty. Figure 2 illustrates the geographical distribution of multidimensional poverty in Malawi. The darker colours represent areas with higher levels of multidimensional poverty. Upon analysing the distribution of multidimensional poverty across districts, it becomes apparent that districts close to one another or those that share borders tend to have similar poverty levels. This observation suggests the presence of positive spatial dependence of multidimensional poverty within the country. Additionally, the figure reveals that districts in the northern region of Malawi experience lower poverty levels than districts in the central and southern regions. Furthermore, it is noteworthy that the four cities of Malawi, namely Mzuzu, Lilongwe, Zomba, and Blantyre, exhibit the lowest levels of multidimensional poverty.

Table 5 Multivariate Moran's I test for spatial dependence.

Test	Chi-square (1)	P-value
Moran's I	26.76	0.000

Author's calculations based on IHS V data.

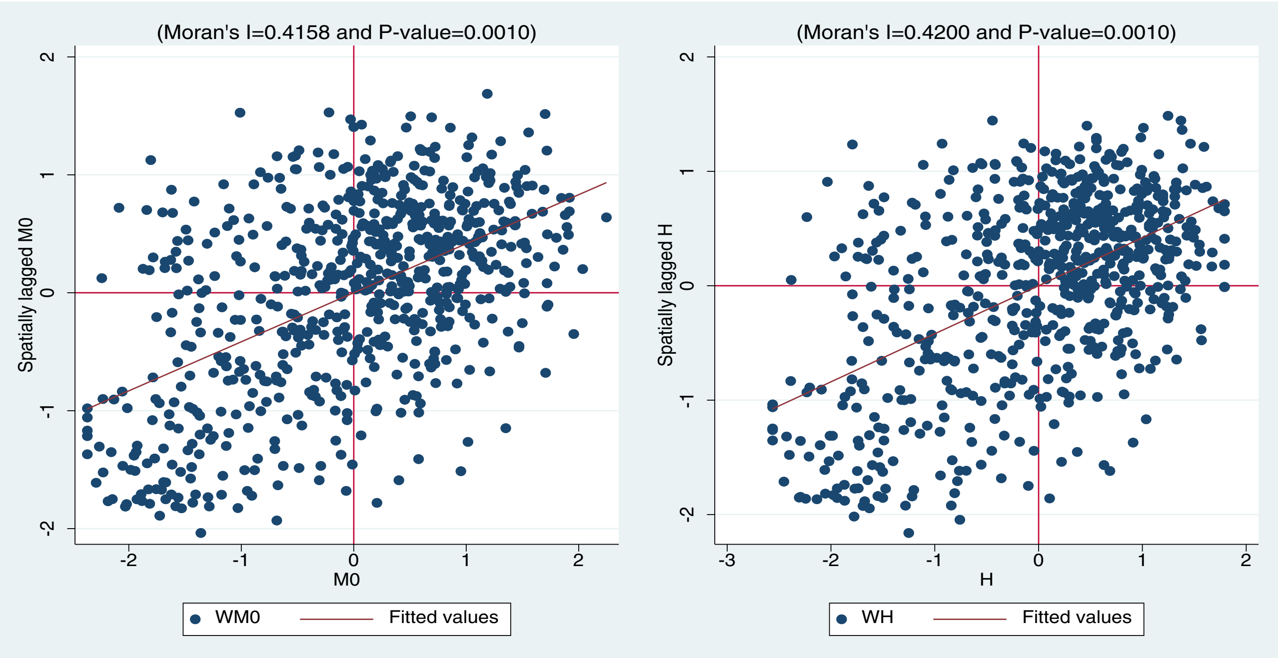

Fig. 3 Moran's I scatter plots for Multidimensional Poverty Index and Incidence. Author's construction based on IHS V data.

Measures of spatial dependence. To examine whether neighbouring clusters depend on each other, the study employed the multivariate Moran's I test for spatial autocorrelation and the results are presented in Table 5. The Chi-square statistic of 26.76 is highly statistically significant, indicating that neighbouring clusters depend on each other.

However, the multivariate Moran's I test does not explicitly indicate the source of spatial dependence; whether it emanates from the dependent variable (multidimensional poverty), the explanatory variables or the error terms. Therefore, to examine whether multidimensional poverty levels in one cluster is correlated with multidimensional poverty levels in neighbouring clusters, this study employed the univariate global Moran's I and Geary's C tests for spatial autocorrelation. The findings are presented in Table 8 in Appendix. Both the coefficient estimates for Moran's I and Geary's C statistics are positive and statistically significant. This implies that the levels of multidimensional poverty in one cluster is correlated with the levels of multidimensional poverty in neighbouring clusters. The Moran's scatter plots depicted in Fig. 3 further demonstrate the positive spatial correlation in multidimensional poverty. The fitted lines in the Moran's plots for MPI scores and incidence (H) display a positive slope, indicating that a cluster's multidimensional poverty is correlated with the levels of multidimensional poverty in its neighbouring clusters.

Spatial lag regression model results. The presence of spatial correlation necessitates estimating the spatial regression model to accommodate it. Failing to account for the presence of spatial correlation in the model specification, despite its existence in the underlying data-generating process, leads to biased, inefficient, and inconsistent estimates (omitted variable bias) (Le Gallo, 2021).

Different spatial regression models can be estimated depending on the type of spatial dependence present in the data-generating process. Spatial dependence can occur when values of the dependent variable in a specific cluster are correlated with those in neighbouring clusters (spatial lag), when unobserved characteristics in one area are correlated with unobserved characteristics in neighbouring clusters (spatial error), or when observed characteristics in neighbouring clusters correlate with values of the dependent variable in a specific cluster (spatial X) (Anselin, 2022; Le Gallo, 2021). To identify the form of spatial dependence and select the most suitable model for the data, Lagrange multiplier (LM) tests were employed.

Table 6 Lagrange multiplier tests for spatial dependence.

Test	Chi-square	df	*p*-value
Spatial error:			
Moran's I	3.213	1	0.001
Lagrange multiplier	9.195	1	0.002
Robust Lagrange multiplier	5.650	1	0.017
Spatial lag:			
Lagrange multiplier	18.032	1	0.000
Robust Lagrange multiplier	14.486	1	0.000

Author's own estimation in Stata.

The results of the LM tests are presented in Table 6. The findings reveal that the Chi-square statistics for both the spatial error and spatial lag specifications are significant, indicating that both models are appropriate. However, both the LM-Error and LM-Lag tests have the power to reject the null hypothesis in the presence of the other. To address this, robust LM tests were developed. When both the robust LM error and lag tests are significant, the model with the highest test statistic is chosen (Anselin, 2022). The findings indicate that both robust LM tests were significant, with the test statistic for the spatial lag model being the most significant. Therefore, a spatial lag model was selected.

Following the results from the robusts LM tests, a Spatial lag model was estimated and the findings are presented in Table 9 in Appendix. The coefficient (W.M0 = 0.204) for the spatial lag is both positive and statistically significant, as evidenced by the p-value being less than 1%. The spatial lag coefficient serves as an indicator for the extent of spatial correlation of multidimensional

Table 7 Marginal effects: Direct, indirect and total effects.

	Direct effect	Indirect effect	Total effect
School	−0.030***	−0.007***	−0.037***
Household size	0.011**	0.003*	0.014**
Rural	0.109***	0.027***	0.136***
Climate shock	0.005***	0.001***	0.007***
Health clinic	−0.021**	−0.005**	−0.026**
Community market	−0.017**	−0.004**	−0.022**
Age_head	−0.002***	−0.001**	−0.003***
Male headed	−0.001**	0.000**	−0.001**
Dependency ratio	0.001***	0.0001***	0.001***

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.
Author's calculation based on IHS V data.

poverty levels in neighbouring clusters while accounting for the influence of other variables.

As previously mentioned, and cautioned by LeSage and Pace, (2021), the coefficients derived from the spatial lag model should not be interpreted directly, but rather computed as marginal effects. Consequently, instead of interpreting the results of the spatial lag regression, the focus will be on interpreting the marginal effects.

Marginal effects: Direct and indirect (spillovers) effects. The calculation of marginal effects from a spatial lag model results in a matrix of partial and cross-partial derivatives. The partial derivatives represent direct effects, whereas the cross-partial derivatives represent indirect or spillover effects. The computed marginal effects are displayed in Table 7.

The findings demonstrate that having a school within a cluster reduces multidimensional poverty, both within the cluster and in neighbouring clusters. Specifically, clusters that have a school have an average multidimensional score that is 0.03 lower than clusters without a school. Additionally, clusters with neighbouring clusters that have a school are 0.007 less poor than clusters without neighbouring schools. The availability of schools has a spillover effect because government schools are congestible public goods. When a school is available in one area, residents from neighbouring clusters can also attend, as long as the school is not already full. This means that even if social services, like schools, are not available in one cluster, individuals can still access services in neighbouring clusters. This finding also explains the socio-economic interdependence among geographical areas, especially those that are closer or share borders.

Regarding the control variables, the findings show that climate shocks in Malawi have both direct and spillover effects on multidimensional poverty. They indicate that climate shocks not only affect the communities directly impacted, but also have ripple effects on nearby communities. More specifically, for each additional household affected by a climate shock within a cluster, the cluster's multidimensional poverty index increases by 0.005. Additionally, neighbouring clusters experience an increase of 0.001 in their multidimensional poverty index.

Having a healthcare facility in a cluster reduces multidimensional poverty, not only within the cluster itself but also in neighbouring clusters. Specifically, clusters that have a healthcare facility have an average multidimensional score that is 0.021 lower than clusters without such facilities. Moreover, clusters that are located near clusters with healthcare facilities tend to be 0.005 less impoverished than clusters without neighbouring healthcare facilities. The presence of a healthcare facility allows individuals to access healthcare services easily, leading to improved health outcomes. This aligns with human capital theory, which suggests that improved health enhances worker productivity and ultimately leads to higher income levels. As a result, higher income levels contribute to a reduction in multidimensional poverty.

The presence of a market in one community reduces multidimensional poverty in that community as well as multidimensional poverty in neighbouring communities. Clusters that have a market have an average multidimensional score that is 0.017 lower than clusters without a market. Additionally, clusters with neighbouring clusters that have a market are 0.004 less poor than clusters that together with their neighbours do not have a community. The availability of markets allows households, particularly smallholder farmers, to sell their goods and generate income. This additional income then enables these households to access improved housing, education, healthcare, and nutrition, thus effectively decreasing levels of multidimensional poverty. Similar to the effect of the availability of a school, having a market in one cluster does not exclude neighbours from using it.

Furthermore, the results show that household size directly affects multidimensional poverty positively, but this effect does not extend to neighbouring clusters. This means that clusters containing larger households tend to have higher levels of multidimensional poverty compared to clusters with smaller households. Specifically, having one additional household member increases the multidimensional poverty index by 0.011. This finding reflects the situation in Malawi, where many households live in extended families. As a result, one household head is responsible for providing for a larger number of individuals. For example, they have to pay school fees for more children and provide food for more people. Consequently, the available resources are stretched thin and often insufficient to support everyone in the household. As a result, these households face food insecurity, children are more likely to drop out of school, and they may engage in economic activities to help support the household.

This finding is supported by the positive effect that the dependency ratio has on multidimensional poverty. The results indicate that clusters with a higher number of dependents, both young (under 18 years old) and elderly (60 years and older), experience higher levels of multidimensional poverty compared to clusters with fewer dependents. Specifically, a one percentage point increase in the dependency ratio within a cluster leads to a 0.001 increase in multidimensional poverty levels within that same cluster. Similar to the impact of household size, having more dependents means that the breadwinner must support a greater number of individuals. Consequently, the available resources are thinly shared among a larger number of people, which is insufficient to meet their needs.

The results also indicate that the age of the household head has a negative effect on multidimensional poverty. Clusters with older household heads have lower levels of multidimensional poverty compared to clusters with younger household heads. Specifically, each additional year of age decreases the levels of multidimensional poverty in a particular cluster by 0.002 and in neighbouring clusters by 0.001. The reduction in multidimensional poverty can be attributed to the fact that older household heads have accumulated more assets and wealth over a longer period of time than younger household heads. Consequently, older household heads are more economically and financially stable, enabling them to better support their households compared to younger households who are still in the early stages of asset accumulation. In addition to that, older household heads might have adult children who support them economically through domestic or international remittances.

Furthermore, the results indicate that clusters with a higher percentage of male-headed households have lower levels of multidimensional poverty, as compared to clusters with a relatively lower percentage of male-headed households. Specifically, a one percentage point increase in male-headed households within a cluster leads to a 0.001 reduction in multidimensional poverty for that cluster. This finding can be attributed to the greater economic engagement of men, particularly in rural areas.

Regarding the effect of location or residence area, the findings indicate that rural clusters experience higher multidimensional poverty compared to urban clusters. On average, the multidimensional poverty index for a rural cluster is 0.07 higher than that of an urban cluster, and having neighbouring rural clusters further widens the poverty gap by 0.01 between rural and urban clusters. Taking into account both direct and indirect effects, the overall level of multidimensional poverty in a rural cluster is 0.08 higher than that in an urban cluster. This result emphasizes the significance of urbanization in reducing multidimensional poverty.

Discussion

The findings show that levels of multidimensional poverty in one area are positively correlated with levels of multidimensional poverty in neighbouring areas. This finding is consistent with the findings by Turriago-Hoyos et al. (2020), Álvarez-Gamboa et al. (2021), Khan and Sloboda (2023), and Ramírez et al. (2017) in relation to multidimensional poverty. At the same time confirms the theory discussed ealier. The existence of spatial dependence in the levels of multidimensional poverty across clusters can be explained by the economic interdependencies among clusters or areas that are in close proximity to each other. For instance, neighbouring areas rely on each other for trade, infrastructure, and social services such as education and healthcare (Bihin et al. 2022; Chang and Hobbs, 2024; Delprato et al. 2024; Roxberg et al. 2020), which directly impact multidimensional poverty. Consequently, any changes in these factors in one area affect not only the levels of multidimensional poverty in that area but also in the surrounding areas that depend on it.

Apart from the previously mentioned findings, the study results also demonstrate that the presence of a school in a cluster is associated with lower levels of multidimensional poverty. Clusters that are associated with a school have lower levels of multidimensional poverty compared to those without a school. It is important to note that the education dimension of the Malawi Multidimensional Poverty Index (MPI) comprises two indicators: school attendance and literacy. The construction of a school has the potential to increase school attendance in the short term, as children who previously could not attend due to long distances may immediately enrol (Nyoni, 2023). Additionally, improved school accessibility can contribute to reducing dropout rates, as proximity to schools lowers barriers to continued education. The effect of school in reducing poverty has been documented in the case of monetary poverty (Ayoo, 2022) since it offers the needed human capital, which is essential for the development of the society (Todaro and Smith, 2020). Furthermore, school attendance directly influences literacy, even in the short run. In early education (e.g., Grade 1), learners begin acquiring basic reading and writing skills. According to our definition of literacy, an individual can achieve basic literacy within one year of schooling. This suggests that investments in school infrastructure can have a swift and measurable impact on both school attendance and literacy, thereby addressing two key components of the education dimension of multidimensional poverty in Malawi.

The finding that the presence of a school in a cluster of multidimensional poverty is associated not only with lower levels of multidimensional poverty in the host cluster but also in neighbouring clusters can be explained by public goods theory. This theory posits that a school is a congestible public good with positive externalities (Abramitzky, 2021; Samuelson, 2024). A school in a cluster is not exclusively attended by children from that cluster; children from neighbouring clusters can also enrol. However, the closer a school is, the greater the likelihood that children will attend it. Consequently, we can expect that the effect of a school's presence will be more pronounced in the host cluster compared to neighbouring clusters.

The estimated negative effect of school presence on the Multidimensional Poverty Index (MPI) is −0.037, indicating that areas with schools tend to have slightly lower multidimensional poverty. However, since the MPI ranges from 0 (no deprivation) to 1 (maximum deprivation), a change of −0.037 represents a relatively small shift in the overall index. This effect size must be understood within the broader context of multidimensional poverty reduction, where multiple interacting factors—such as economic opportunities, service delivery, and social policies—also play a significant role. Furthermore, while the presence of a school provides potential access to education, it does not directly measure school attendance, the quality of instruction, or learning outcomes, all of which more directly contribute to poverty reduction. As a result, the relationship between school presence and the MPI should be interpreted as correlational rather than causal.

Additionally, the relatively small magnitude of the effect suggests that the presence of a school alone is insufficient to drive substantial reductions in multidimensional poverty. Instead, complementary policies, such as investments in teacher quality, school accessibility, and household income support, may be necessary to enhance the effect of educational infrastructure on poverty alleviation. This argument is bolstered by findings indicating that the presence of other infrastructures, such as health facilities and community markets, correlates with lower levels of multidimensional poverty. Moreover, the poverty-reducing benefits of these infrastructures extend beyond the clusters in which they are located, to neighbouring areas. This supports our assertion that investing in schools alone is not enough to substantially reduce multidimensional poverty; instead, it is essential to include complementary services, such as health facilities, markets, and additional infrastructural investments, to more effectively tackle multidimensional poverty.

As alluded previously, another significant finding is the spillover effect of climate shocks on multidimensional poverty. The results show that, apart from increasing multidimensional poverty in the areas directly affected, climate shocks have ripple effects on nearby communities. This finding is also not very common in the literature. Suffice to say that climatic shocks have been so rampant in Malawi (Manda and Mumbo Thindwa, 2025). Climate shocks such as floods, earthquakes, and landslides result in the displacement of households temporarily or permanently in Malawi (Abid et al. 2020). This displacement leads to an influx of people into nearby communities. This, in turn, increases the need for housing, jobs, healthcare, and education, which puts a strain on local resources and infrastructure, as has been the case in Malawi (Government of Malawi, 2023). Additionally, nearby communities often have economic ties to the affected area.

For instance, if a climate shock damages a major transportation route or a primary agricultural area, it can result in disruptions to the supply of goods not only in the affected communities but also in the neighbouring communities that depend on them. Floods and droughts in significant agro-ecological zones, like the Lower Shire valley and the lakeshore plains in Malawi, result in food shortages within those zones and in the surrounding regions (Maganga et al. 2021). Given the strong spillover effects of climate shocks, national poverty reduction policies must integrate climate resilience measures such as strengthening disaster preparedness programmes to mitigate the impact of floods, droughts, and other environmental hazards in addition to infrastructural investments.

Conclusion

The study used Malawi's IHS V data to investigate the spatial spillover effect of multidimensional poverty in Malawi. Specifically, the study sought to examine whether multidimensional poverty in one area is correlated with multidimensional poverty in neighbouring areas. Furthermore, the study sought to investigate the spillover effect of education on multidimensional poverty; the effect of education levels in one area on multidimensional poverty in neighbouring areas. The study employed the Malawi multidimensional poverty index, which is constructed using the Alkire-Foster methodology but customised to suit Malawi's specific needs and priorities and reflect the country's national understanding of poverty as well as policy priorities.

To achieve its objectives, the study employed the spatial lag model. We used the global Moran's I test for spatial autocorrelation to determine whether neighbouring clusters depend on each other, and the results confirmed the dependence of neighbouring geographical units or clusters. This was complemented by the univariate global Moran's I and Geary's C tests for spatial autocorrelation, which confirmed the presence of spatial clusters of multidimensional poverty.

Our findings revealed the existence of spatially dependent clusters. Neighbouring clusters share similar characteristics that affect multidimensional poverty. Furthermore, the results of the spatial lag regression model indicate that the levels of multidimensional poverty in a particular cluster are positively correlated with the levels of multidimensional poverty in neighbouring clusters, meaning that the multidimensional poverty levels in neighbouring clusters are similar. Additionally, the marginal effects indicate that the presence of a school in a cluster is not only associated with lower multidimensional poverty for that particular cluster but also for neighbouring clusters. Notably, other infrastructure developments, such as markets and health facilities, are also associated with lower multidimensional poverty. On the other hand, climate shocks exacerbate the poverty levels of both directly affected clusters and their neighbours.

Policy implications. The findings of this study reveal that multidimensional poverty is spatially correlated, indicating that poverty in one area is interconnected with poverty levels in surrounding communities. This discovery has significant implications for policy, particularly as the government intensifies its efforts to achieve Sustainable Development Goal No. 1, which aims to eradicate poverty in all its forms by 2030. It emphasises the necessity for targeted and effective strategies to address multidimensional poverty, suggesting that a comprehensive approach is essential for its reduction or elimination. This underscores the importance of coordinated, cross-sectoral interventions rather than fragmented, sector-specific programmes.

Traditional poverty alleviation strategies often focus on single-sector interventions, such as improving education, healthcare, infrastructure, or economic opportunities in isolation. However, our findings indicate that addressing one dimension of poverty independently is insufficient, as the causes and effects of poverty are interconnected. Interventions must be multifaceted and spatially coordinated. Without holistic approaches, poverty can perpetuate itself, creating a self-reinforcing cycle.

Furthermore, the existence of spatial clusters necessitates targeted anti-poverty interventions in poverty hotspots. Focusing interventions on clusters that are highly interdependent will yield a greater impact, as the benefits of an intervention in one cluster will spill over to neighbouring clusters. Therefore, strategic interventions are required to break poverty traps and ensure that investments lead to widespread poverty reduction.

The spatial interdependence identified in this study provides empirical support for coordinated, multi-dimensional approaches to poverty reduction. These findings emphasize the importance of integrated interventions that address multiple dimensions of poverty simultaneously rather than relying on isolated, sector-specific strategies. Based on these insights, multilateral agencies and government programmes may consider redesigning their poverty reduction strategies to enhance effectiveness.

For instance, investments in education may yield greater impact when aligned with healthcare access improvements. A practical example of an integrated approach could involve combining the Affordable Input Programme (AIP) (Moyo and Chirwa, 2025) with the proposed national health insurance scheme to better support hard-to-reach communities (Gheorghe et al. 2019; Mchenga et al. 2021). Research has shown that AIP generates spillover effects on key areas such as education, health, and food security (Novignon et al. 2024).

Furthermore, implementing an integrated approach would be more efficient if social programme beneficiaries were registered under a unified system, which is currently being developed by the Malawi government. Expanding school feeding programmes alongside these interventions could further improve multidimensional poverty outcomes. Despite being implemented on a smaller scale, school feeding programmes have demonstrated significant multiplier effects, including reducing absenteeism, improving cognitive development, and enhancing nutrition (Manea, 2021; World Food Programme, 2025). Additionally, these programmes indirectly alleviate poverty by generating income opportunities for local communities involved in food supply chains (World Food Programme, 2025).

Limitations of the study. We recognise our limitations. The IHS V collected data from 717 clusters or enumeration areas, which provided geographical coordinates for the households. However, the geographical coordinates for nine clusters were not recorded. As a result, these clusters were not included in the spatial analysis of multidimensional poverty. The exclusion of these nine survey clusters may influence the strength of spatial autocorrelation. This is because the exclusion of these clusters has created islands (clusters without neighbours) or has led to some clusters having distant neighbours. According to LeSage and Pace, (2021), the strength of spatial correlation decreases with distance. Therefore, the results should be interpreted with caution.

We acknowledge the limitation that our Spatial Lag Model (SAR) primarily identifies spatial correlation rather than establishing a direct causal relationship between poverty levels across regions. While the model effectively captures the interdependence of multidimensional poverty, it does not fully explain the underlying mechanisms driving these relationships. This is an inherent structural limitation that cannot be fully resolved. Therefore, our findings should be interpreted as correlational rather than causal.

Further direction of the study. As a way of extension, the study can be further extended by conducting a spatial analysis of multidimensional poverty vulnerability. This analysis allows us to identify groups of people or areas that are currently poor and in need of poverty alleviation strategies. However, expanding the study to spatially explore multidimensional vulnerability will enable the researcher to identify areas or groups of people who are not currently poor but have a high chance of becoming poor in the future, hence needing poverty prevention strategies.

Data availability

The data that support the findings of this study are openly available online at Word Bank's Microdata Library, under the Living Standards Meaurement Study (LSMS) at https://doi.org/10.48529/mpyk-ds48. Additionnaly, data and other materials for the analysis will be made available upon request.

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Author contributions
First Author: Conception, design, data acquisition, data analysis, interpretation of data, writing draft, revising the draft. Co-authors: Constructing the Malawi Multidimensional poverty index, reviewing and revising a draft, final approval of manuscript. Note: All authors agree to be accountable for all aspects of the work.

Competing interests
The authors declare no competing interests.

Ethical approval
This study did not involve the collection or use of primary data. Instead, it was entirely based on secondary data, the Malawi Integrated Household Survey data (2019/2020) obtained from the National Statistical Office of Malawi (NSO)—the official government agency responsible for the collection and dissemination of national statistics. The data used were drawn from an existing survey conducted by the NSO, which follows strict ethical procedures and obtains approval from the National Commission for Science and Technology (NCST). As no new data were collected and no direct contact or interaction with human participants occurred, the study did not require additional ethical clearance from an Institutional Review Board (IRB). Moreover, the secondary dataset contained no personally identifiable or sensitive information. All analyses were conducted in accordance with standard academic practices, ensuring the anonymity and confidentiality of respondents. The research was carried out in full compliance with ethical guidelines, including the principles outlined in the Declaration of Helsinki and those set forth by the NCST.

Informed consent
This study utilized secondary data from the 2019/2020 Malawi Integrated Household Survey, a nationally representative survey conducted by the National Statistical Office of Malawi (NSO). During the original data collection process, the NSO followed all established research protocols, including obtaining informed consent from participants. As the dataset was fully anonymized and made publicly accessible by the NSO prior to our use, this study did not involve any direct interaction or additional data collection from participants. Therefore, obtaining informed consent specifically for this research was not applicable. We confirm that the use of this secondary data complies with all relevant ethical guidelines and regulations. Throughout the analysis, the anonymity and confidentiality of all participants were strictly upheld.

Additional information
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