The Analysis of Sustainability Development of Eastern and South Eastern Europe in the Post Socialist Period

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Abstract

Since the collapse of socialism, Eastern Europe and South Eastern (Balkans) Europe countries have been expeditiously changing as social, economic and politic structure. Some former socialist countries (as Bulgaria, Slovenia, Slovakia, Latvia, Lithuania, Poland and Romania) and Greece became full member of European Union. Some Balkan countries (Serbia, Montenegro, Croatia, Bosnia-Herzegovina, and Macedonia) lived difficult war years. After the wars, they have started to struggle for economic, social and political reconstruction process. Some CIS (Commonwealth of Independent States) countries (as Moldova, Ukraine and Belarus) tried to adapt market economics. Each country in this region wants bigger real per capita income, better welfare level, and generally become a developed country. But these countries have some political, economic and social problems in development and sustainability process. The aim of this paper is to analysis the countries in terms of development indicators such as per capita GDP growth rates, Human Development Index values and Sustainable Human Development Index values in the period of 2000-2010. It will be used the tools of spatial statistics (ESDA -Exploratory Spatial Data Analysis).

Keywords***: Sustainable Development, per capita GDP growth, Human Development Index, Sustainable*** Human Development Index, ESDA (Exploratory Spatial Data Analysis)

1. INTRODUCTION

Eastern and South Eastern Europe are an important area because of witness historic and politic experiences and incidents for ages. But it has been also living historical alteration in recent decades. Although some Balkan countries were relatively stable in 1990s, there was war in Balkan Peninsula. Some former socialist countries (as Bulgaria, Slovenia, Slovakia, Latvia, Lithuania, Poland and Romania) and Greece became full member of European Union. The others have been struggling for this aim. In spite of Kosovo declared of independence in 2008, many countries haven't been accepting this situation. Besides, CIS (Commonwealth of Independent States) countries (as Moldova, Ukraine and Belarus) tried to adapt market economics. Nevertheless these regions of Europe are living relatively stable condition nowadays, compare with last ten years. Whole countries in these regions, especially gain independence in recent decades, wants to become rapidly developed country.

After a long war and unstable political period, the countries have taken an opportunity about their development process nowadays. These regions have been gaining stable structure overtime and this stable period has been supporting development indicators. In this paper, Balkan countries are being analyzed in terms of development indicators such as average rates of per capita GDP growth in the period of 2000-2010, Human Development Index in 2010, and Sustainable Human Development Index in 2010.

2. HUMAN DEVELOPMENT INDEX (HDI) AND SUSTAINABLE HUMAN DEVELOPMENT INDEX (SHDI)

UNDP calculates The Human Development Index (HDI). HDI includes some special data such as life expectancy at birth, adult literacy rates, gross primary-secondary and tertiary enrolment, GDP (gross domestic product) per capita (PPP - purchasing power parity- US$). HDI separates three subgroup as developed (high development), developing (middle development), and underdeveloped (low development) countries.

Africa, Middle East, South Asia and some South American countries have big problems in terms of level of human development. Especially in Africa, the level of human development is lower than other regions of the world.

Besides, The Sustainable Human Development Index (SHDI) was calculated by the Ministry of Environment and Natural Resources of Sri Lanka in 2008. The new version of the index has been revised in 2010. This index calculated with the contributions of United Nations University in Tokyo, Japan. The index calculated by incorporating environmental aspects and quality of the life such as carbon emission, bio capacity, ecological footprint and poverty to Human Development Index (HDI) developed by UNDP to consider the sustainable human development aspects which ignore in HDI. (environmentmin.gov.lk, April 12, 2012).

Acoording to Togtokh and Gaffney (April 15, 2012); by including carbon emissions in recalculation of the HDI, it has gotten an indication of the cost of one country's quality of life to another's. If a country has a very high HDI but also high carbon emissions, it can be said that the high quality of life enjoyed by this nation comes at a price to the quality of life in other countries, particularly developing nations, and to future generations. The index shows that, while the US is vilified for its poor record on tackling emissions, Canada is a long way from being a role model. Yet, with the traditional HDI, the UN is using such countries with very high human development as examples to the rest of the world. Other nations attempting to emulate the success of these particular countries in terms of human development look at the economic model and policies adopted to bring about that success.

Sustainable Human Development Index (SHDI) has been calculating by using HDI and different indexes as the following:

SHDI = ¼(HDI +Ecological Index-Climate Change Index +Poverty Index)

3. DATA, METHODOLOGY AND FINDINGS

3.1. Data

GDP (Gross Domestic Product) per capita growth (annual %) data set comes from World Development Online Database (WDI online) for 21 countries in the period of 2000-2010. Human Development Index data (2010) has been prepared by UNDP (United Nations Development Programme). Sustainable Human Development Index was calculated by Ministry of Environment and Natural Resources of Sri Lanka in 2008. The last version of the index was published in 2010.

To analyze spatial relations between Eastern and South Eastern Europe countries, we use GeoDa (Geographic Data Analysis) software package which conducts Spatial Data Analysis, geo-visualization, spatial autocorrelation and spatial modeling[78].

3.2. Methodology

3.2.1. Quartile Maps

Our analysis start with the quartile maps of the distribution of our variables for each country. Darker colors explain higher values and lighter colors show lower values in quartile map in for all variables.

Figure 1: Per capita GDP annual growth rates in the period of 2000-2010

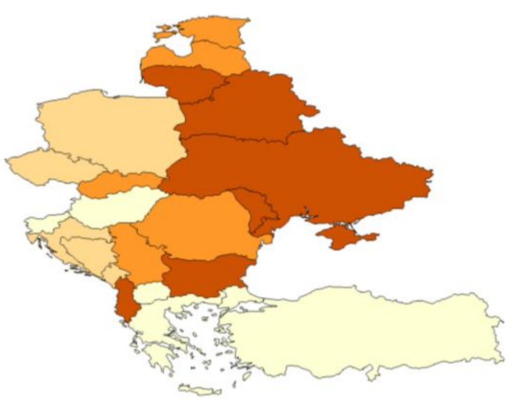


Figure 2: Human Development Index Values (2010)

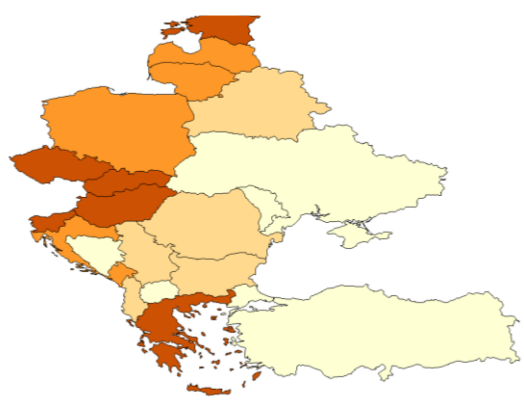


Figure 3: Sustainable Human Development Index (SHDI) values in 2010

78 Here are some of the studies in this regard: Rey and Montouri (1999), Ying (2000), Manfred et al. (2001), Le Gallo and Ertur (2003), Van Oort and Artezema (2004), Dall'erba (2005), Voss et al. (2006), Ezcurra et al. (2007), Ezcurra et al. (2008), Battisti and Di Vaio (2008), Celebioglu and Dall'erba (2010).

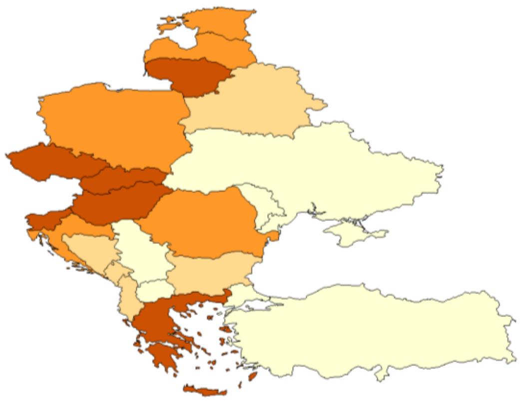


Figure 1 shows that per capita GDP growth rate is especially high values in Albania, Bulgaria, Belarus, Lithuania, Moldova, and Ukraine. On the contrary, Macedonia, Greece, Turkey, Hungary, and Slovenia have the lowest values in this analysis. Figure 2 displays distribution of each country. According to figure 2, especially Greece, Czech Republic, Hungary, Slovenia, Slovakia, and Estonia have the highest Human Development Index values. Bosnia Herzegovina, Macedonia, Turkey, Moldova, and Ukraine have the lowest HDI figures. Figure 3 presents Sustainable Human Development Index (SHDI) values. In this figure, we can see only one difference compare with Figure 2 in terms of highest values. While Estonia is one of the highest value countries in HDI, there is Lithuania in SHDI in place of Estonia. We understand from quartile maps that disparity is clear in this region. For this reason we start ESDA analysis with spatial weight matrix.

3.2.2. Spatial Weight Matrix

A spatial weight matrix is the necessary tool to impose a neighborhood structure on a spatial dataset. As usual in the spatial statistics literature, neighbors are defined by a binary relationship (0 for non-neighbors, 1 for neighbors). Weight matrix calculation is performed under GeoDa. It can be used two basic approaches for defining neighborhood: contiguity (shared borders) and distance. Contiguity-based weights matrices include rook and queen. Areas are neighbors under the rook criterion if they share a common border, not vertices. Distance-based weights matrices include distance bands and k nearest neighbors. Based on these two concepts, we decided to create weight matrices to investigate the distribution of our variables of interest: k_3 nearest neighbor matrix. Due to space constraints, we present the k_3 nearest neighbor matrix only below:

$$\begin{cases} w_{ij}(k)=0 \; if \;\; i=j \\ w_{ij}(k)=1 \, if \;\; d_{ij} \le D_i(k) \; and \; \overset{*}{w}_{ij}(k)=w_{ij}(k)/\sum_j w_{ij}(k) \;\; for \; k=3 \\ w_{ij}(k)=0 \; if \;\; d_{ij} > D_i(k) \end{cases} \tag{1}$$

where di,j is great circle distance between centroids of country i and j and Di(k) is the 3th order smallest distance between regions i and j such that each region i has exactly 3 neighbors. Now that the weight matrix has been defined, we estimate a couple of spatial statistics that will shed some light on the spatial distribution of our variables. The most common of them is Moran's I which is a measure of global spatial autocorrelation (Anselin, 1988).

3.2.3. Calculation of Moran's I for Global Spatial Autocorrelation

Spatial autocorrelation refers to the correlation of a variable with itself in space. It can be positive (when high values correlate with high neighboring values or when low values correlate with low neighboring values) or negative (spatial outliers for high-low or low-high values). Note that positive spatial autocorrelation can be associated with a small negative value (e.g., -0.01) since the mean in finite samples is not centered on 1. Spatial autocorrelation analysis includes tests and visualization of both global (test for clustering) and local (test for clusters) Moran's I statistic (Anselin et al. 2006).

Global spatial autocorrelation is a measure of overall clustering and it is measured here by Moran's I. It captures the extent of overall clustering that exists in a dataset. It is assessed by means of a test of a null hypothesis of random location. Rejection of this null hypothesis suggests a spatial pattern or spatial structure, which provides more insights about a data distribution that what a quartile map. For each variable, it measures the degree of linear association between its value at one location and the spatially weighted average of neighboring values (Anselin et al. 2007; Anselin 1995) and is formulized as follows:

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

Where $\overset{*}{w}_{ij}$ is the (row-standardized) degree of connection between the spatial units i and j and Xi,j is the variable of interest in country i at year t (measured as a deviation from the mean value for that year). Values of I larger (smaller) than the expected value E(I) = -1/(n-1) indicate positive (negative) spatial autocorrelation. In our study, this value is (-0.050). There are different ways to draw inference here. The approach we use is a permutation approach with 999 permutations. It means that 999 re-sampled datasets were automatically created for which the I statistics are computed. The value obtained for the actual dataset has then been compared to the empirical distribution obtained from these re-sampled datasets.

The results of Moran's I are presented in table 1 below. All the results indicate a positive spatial autocorrelation, i.e. the value of a variable in one location depends positively on the value of the same variable in neighboring locations. For instance, when the per capita income in one country increases by 1%, the one of its neighbors increases by slightly more than 33%. All of our three variables of interest are significant (at 1%) with the k_3 nearest neighbor matrix. For this reason, this is the weight matrix we will use in the rest of our study.

Table: The results of Moran's I for the nearest four neighbors

Variables	**K_3**
Per capita GDP (average values of 2000-2010)	0.3310 (0.010)
Human Development Index Values (2010)	0.2421 (0.029)
Sustainable Human Development Index Values (2010)	0.2672 (0.027)
Note: p-values are into brackets	

3.2.4. Moran's Scatterplots of Variables

The Moran scatter plot complements Moran's I because it provides to categorize the nature of spatial autocorrelation into four types: low-low (LL), low-high (LH), high-low (HL) and high-high (HH). The x-axis captures the value of a variable compared to the average value of the sample. For example, all the points on the right hand side of the figure mean (the vertical axis in the middle) that in the corresponding provinces, the value of the variable under study was above the sample's average. On the other hand, the y-axis captures the average value of the same variable in the neighboring locations (with the neighbors being defined by the weight matrix). For instance, all the points below the mean (the horizontal axis in the middle of the figure) represent provinces of which neighbors display, on average, a lower value than the sample's mean.

The result of this approach is a figure with four windows which reflect the correlation between the relative (to the mean) value of a variable in one location and the relative value of the same variable in neighboring locations. For instance, the quadrant HH means a high value in the studied area and a high value in the neighboring areas. Countries located in quadrants I and III refer to positive spatial autocorrelation, i.e. the spatial clustering of similar values, whereas quadrants II and IV represent negative spatial autocorrelation, i.e. the spatial clustering of dissimilar values. Note also that the link between a scatter plot and Moran's I is reflected by a line of which slope is the value of Moran's I statistic.

Figure 4: Moran's Scatterplot for average of per capita GDP growth in the period of 2000-2010

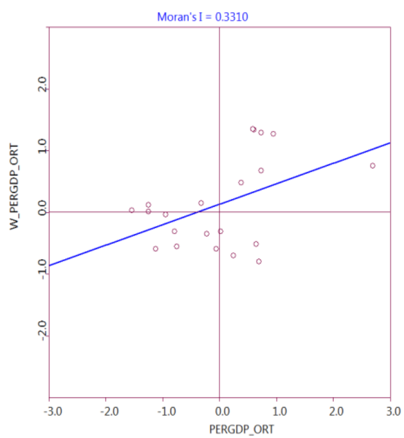


Figure 5: Moran's Scatterplot for Human Development Index in 2010

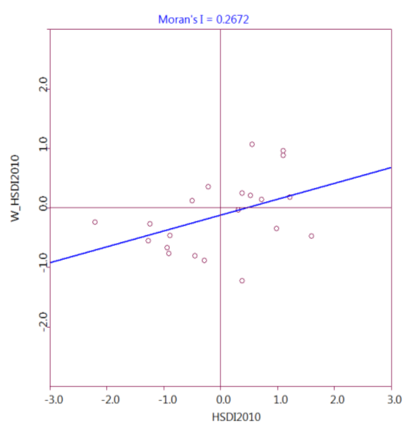
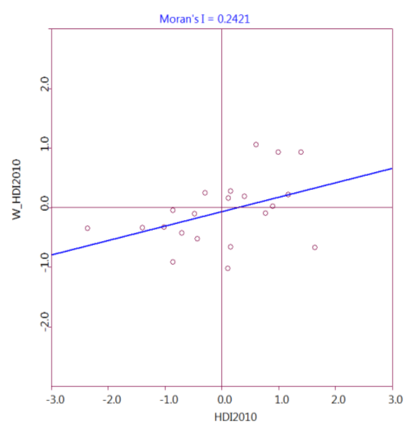


Figure. 6: Moran's Scatterplot for Sustainable Human Development Index in 2010



Figures 4 to 6 above show the Moran scatter plots of our variables of interest. All of the per capita GDP, Human Development Index and Sustainable Human Development Index have positive spatial autocorrelation that is reflected by the value of Moran's I and the fact that most of the countries are located in quadrants HH and LL.

When we look at the HH quadrant in scotterplot of per capita GDP growth, we see mostly Eastern Europe such as Belarus, Estonia, Latvia, Lithuania, Moldova, Romania, and Ukraine. In the contrary, the HH quadrant in scotterplot of HDI has been composed by Croatia, Czech Rep., Poland, Slovakia, Slovenia, Estonia, Latvia, and Lithuania.

Besides, Czech Rep., Poland, Slovakia, Slovenia, Estonia, Latvia, and Lithuania take part in HH quadrant of SHDI.

3.2.5. LISA Statistics for Local Spatial Autocorrelation

LISA statistics (Local Indicators of Spatial Association) measure, by definition, the presence of spatial autocorrelation for each of the location of our sample. It captures the presence or absence of significant spatial clusters or outliers for each location. Combined with the classification into four types defined in the Moran scatter plot above, LISA statistics indicates significant local clusters (high–high or low–low) or local spatial outliers (high–low or low–high). The average of the Local Moran statistics is proportional to the Global Moran's I value (Anselin 1995; Anselin et al. 2007).

Anselin (1995) formulated the local Moran's statistics for each country (I) and year (t) as follows:

$$I_i = \left(\frac{x_i}{m_0}\right)\sum_j w_{ij}x_j \quad with \;\; m_0 = \sum_i x_i^2 / n \tag{3}$$

where wij is the elements of the row-standardized weights matrix W and xi(xj) is the observation in country i(j). Their significance level is based on a randomization approach with 999 permutations of the neighboring provinces for each observation.

Figure 7: LISA Cluster Map of per

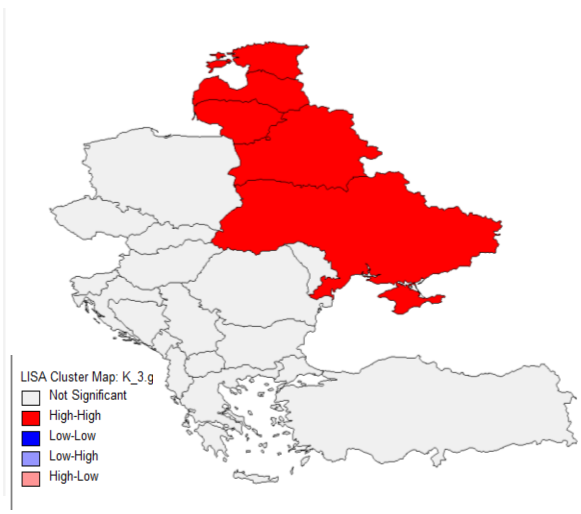
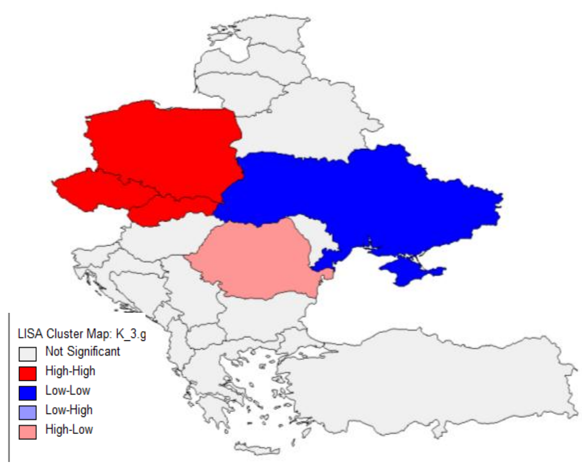
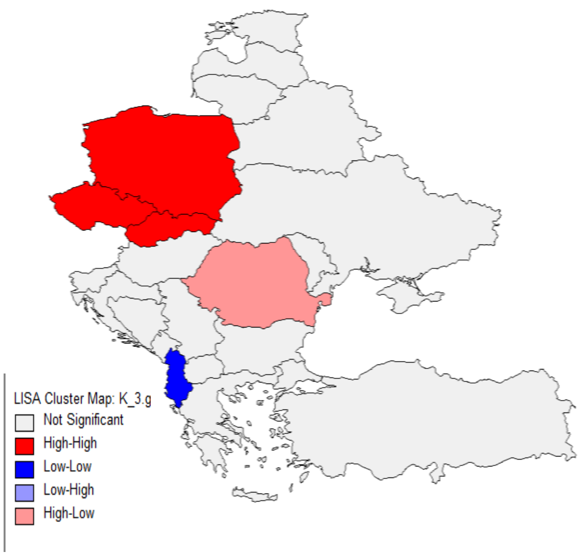


Figure 8: LISA Cluster Map of HDI (2010)



The randomization approach is used in the context of a numeric permutation approach to describe the computation of pseudo significance levels for global and local spatial autocorrelation statistics. In order to determine how likely it would be to observe the actual spatial distribution at hand, the actual values are randomly reshuffled over space 999 times.

Figure 9: LISA Cluster Map of



Countries that are in HH area (red color) in Figure 7 are Belarus, Estonia, Latvia, Lithuania, and Ukraine. HH type autocorrelation is very strong in Eastern Europe. In Figure 8 is LISA cluster map of HDI. This figure point out that Czech Republic, Poland and Slovakia are in HH quadrant (red color), Romania is in HL area (pink color) and Ukraine is in LL area (blue). It is interesting that although Ukraine is in HH quadrant of per capita GDP growth, there is a different situation in the figure. Though Figure 9 is similar to Figure 8, Albania is in LL area of SHDI. But in LISA map of SHDI, Ukraine was in HH type autocorrelation.

4. CONCLUSIONS

The aim of this paper is to analysis spatial distribution of development indicators such as per capita GDP growth rates, Human Development Index values and Sustainable Human Development Index values in the period of 2000-2010. For this purpose we use quartile maps, Moran's Scotterplots and LISA (Local Indicators of Spatial Association) statistics.

We investigate spatial distribution of per capita GDP growth in the period of 2000-2010, Human Development Index (2010) and Sustainable Human Development Index (2010). First of all, our quartile maps show that there is an important development level gap between countries of Europe. Secondly, when we estimate spatial autocorrelation by means of Moran's I, our results indicate positive (and significant) global autocorrelation for all of our variables and thus indicating the geographical location of a country influences its level of per capita GDP growth rate, Human Development Index and Sustainable Human Development Index.

Secondly, these results are corroborated by the corresponding Moran's Scatterplots that display the HH quadrant in scotterplot of per capita GDP growth includes mostly Eastern Europe such as Belarus, Estonia, Latvia, Lithuania, Moldova, Romania, and Ukraine. In the contrary, the HH quadrant in scotterplot of HDI has been composed by Croatia, Czech Rep., Poland, Slovakia, Slovenia, Estonia, Latvia, and Lithuania. Besides, Czech Rep., Poland, Slovakia, Slovenia, Estonia, Latvia, and Lithuania take part in HH quadrant of SHDI.

Thirdly, LISA statistics confirm the significant presence of local spatial autocorrelation and highlight spatial heterogeneity in the form of two distinct spatial clusters of high and low values of per capita GDP growth rate, Human Development Index and Sustainable Human Development Index.

And finally, we can say that there is an important spatial heterogeneity and spatial disparity in terms of our all variables. But the countries in the east part of Europe are divided two groups in the region. Firstly, swiftly growing countries in terms of per capita GDP growth rate and secondly, countries that has high level of SHDI –HDI. For this reason, we can say that swiftly growing countries in terms of per capita GDP growth rate should be developed also in terms of human development.

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