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Exploratory Analysis of Regional Disparities in Human Development in Cameroon

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ABSTRACT: The objective of this paper is to analyze the link between geographic location and the level of human development in Cameroon. To achieve that objective, we use Exploratory Spatial Data Analysis (ESDA) techniques on regional human development indices (HDI) in Cameroon from 2001 to 2014. The Moran test confirms the presence of a positive and significant global spatial autocorrelation of the regional human development indices. Thus, the values of the regional human development index in Cameroon are not randomly distributed. There is thus spatial clustering of regions with similar HDI levels. The spatial dependence of the regional HDI in Cameroon suggests cooperation and synergy of action by the regions within the framework of their competences resulting from decentralization, in order to take advantage of the spatial diffusion effects of human development. The Cameroonian government could pursue geo-targeting policies in the implementation of development programs, focusing on regions where spatial externalities would have a greater impact.

KEYWORDS: Regional Human Development Index, regional disparities, exploratory spatial data analysis, spatial dependency, Cameroon.

I. INTRODUCTION

The evolution of Cameroon's Human Development Index (HDI) over several decades reflects the country's progress in improving the well-being of its people. In 2021, Cameroon ranked 153rd in terms of human development, with an HDI of 0.52. This score keeps Cameroon among the countries of the world with an average level of human development.

However, the HDI measured at the national level does not capture the human development dynamics of each region within a country (Hammouda, 2012). The 2019 Cameroon National Development Report, which for the first time estimates the HDI by region, highlights large disparities in the HDI between regions of the country (UNDP, 2020). For example, in 2014, the cities of Yaoundé and Douala recorded the highest level of human development in Cameroon, with HDI values of 0.685 and 0.681 respectively. The Far North, North, Adamaoua and East regions have HDI levels below the national average, with values of 0.371, 0.398, 0.468 and 0.469 respectively. The other regions are close to the national HDI. These regional disparities in human development may compromise the country's national development strategy.

Regional disparities are central to public and social policy issues as well as theoretical and empirical debates on equitable development (Fadlallah and Chakhat, 2019). Cameroon's National Development Strategy 2020-2030 advocates harmonious, balanced and equitable development throughout the country. Its main objective is to create the conditions for economic growth and improve the living conditions of the population, with particular emphasis on the development in terms of human capital and well-being.

Recent advances in the analysis of the convergence of economies with the advent of the New Geographical Economy show the interest of taking spatial dependence into consideration in studies of the convergence of economic phenomena (Ertur and Kalidou, 2005). Indeed, geographical areas, the very seats of economic activities, have long been ignored in economic issues.

However, their positioning as well as their proximities can influence their economic performances through geographical spillover effects. This reflects a spatial dependence of socio-economic variables: the value of a variable in a geographical area (country, region, city, etc.) can be influenced by the values of this variable in neighbouring localities (Le Gallo, 2000).

Several studies have been interested in analysing the spatial dependence of socioeconomic phenomena with a spatial dimension, including human development. These studies have shown that taking into account this spatial dependence between regions can influence the convergence process of the variable of interest differently. Spatial dependence can either be a factor improving the speed of convergence, or a factor slowing it down or even having no effect (Miranti and Mendez, 2020). Despite their growth in several African countries (Nacer, 2019; Diandy, 2018; Fadlallah and Chakhat, 2019), economic studies on spatial dependence on Cameroonian data at the regional level are rare or even non-existent.

The objective of this article is to determine and characterize the possible spatial dependence of the regional HDI in Cameroon over the period 2001 - 2014, through the implementation of an exploratory analysis of spatial data. The article is organised as follows: after this introductory section 1, section 2 presents a review of the theoretical and empirical literature on spatial dependence. Then, section 3 focuses on the methodology of the exploratory spatial data analysis, section 4 presents the results and the last section 5 concludes.

II. A REVIEW OF THEORETICAL AND EMPIRICAL LITERATURE ON SPATIAL DEPENDENCE IN ECONOMIC ANALYSIS

A. Review of the Theoretical Literature

Spatial dependence is a concept that is increasingly taken into account in economic and convergence analyses. Indeed, observations made in geographical locations are characterised by mutual influences which are all the stronger the closer the locations are. This was already mentioned by Tobler (1970) in what is commonly referred to as "the first law of geography": "Everything is related to everything else, and near things are more related than distant things".

The existence of spatial dependence of observations, also called spatial autocorrelation, reflects the fact that the value of a variable in one locality is influenced by the value taken by the variable in neighbouring localities. Le Gallo (2000) defines spatial autocorrelation as the correlation, positive or negative, of a variable with itself resulting from the geographical distribution of the data. For Anselin (2001), spatial autocorrelation is defined as a coincidence between a similarity of values and a similarity of observations.

Spatial data can be either positively auto correlated, negatively auto correlated or not auto correlated at all (Ertur and Koch, 2005). A positive spatial autocorrelation reflects a tendency for similar values of a random variable to be geographically concentrated. In other words, the observed value of a variable in one locality is similar to the average value observed in neighbouring localities.

Negative spatial autocorrelation indicates a tendency for dissimilar observations to cluster geographically: spatial units are surrounded by neighbours with very different values for a given random variable. A lack of spatial autocorrelation indicates that the spatial distribution of observations is random: there is no relationship between the proximity of regions and the degree of similarity of observations for a given random variable.

The identification of spatial dependence on data is commonly done through exploratory spatial data analysis (ESDA). Exploratory spatial data analysis is a set of techniques for detecting patterns of spatial association, local concentrations and spatial regimes present in a data set with a spatial dimension that must necessarily be considered (Anselin, 1994, 1998a, 1998b).

B. Review of the empirical literature

The economic literature has long analysed economies as isolated entities, i.e characterised by an absence of interactions. Increasingly, recent studies assess spatial dependence on human development data in various countries or regions of the world. Indeed, the exploratory analysis of spatial data is often a preliminary step in many socio-economic analyses of phenomena whose geographical location is not to be neglected.

Diandy (2018), through an exploratory analysis of spatial data on income levels of West African countries, shows that there is a positive spatial dependence of incomes in these countries. His results indicate a trend towards geographical clustering of countries with similar income levels. Amaghous and Ibourk (2016) studied spatial disparities and convergence in Moroccan education. They show that there is a very strong spatial disparity between provinces in Moroccan education. In the same field, Nacer (2019) conducts an exploratory analysis of disparities in educational inequality in Algeria. His analyses highlight a strong global and local spatial autocorrelation. Indeed, the distribution of educational inequalities shows a concentration for neighbouring regions with similar attributes.

Miranti and Mendez (2020) have focused on the spatial analysis of human development in Indonesian regions. Their results for the different periods considered in their studies show a strong autocorrelation of HDI levels in Indonesia. They show the value of considering this spatial dependence in convergence analyses of human development.

While the number of studies concerned with the analysis and consideration of spatial dependence of socio-economic phenomena in developing countries, and African countries in particular, is growing, it is practically rare to find such studies concerning the case of Cameroon, probably due to the lack of disaggregated data at the sub-national level (regions, departments, districts). The literature on human development in Cameroon has indeed paid little attention to issues of spatial dependence. The majority of studies on human development in Cameroon have focused on analysing the dynamics of the human development index and its components by considering their values at the national or regional level, but did not focus on geographical spillover effects (Nembot and others, 2009; Saha, 2015). The existence of spatial disparities, as well as a certain polarisation of the human development index, seems to be sufficient reason to look into the analysis of the spatial dependence of human development in Cameroon.

III. RESEARCH METHODOLOGY

A. Definition of the Proximity Structure between Spatial Units

The first step in the exploratory analysis of spatial data is to give a specification of the proximity structure (or neighbourhood links) between the spatial units considered (localities, regions, countries, etc.). The neighbourhood links of a set of N spatial units are specified by the construction of a square matrix of order N, denoted W, called spatial weight matrix. Each term w_{ij} of the matrix W, called spatial weight, indicates the measure of the degree of spatial proximity existing between two spatial units *i* and *j*. All terms w_{ij} are positive and by convention the diagonal terms w_{ii} are zero.

The most commonly used spatial weight matrix is the adjacency matrix whose terms w_{ij} are equal to 1 when regions *i* and *j* share a common border, and 0 otherwise.

$$\begin{cases} w_{ij} = 1 \text{ if } i \text{ and } j \text{ share a common border} \\ w_{ij} = 0 \text{ otherwise} \end{cases} \quad (1)$$

The weight matrix can also be constructed from the geographical distance between spatial units. A specification proposed by Cliff and Ord (1981) defines the element w_{ij} of the distance matrix as:

$$\begin{cases} w_{ij} = (d_{ij})^{-a}(\beta_{ij})^{b} \\ w_{ii} = 0 \end{cases} \quad (2)$$

Where d_{ij} is the distance between regions *i* and *j,* β_{ij} represents the proportion of the perimeter of region *i* that is in contact (border) with region *j;* a and b are parameters determined a priori. Here, the interaction between i and j increases with the length of the common border and decreases with the distance.

Another form of distance-based matrix is the k-nearest neighbour matrix. The term w_{ij} is in this case defined by:

$$\begin{cases} w_{ij} = 1 \text{ if } j \in v_k(i) \\ w_{ij} = 0 \text{ otherwise} \end{cases} \quad (3)$$

where $v_k(i)$ is the set of k nearest neighbours of region i (locality i not being included). Each territorial unit thus has exactly k neighbours whatever the distance between them. The neighbourhood can be geographical or not (distances, travel times, population densities, incidence of a phenomenon ...).

In order to make the spatial parameters comparable across several econometric models, the neighbourhood matrices are generally normalised into rows: w_{ij} becomes $\tilde{w}_{ij} = w_{ij} / \sum_i w_{ij}$. Consequently, the sum of the elements of each row is equal to 1.

The matrix of contiguity is used in this paper. The spatial proximity between two regions means that they share a common border.

B. Detection and Measurement of Spatial Dependence at the Global Level

The calculation of spatial autocorrelation indicators can be done at the global scale or at the local scale. Indeed, it can have two types of effects. Firstly, the global effect is characterised by the fact that all regions show interdependent behaviour. Secondly, the local effect is characterised by the fact that some regions show interdependent behaviour while others show independent behaviour.

The most commonly used statistic for measuring overall spatial dependence is the Moran I statistic or Moran index (Moran, 1950). It indicates the degree of linear association between the value taken by a variable in a given location and the spatially weighted average of that variable for neighbouring locations.

For a given variable *y* and two locations *i* and *j*, the Moran statistic is defined as follows:

$$I = \frac{\sum_i \sum_j w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\frac{1}{N}\sum_i (y_i - \bar{y})^2 \sum_i \sum_j w_{ij}} \quad (4)$$

Where y_i is the observation corresponding to region i, *y* is the mean of the variable of interest *y*, and N is the number of regions.

The Moran statistic is used to test the null hypothesis of no overall spatial autocorrelation. The expected value of Moran's I in the absence of spatial autocorrelation is (Moran, 1950; Cliff and Ord, 1981):

$$E(I) = -\frac{1}{N-1} \tag{5}$$

A value of the Moran statistic below *E*(*I*) indicates negative spatial autocorrelation, while its value above *E*(*I*) indicates positive spatial autocorrelation in the distribution of the variable under consideration.

C. Detecting and Measuring Spatial Dependence at the Local Level

While Moran's I statistic provides a global measure of spatial dependence, it is not sufficient to analyse the local structure of spatial dependence. As a complement to the global Moran test, the Moran diagram (Anselin, 1993) and the local indicators of spatial association make it possible to evaluate the local structure of spatial association. They make it possible to identify the regions that contribute most to the overall spatial autocorrelation, as well as the regional clubs of strong/weak values of the variable of interest. They also allow the identification of regions or groups of regions that deviate from the overall pattern of spatial dependence.

The HH and LL quadrants of the Moran diagram indicate a spatial clustering of similar values indicating positive spatial autocorrelation, while the HL and LH quadrants indicate a spatial clustering of dissimilar values indicating negative spatial autocorrelation.

The Local Indicators of Spatial Association (LISA) defined by Anselin (1995) measure the propensity of an area to group together strong or weak values of a spatial variable or, on the contrary, values of varying amplitude. They thus make it possible to identify areas of concentration on a local scale and to measure the degree of similarity of a spatial unit with its neighbours. The LISA statistics indicate the significance of the spatial groupings HH or LL and at the same time identify regions that deviate from the overall pattern of spatial association.

The local Moran spatial association indicators are defined for each region *i* by:

$$I = (y_i - \bar{y}) \frac{\sum_j w_{ij}(y_i - \bar{y})}{\sum_i (y_i - \bar{y})^2} \tag{6}$$

This statistic is used to test the null hypothesis of no local spatial association. A significant and positive value of the local Moran index indicates a spatial concentration of similar values (HH or LL) while a significant and negative value indicates a spatial concentration of dissimilar values (HL or LH).

D. Variable of Interest and Weight Matrix Used in this Study

The exploratory analysis of spatial data in this study focuses on the regional Human Development Index (HDI) in Cameroon. The data on this index (Table 1), illustrated by figure 1,come from the Cameroon National Human Development Report 2019 (UNDP, 2020). They cover the years 2001, 2007 and 2014 for the 10 regions of Cameroon and also for cities Yaounde and Douala . Given the irregularity of the administrative division of the Cameroonian territory into regions as well as the irregularity of the distribution of inter-regional distances, we will use the k nearest neighbours matrix, based on the geographical distance between the main towns of the regions. In our analysis we will use the value k=2, assuming a relevant influence for the two nearest neighbours.

Table 1. Evolution Of The Regional And National Human Development Index In Cameroon From 2001 To 2014.

Years	2001		2007		2014	
Regions and codes	HDI	Rank	HDI	Rank	HDI	Rank
Douala (DLA)	0.608	1	0.640	2	0.681	2
Yaounde (YDE)	0.593	2	0.648	1	0.685	1
Adamaoua (AD)	0.368	10	0.403	10	0.468	10
Center, Without Yaoundé (CE)	0.472	7	0.538	6	0.545	8
East (ES)	0.414	9	0.438	9	0.469	9
Far North (EN)	0.297	12	0.336	12	0.371	12
Littoral, Without Douala (LT)	0.504	3	0.552	4	0.563	5
North (NO)	0.330	11	0.361	11	0.398	11
Northwest (NW)	0.467	8	0.526	8	0.556	6
West (OU)	0.473	6	0.548	5	0.556	7
South (SU)	0.486	5	0.559	3	0.558	4
South West (SW)	0.500	4	0.537	7	0.591	3
Total for Country Cameroon	**0.459**		**0.505**		**0.528**	

Source: National Human Development Report 2019, Cameroon (UNDP, 2020).

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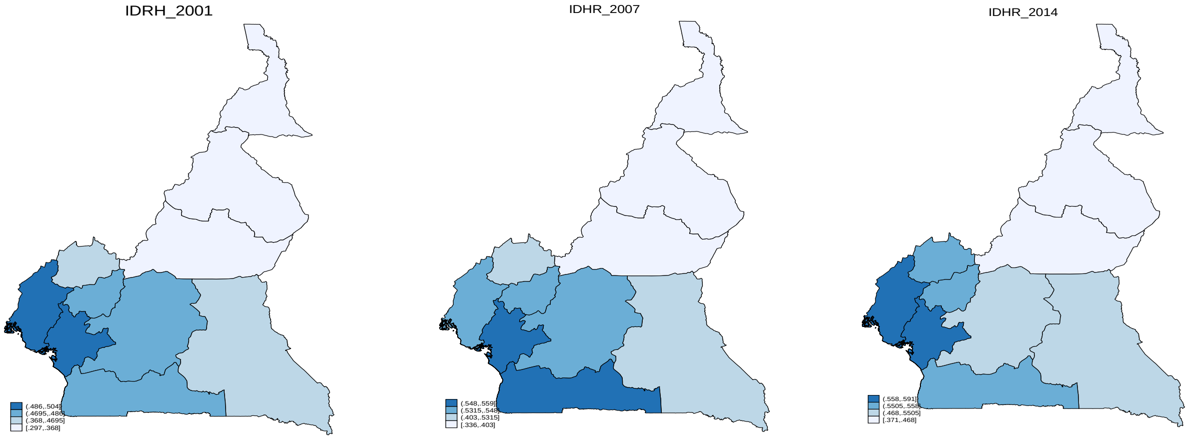
Figure 1- Distribution of the Regional Human Development Index in Cameroon from 2001 To 2014



Source: Developed by the author, based on data from National Human Development Report 2019, Cameroon (PNUD, 2020)**.**

IV. RESULTS AND INTERPRETATION

We now present the results of the exploratory spatial analysis that allows us to assess the spatial dependence of regional human development index values in Cameroon over the period 2001 - 2014.

A. Analysis of the Global Spatial Autocorrelation of Regional Human Development Index Values

The exploratory analysis of the spatial data starts with the assessment of the global spatial autocorrelation to see if there is, globally, a spatial concentration of similar regions regarding the level of human development. This overall spatial dependence is assessed using the Moran's I-statistic test. The Moran test for all the different periods of our analysis allows us to reject the null hypothesis of no spatial autocorrelation. There is thus a positive and significant overall spatial autocorrelation of regional human development levels.

Table 2. Measurement Of The Global Spatial Autocorrelation Of The Regional Human Development Index.

Years	Moran's Statistics I	p-value
2001	0,792***	0.000
2007	0,762***	0.000
2014	0,717***	0.000

Note: *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Source: Developed by the author.

The value of the Moran statistic is 0.792 in 2001, 0.762 in 2007 and 0.717 in 2014 respectively. Thus, on average, 79% of the variation in the HDI value of a region is explained by the variation in the average HDI value in its neighbourhood. An average increase of one point in the average value of the human development index in the neighbouring regions of a given region translates into an increase of 0.7 points in the HDI in that region. Table 2 shows the results of the spatial autocorrelation tests of the regional HDI values for each of the years 2001, 2007 and 2014.

This result reflects the tendency for a significant clustering of regions with similar levels of development: regions with high (respectively low) HDI levels are located near regions with high (respectively low) HDI levels. A process of spatial interactions then underlies the dynamics of human development due to the geographical proximity of the regions. The economic phenomena and characteristics of the regions depend on their relative position to each other.

For a more detailed analysis of the spatial dependence of human development, the Moran test obtained at the global level must be supplemented by the Moran diagram and tests of local spatial autocorrelation through the LISA statistics (Local Indicators of Spatial Association).

B. Analysis of the Overall Spatial Autocorrelation of Regional Human Development Index Values

LISA statistics (Table 4) are determined to measure local spatial dependence in order to see which regions have significant potential for clustering of similar values. The Moran diagram is used to visualise the global and local patterns of spatial association of regional human development (see Figures 2, 3 and 4).

Table 3. Distribution Of The Different Types Of Spatial Association In The Moran Diagram.

Spatial associations	Positive spatial associations		Negative spatial associations	
	HH Quadrant	LL Quadrant	HL Quadrant	LH Quadrant
Number of regions and percentage	6 (60%)	3 (30%)	0 (0%)	1 (10%)
	9 (90%)		1 (10%)	

Note: the distribution of spatial associations in the Moran diagram is the same for each year of the study (2001, 2007 and 2014)
Source: Developed by the author.

Table 4. Lisa Statistics Of The Regional Hdi In Cameroon In 2001, 2007 And 2014

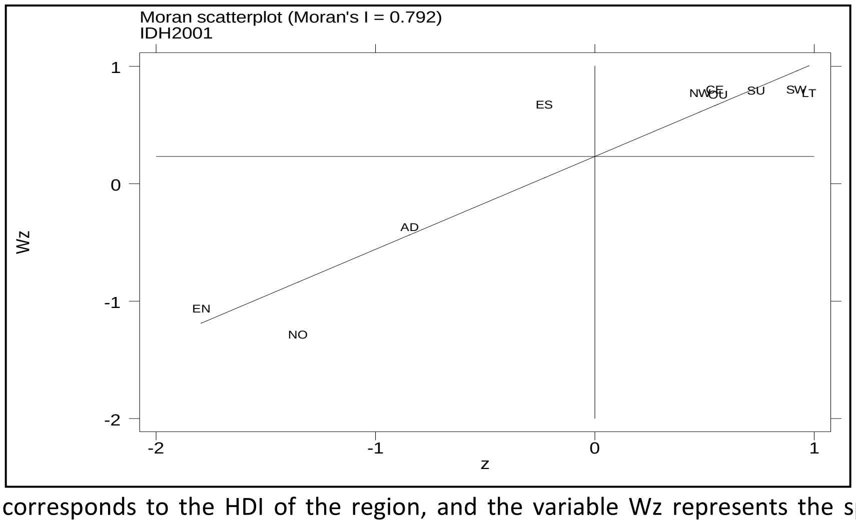
	IDHR 2001			IDHR 2007			IDHR 2014		
	Ii	E(Ii)	Sd(Ii)	Ii	E(Ii)	Sd(Ii)	Ii	E(Ii)	Sd(Ii)
AD	0.378	-0.111	0.624	0.271	-0.111	0.622	0.345	-0.111	0.634
CE	0.467	-0.111	0.624	0.372	-0.111	0.622	0.606	-0.111	0.634
ES	-0.163	-0.111	0.624	-0.323	-0.111	0.622	-0.426	-0.111	0.634
EN	2.190***	-0.111	0.624	1.941***	-0.111	0.622	2.088***	-0.111	0.634
LT	0.803*	-0.111	0.624	0.699	-0.111	0.622	0.672*	-0.111	0.634
NW	0.396	-0.111	0.624	0.611	-0.111	0.622	0.430	-0.111	0.634
NO	1.983***	-0.111	0.624	1.840***	-0.111	0.622	1.945***	-0.111	0.634
OU	0.453	-0.111	0.624	0.481	-0.111	0.622	0.599	-0.111	0.634
SW	0.787*	-0.111	0.624	0.829	-0.111	0.622	0.596*	-0.111	0.634
SU	0.621	-0.111	0.624	0.448*	-0.111	0.622	0.767	-0.111	0.634

Note: *** significant at 1% level; ** significant at 5% level; * significant at 10% level.
Source: Developed by the author

The LISA statistics indicate a strong spatial dependence of the Cameroonian regions reflected by a strong spatial clustering of similar regions. The analysis of the Moran diagram confirms the overall pattern of positive spatial dependence, which can be visualised by the positive slope of the regression line. The synthesis of the spatial association pattern is given in Table 3. From this table, it can be seen that 9 regions have a positive spatial association corresponding to the global pattern and 1 region is atypical, deviating from the global pattern (negative spatial association).

As far as positive spatial associations are concerned, they concern 90% of the regions, i.e. 9 regions out of the 10 in Cameroon. Three regions (30% of Cameroon's regions) are located in quadrant LL of regions with low levels of human development surrounded by neighbours with equally low average levels of human development. These are the northern regions of the country, namely Far North, North and Adamaoua.

Figure 2. Moran Diagram Of The Regional Hdi In Cameroon For The Year 2001



Note: The variable z corresponds to the HDI of the region, and the variable Wz represents the spatial lag of the HDI of the region.
Source: Developed by the author.

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There are six regions in the HH quadrant (60% of Cameroon's regions). Their pattern of spatial dependence is reflected in a grouping of regions with a high level of human development, surrounded by neighbours with equally high average levels of human development. These are the Centre, Littoral, West, North-West, South-West and South regions.

Moran diagrams and LISA statistics, while confirming the overall pattern of spatial association, allow the detection of atypical regions that deviate from the overall pattern of spatial association, thus reflecting spatial heterogeneity.

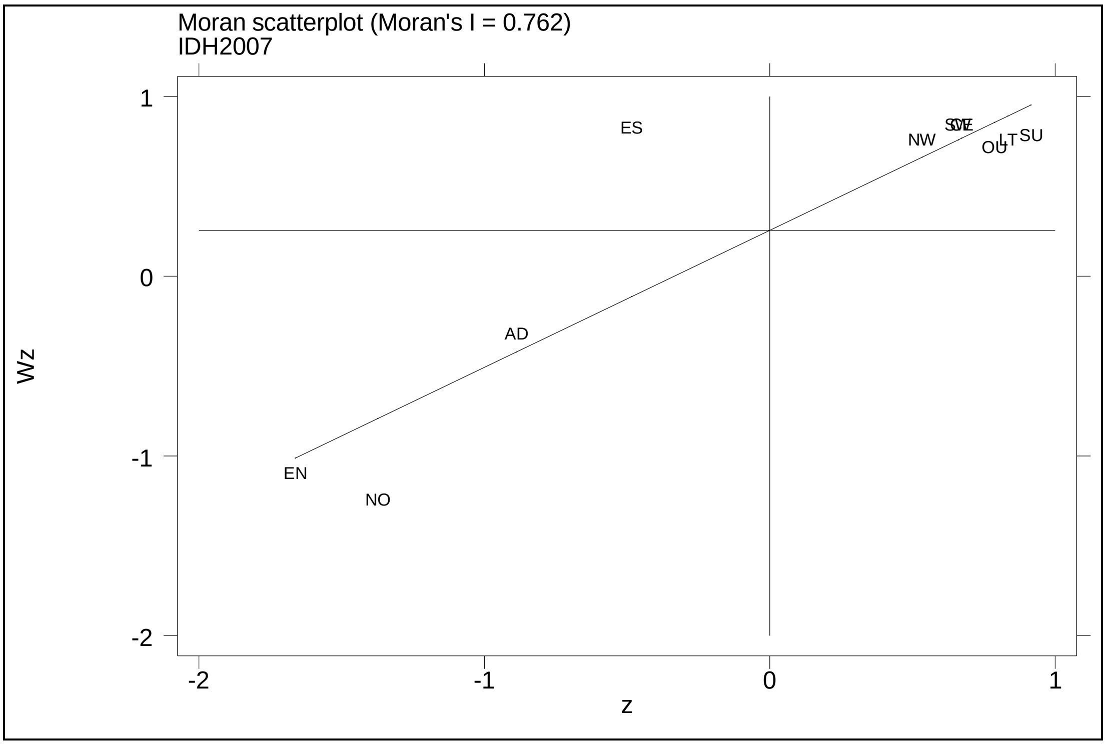
Only one region of the country deviates from the overall pattern of spatial dependence. This is the Eastern region, which is located in the LH quadrant. It is therefore a region with low human development surrounded by neighbouring regions with high average levels of human development. This is the only case of negative local spatial autocorrelation. The LISA statistics and the Moran diagram do not identify a region in the LL quadrant.

The pattern of association has remained stable over the three years: no region in the three years of interest has changed quadrant. This can be explained by the fact that public policies on human development do not take into account the potential for spatial diffusion due to the spatial dependence of regions.

Concerning the significance of the LISA statistics: Two regions show a positive and significant local spatial association at the 1% level: the Far North and North regions (in 2001, 2007 and 2014); Two regions show a positive and significant local spatial association at the 10% level: the Littoral and the South-West regions, in 2001 and 2014;

Spatial exploratory analysis at the local level using Moran statistics shows a geographical disparity in regional human development levels. It follows that, in order to reduce these regional disparities and encourage the spatial diffusion of human development across the country, the government should seek to strengthen complementarities and interactions between different regions, as their proximity to each other is a discriminating factor in the regional HDI.

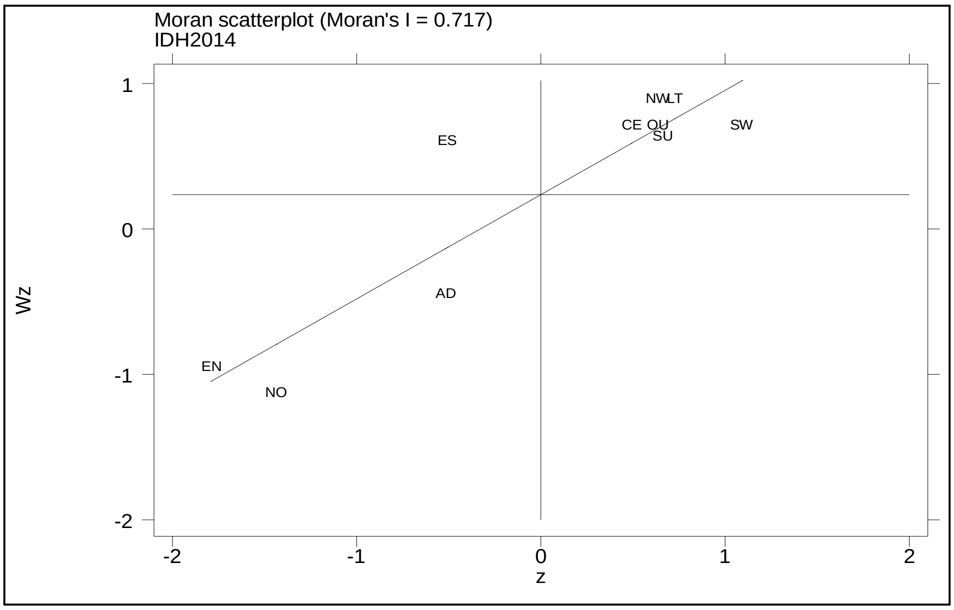
Figure 3. Moran Diagram Of The Regional Hdi In Cameroon For The Year 2007



Note: The variable z corresponds to the HDI of the region, and the variable Wz represents the spatial lag of the HDI of the region.

Source: Developed by the author.

Figure 4- Moran Diagram Of The Regional Hdi In Cameroon For The Year 2014



Note: The variable z corresponds to the HDI of the region, and the variable Wz represents the spatial lag of the HDI of the region.

Source: Developed by the author.

V. CONCLUSION

The objective of this work was to evaluate and analyse the spatial dependence of the regional human development index in Cameroon. The exploratory analysis of the spatial data revealed a strong and significant spatial autocorrelation of the regional human development index in Cameroon. This result indicates that regional HDI values are not randomly distributed across the country. Spatial interactions in human development exist between Cameroonian regions due to their geographical proximity. This spatial autocorrelation is reflected in the Moran indicator, which fluctuates between 0.792 and 0.717 over the period 2001 - 2014.

Moran diagrams constructed for the three years 2001, 2007 and 2014 illustrate the positive spatial association pattern. The LISA statistics confirm the spatial association pattern with a spatial association rate of 90%. 6 out of 10 regions, i.e 60% of the country's regions, are high HDI regions surrounded by neighbours also with high HDI values. The three northern regions (Far North, North and Adamaoua), i.e. 30% of the country's regions, have low HDI values and are surrounded by regions with low HDI values. Only the East region (10% of the country's regions) deviates from this overall pattern of positive association. It shows a negative local spatial association indicated by its negative and significant LISA statistic.

These results show that the geographical location of regions and their geographical proximity play an important role in the dynamics of human development in Cameroon. The modification of the average level of the human development index in the neighbourhood of a region has an impact on the modification of the value of that index in the concern region.

The significance of spatial dependence in the levels of human development of the Cameroonian regions suggests cooperation between the different regions of the country (those closest to each other in particular) in the implementation of their regional development policies in sectors related to human development. The central state would benefit from pursuing geo-targeting policies in the implementation of development programmes, with a focus on regions where geographical externalities would have a greater impact.

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