British Journal of Applied Science & Technology
2(4): 390-405, 2012

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Spatial Analyses of Illiteracy and Unemployment at Governorate Level in Egypt

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Author's contribution

Author FGK designed the study, performed the statistical analysis, wrote the protocol, wrote the draft of the manuscript, and managed the analyses of the study. Author read and approved the final manuscript.

Research Article

Received 21st June 2012
Accepted 3rd October 2012
Published 10th November 2012

ABSTRACT

The objective is to investigate the spatial pattern of each of illiteracy rate (IR) and unemployment rate (UR) and the spatial correlation between these patterns. This study is important for both researchers and policy makers. The study design was cross-sectional data analysis. The present study utilizes census data conducted in Egypt in 2006 for 27 governorates. Mapping was used as the first step to conduct visual inspection for IR and UR. Several spatial econometric techniques are available in the literature, which deal with the spatial autocorrelation in geographically referenced data. Two statistics of spatial autocorrelation, based on sharing boundary neighbours, known as global and local Moran's I, were carried out. Wartenberg's measure was used to detect the bivariate spatial correlation between IR and UR based on simulation study. The hypothesis of spatial clustering for IR was not confirmed by a positive global Moran's I of .03. While for UR, it was confirmed by a positive global Moran's I of .25 with $P = .008$. The bivariate spatial correlation between IR and UR was found -.19 and $P = .978$. Based on visual inspection of mapping, global clustering was found for IR in western-northern and middle governorates and for UR in eastern-northern and southern governorates. Global clustering was found for UR but was not found for IR based on spatial measure. Out of 27 governorates, two were found as local clusters in each of IR and UR. The bivariate spatial correlation between IR and UR was not found significant.

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Keywords: Spatial autocorrelation; unemployment; illiteracy; mapping; Moran statistics; governorates of Egypt.

1. INTRODUCTION

Regions, independent of their geographic level of aggregation, are known to be interrelated partly due to their relative locations. Similar economic performance among regions can be attributed to proximity. Consequently, a proper understanding and accounting of spatial liaisons are needed in order to effectively forecast regional economic variables. Spatial statistics relates to the analysis of the spatial aspect of data sets. All data have, implicitly or explicitly, a spatial component. The reasons why spatial statistics are important for many areas are threefold: (i) Data that are spatially close, are usually more similar than those that are further apart. Hence, there is spatial and temporal dependence for most data sets. (ii) Spatial models used to explain and make inference about data structures have important implications in many fields. (iii) The literature on spatial statistics is substantial, but there is still a lot to uncover and many questions to answer. This study showed visual picture for each of illiteracy rate (IR) and unemployment rate (UR), investigated the global and local clusters, examined the spatial relationship between UR and IR, and provides implications for policy makers.

In recent years, a growing interest has been seen in examining the existence of spatial autocorrelation for (UR) and its spatial relationship to several indicators such as IR, level of education, etc. across geographic areas in developing countries. Historically, UR was slightly increased in Egypt from 10.6% in 2006 compared to 9.7% in 1996. While IR was dramatically decreased to 29.64% in 2006 compared to 39.36% in 1996.

The spatial clustering problem of UR and IR exists in several developing and even some developed countries. It is very difficult to control and find potential solutions for this problem. For, the inequality of UR and IR is affected by several factors. For example, people move continuously from governorate to other, the biasedness of the distribution of economic resources across geographical locations, the job and education opportunities are much differed across geographical locations, etc. However, this study is important for both researchers and policy makers. The author hopes to achieve some improvement in reducing the inequality in UR and IR in Egypt. This study wants to show policy makers the location of clusters in UR and IR problem. The purpose of spatial analysis is to identify the pattern in geographical data and attempting to explain this pattern. Thus, findings are expected to enhance monitoring disadvantaged people and policy interventions across governorates of Egypt. Findings also enable the decision maker to re-orient socioeconomic resources toward sectors and governorates that suffering from unemployment and illiteracy.

UR and IR were studied in several countries using different statistical measures. Based on spatial regression analysis, Hooghe et al. (2011) demonstrated that unemployment figures have a strong and significant impact on crime rates in Belgium. According to the study in Jordan by Amerah, (1993), health was affected negatively by unemployment. Amerah stated that since the mid-1980s unemployment had become a serious problem in Jordan, manifesting a widening gap between the demand for and supply of labour. Lack of well-paying jobs, little education and illiteracy are all associated with poverty (Arab Republic of Egypt, 2007). Elhorst (2003) proposed several reasons that make the study of spatially uneven distribution of unemployment worthwhile. One of these reasons is the wide unemployment differentials imply inefficiency in the economy as a whole and reduces growth. Jin et al. (1995) found a strong positive association in Canada between unemployment and many adverse health outcomes. El-Gamal (2012) stated that illiteracy has been a major issue for the government as it prevents several millions of Egyptian citizens from contributing effectively to the economy of the country. The negative impact of illiteracy on individuals and society makes it a key obstacle that threatens the efforts towards achieving integral and comprehensive development. Osman, Zakareya, and Mahrous (2006) emphasized the importance of education for the alleviation of poverty and the adversities that are particularly associated with illiteracy on poverty in Egypt. Some 68 million people in Arab countries are illiterate, an alarming proportion that threatens development, an Arab League culture official said (New York Times, 2002). In their study in Egypt, Wahba and Zenou (2005) found the predicted probability to find a job can decrease for the illiterate and the less-educated workers. Unemployment and illiteracy are a major concern in Egypt. In 2006, they were 10.6% and 29.64% respectively. The report conducted by United Nations Development Program and the Institute of National Planning (2003) stated that the relatively high UR among females was influenced by their higher rates of illiteracy. Unemployed and/or illiterate persons have an increased risk of death. These persons are facing financial problems regarding the quality of living conditions.

To understand the linkages between socioeconomic variables, investigation should focus on features of the areas rather than on the compositional characteristics of residents of the area, which cannot fully describe the social environment in which people live (Macintyre, Maciver and Sooman, 1993). So, the aim of the research is to study geographical mapping and spatial autocorrelation regarding UR and its spatial relationship to IR. Spatial autocorrelation is the term used for the interdependence of the lattice data over space. It is argued that lattice data are spatially correlated. We used exploratory spatial data analysis (ESDA) using lattice data. The ESDA quantifies the spatial pattern in order to increase the analyst's knowledge of the spatial system. As well as mapping plays an important role in monitoring disadvantaged people. Maps can reveal spatial patterns that is neither recognized previously nor suspected from the examination of statistics table. It reveals high risk communities or problem areas (Lawson and Williams, 2001).

In this research some hypotheses were tested. Are UR and IR indicators having global clustering across Egypt's governorates? Are there local clusters? If so, how many clusters are there and where they are located? Can clustering in IR be associated with clustering in UR? Governorates are tightly linked by migration, commuting, and inter-governorate trade. These types of spatial interaction are exposed to the frictional effects of distance, possibly causing spatial dependence of governorate labour market conditions. Some of the socioeconomic indicators such as education basically offer greater chance of getting a job. The parents viewed poverty as illiteracy and the inability to earn better incomes (UNICEF, 2010).

Research relevance stems from a statement that reducing UR and IR inequality is not a primary objective but emergent prosperity. The importance of research objective emanates that health was affected negatively by UR and IR. The report of UNICEF (2010) stated that factors that increase vulnerability to HIV include a rise in mobility, the high IR especially among women, poverty and UR. It is very necessary for policy makers to know in which area the problem of UR and IR inequality is existed? Also, to authors' knowledge, no studies used spatial analysis techniques and geographical mapping in studying the inequality in UR and IR in Egypt.

Importance of mapping was stated by Koch (2005): why make the map if detailed statistical tables carry the same results? Perhaps the most important reason for studying spatial statistics is not only interested in answering the "how much" question, but the "how much is where" question (Schabenberger and Gotway, 2005). In light of these: (1) the existence of spatial global clustering, (2) spatial local clusters for each of UR and IR were investigated, (3) mapping was applied for each of UR and IR and for their local Moran's values, and (4) bivariate spatial correlation between UR and IR was examined based on Wartenberg's (1985) measure. The study design was a cross-sectional analysis in a census survey conducted in Egypt in 2006. Findings make a significant contribution by moving beyond the investigation of a single socioeconomic resource. However, findings push us to more fully consider where and why UR and IR matter.

The paper was structured as follows: Section one review the literature of UR and IR inequality generally in several developing countries and particularly in Egypt. Materials and methods including data details and statistical analysis are presented in second Section. Third section shows the results with some details. Discussion is explained in fourth Section. Final section is closed with several conclusions.

2. MATERIALS AND METHODS

2.1 Data

Data were collected from the book of Egypt's description by information (2009), based on census conducted in Egypt in 2006. For each of 27 governorates, UR and IR were studied. UR is an average number of unemployed individuals at the age category (15-64) years who are capable to and looking for work but unable to find a job. It is estimated as a percentage of labor force, where UR varied geographically in 2006. In urban, lower, upper and frontier governorates were 12.1%, 11.0%, 9.4%, and 10.0% respectively. UR fell from round 12% of the labour force in 1998 to 10.6% in 2006. IR is defined as the percentage of persons who cannot read or write (10 years old or more, not in school). In Egypt, the IR was drastically decreased from 39.36% in 1996 to 29.64% in 2006.

2.2 Analysis

Data analysis involved six steps. In step 1, UR and IR were tested for normal distribution. They were found to follow approximately normal distribution. In step 2, visual inspection based on the quantified gradients for each of UR and IR using quartiles were conducted. Step 3 included the calculation of global Moran's I-statistic for each of UR and IR to detect the global clustering. The significance of I-statistic using permutation test was examined. Step 4 involved the calculation of local Moran's for governorate and it's p-value using Monte Carlo simulation to detect the local clusters for each of UR and IR. In step 5, using quartiles, visual inspection for the gradients of local Moran values was inspected based on choropleth mapping. In Step 6, the bivariate spatial correlation between UR and IR was examined based on Wartenberg's (1985) measure.

The UR and IR were categorized into four intervals. These intervals were used for all maps using darker shades of gray to indicate increasing values. Such approach enables qualitative evaluation of spatial pattern. In the neighbourhood researches, neighbours may be defined as governorates which border each other or within a certain distance of each other. In this research neighbouring structure was defined as governorates which share a boundary. The second order method (queen pattern) which included both the first-order neighbours (rook pattern) and those diagonally linked (bishop pattern) was used. A neighbourhood system of Egypt's governorates is explained in Fig. 1, where ID neighbours for each governorate are shown.

ID	Governorate	ID neighbours
1	Dakahleyia	2,3,4,6,10,11
2	Gharbeyia	1,3,4,11,12
3	Menofya	2,4,12,15
4	Qalyubiya	1,2,3,5,6,15
5	Cairo	4,6,7,15,16
6	Sharkeya	1,4,5,7
7	Ismailia	5,6,8,9,16
8	North Sinai	8,16
9	Port Said	7,8
10	Dumyat	1
11	Kafr ash Shaykh	1,2,12
12	El Buhayrah	2,3,11,13,14,15
13	Alexandria	12,14
14	Matruh	12,13,15,27
15	Giza	3,4,5,14,16,17,18,19,27
16	Suez	5,7,8,15,20,21
17	El Fayyum	15,18,19
18	Bani Swaif	15,17,19,21
19	Al Minya	15,18,21,22,27
20	Southern Sinai	8,16
21	Red Sea	15,16,18,19,22,23,24,26
22	Asyut	19,21,23,27
23	Sohaj	21,22,24,27
24	Qina	21,25,26,27
25	Luxor	24,26,27
26	Aswan	21,24,27
27	New Valley	14,15,19,22,23,24,25,26

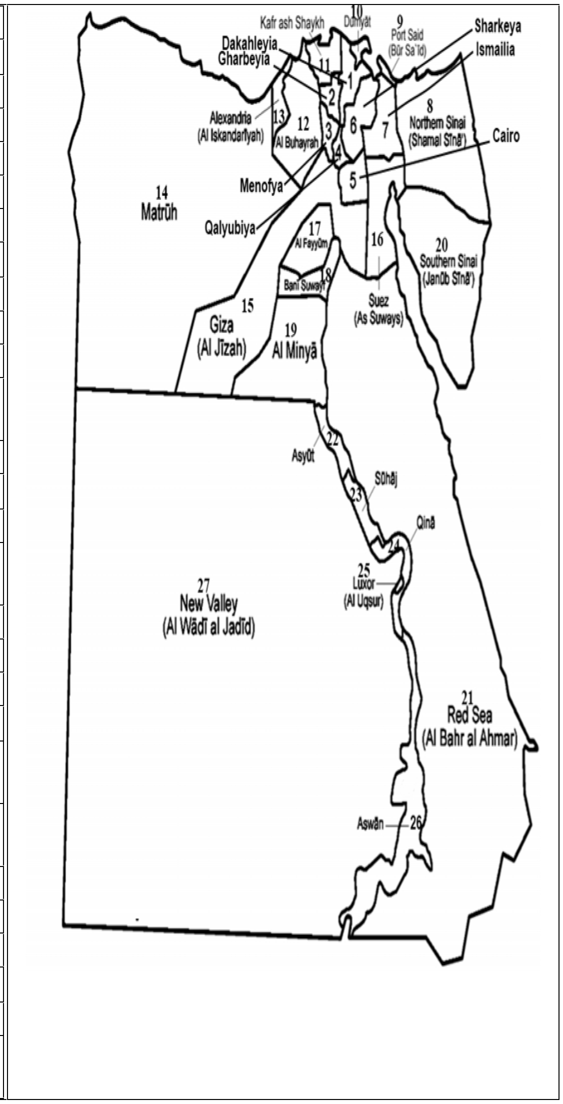

Fig. 1. Study area shows all governorates with its ID and ID neighbours of each governorate

To construct a choropleth map, data for enumeration governorates are typically grouped into classes and a gray tone was assigned to each class. Although maps allow visual assessment for spatial pattern, they have two important limitations: their interpretation varies from person to person, and there is the possibility that a perceived pattern is actually the result of randomness, and thus not meaningful. For these reasons, it makes sense to compute a numerical measure of spatial pattern, which can be accomplished using spatial autocorrelation.

2.2.1 Identification of global spatial clustering

The goal of a global index of spatial autocorrelation is to summarize the degree to which similar observations tend to occur near to each other in geographic space. The spatial autocorrelation using standard normal deviate (z-statistic) of Moran's I under normal assumption was tested. Moran's I is a coefficient used to measure the strength of spatial autocorrelation in regional data. The null hypothesis of no spatial autocorrelation or spatially independent versus the alternative of positive spatial autocorrelation is as follows:

$$H_0: \text{ No clustering exists (no spatial autocorrelation)}$$
$$H_1: \text{ Clustering exists (positive spatial autocorrelation)}$$

Moran's I is calculated as follows (Cliff and Ord, 1981):

$$I = \frac{N \sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{S_0 \sum_{i=1}^{N} (x_i - \bar{x})^2} \quad \text{and} \quad S_0 = \sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij}, i \neq j$$

where, $N = 27$ is the number of governorates, the $w_{ij} = 1$ is a weight denoting the strength of the connection between two governorates i and j, otherwise, $w_{ij} = zero$, and the x_i and x_j represent UR or IR in the ith and jth governorates respectively.

A significant positive value of Moran's I indicates positive spatial autocorrelation, showing the overall pattern for the governorates having a high/low level of UR or IR similar to their neighbouring governorates. A significant negative value indicates negative spatial autocorrelation, showing the governorates having a high/low level of UR or IR unlike neighbouring governorates. To test the significance of global Moran's I, z-statistic that follows a standard normal distribution was applied. It is calculated as follows (Weeks, 1992):

$$z = \frac{I - E(I)}{\sqrt{\text{var}(I)}}$$

Permutation test was applied. A permutation test tells us that a certain pattern in data is or is not likely to have arisen by chance. The observations of each variable was randomly reallocated 1 000 times with 1000 of spatial autocorrelations were calculated in each time to test the null hypothesis of randomness. The hypothesis under investigation suggests that there will be a tendency for a certain type of spatial pattern to appear in data, whereas the null hypothesis says that if this pattern is present, then this is a pure chance effect of observations in a random order. The analysis suggests an evidence of clustering if the result of the global test is found significant; though it does not identify the location of any particular clusters. Besides, the clustering that represents global characteristic of each of UR and IR, the existence and location of localized spatial UR and IR clusters are of interest in geographic sociology. Accordingly, local spatial statistic was advocated for identifying and assessing potential clusters.

2.2.2 Identification of local spatial clusters

A global index can suggest clustering but cannot identify individual clusters (Waller and Gotway, 2004). Anselin (1995) proposed the local Moran's I_i statistic to test the local autocorrelation. Local spatial clusters, sometimes referred to as hot spots, may be identified as those locations or sets of contiguous locations for which the local Moran's I_i is significant. However, Moran's I_i for ith governorate may be defined by Waller and Gotway (2004) as:

$$I_i = \frac{(x_i - \bar{x})}{S} \sum_{j=1}^{N} \left(w_{ij} \Big/ \sum_{j=1}^{N_i} w_{ij} \right) \frac{(x_j - \bar{x})}{S}, \; i = 1, 2, ..., 27$$

where, analogous to the global Moran's I, x_i and x_j represent the UR or IR in the ith and jth governorates respectively, N_i = number of neighbours for the ith governorate, and S is the standard deviation. It is noteworthy to mention that the number of neighbours for the ith governorate was taken into account by the amount: $\left(w_{ij} \Big/ \sum_{j=1}^{N_i} w_{ij} \right)$, where w_{ij} was measured in the same manner as in Moran's I statistic. Local Moran statistic was used to test the null hypothesis of no clusters.

Cluster could be due to either aggregation of high values, aggregation of low values, or aggregation of moderate values. Thereby, high value of I_i suggesting a cluster of similar (but not necessarily large) values across several governorates, and low value of I_i suggesting an outlying UR or IR cluster in a single governorate (being different from most or all of its neighbours). A positive local Moran value indicates local stability, such as governorate that has high/low UR or IR surrounded by governorates that has high/low UR or IR. A negative local Moran value indicates local instability, such as governorate having low UR or IR surrounded by governorates having high UR or IR or vice versa. Each governorate's I_i value was mapped to provide insight into the location of governorates with comparatively high or low local association with their neighbouring values.

2.2.3 Bivariate spatial association

So far, only univariate spatial correlation is presented. It quantifies the spatial structure of one variable at a time. There is much discussion about what is an appropriate measure for bivariate spatial association. However, spatial dependence or spatial clustering causes a loss in the information that each observation carries. When N observations are made on a variable that is spatially dependent and that dependence is positive so that nearby values tend to be similar, the amount of information carried by the sample is less than the amount of information that would be carried, if the N observations are independent. Due to a certain amount of information carried by each observation is duplicated by other observations in the cluster. A general consequence of this is that the sampling variance of statistics is underestimated. As the level of spatial dependence increases, the underestimation increases. Spatial autocorrelation coefficient can be modified to estimate the bivariate spatial correlation between two variables (Wartenberg, 1985):

$$I_{xy} = \frac{1}{S_0} \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}(x_i - \bar{x})(y_j - \bar{y})}{\left[\sqrt{\sum_{i=1}^{N}(x_i - \bar{x})^2 / N}\right]\left[\sqrt{\sum_{j=1}^{N}(y_j - \bar{y})^2 / N}\right]}$$

where x and y represent UR and IR variables respectively. Although the mathematics is quite straightforward, very few software packages offer the option of computing, I_{xy} . Thus, programming was used to find I_{xy} . To test the significance of I_{xy} , z -statistic was applied: $z = I_{xy}\sqrt{N-1}$, which follows approximately standard normal distribution.

2.2.4 Simulation study

Simulated data are useful for validating the results of spatial analysis. Using Monte Carlo simulation, 9 999 random samples (27 values for each sample) were simulated. The process of simulation was conducted under standard normal distribution to calculate P-value for local Moran value. When the word simulation is used, it is referred to an analytical method meant to imitate a real-life system, especially when other analyses are too mathematically complex or too difficult to reproduce.

In Monte Carlo testing, test statistic was calculated based on the data observed. Then the same statistic was calculated for a large number (say, *Nsimu*) of data sets, simulated independently under the null hypothesis of interest (e.g., simulated under complete spatial randomness). The proportion of test statistic values based on simulated data exceeding the value of a test statistic observed for the actual data set provides a Monte Carlo estimate of the upper-tail *P*-value for one sided hypothesis test (Waller and Gotway, 2004).

Specifically, suppose that $I_{i(obs)}$ denotes the test statistic for the data observed and $I_{i(1)} \geq I_{i(2)} \geq \cdots \geq I_{i(Nsimu)}$ denote the test statistic values (ordered from largest to smallest) for the simulated data set. If $I_{i(1)} \geq I_{i(2)} \geq \cdots \geq I_{i(l)} \geq I_{i(obs)} > I_{i(l+1)}$ (i.e., only the l largest test statistic values based on simulated data exceed $I_{i(obs)}$), the estimated $p-value$ is given as follows:

$$p - \text{value} = \Pr(I_i \geq I_{i(obs)} \,|\, \text{H}_0 \text{ is true}) = \frac{l}{Nsimu + 1}, i = 1, 2, ..., N \text{ ,}$$

where one is added to the denominator since the estimate is based on ($Nsimu+1$) values of $(\{I_{i(1)}, \ldots, I_{i(Nsimu)}, I_{i(obs)}\})$. While results were specific to these data, the case study helps identify general concepts for future study. In the statistical analysis, all programs performed using SPLUS8 Software.

3. RESULTS AND DISCUSSION

3.1 Results

Descriptive statistics were calculated for each of UR and IR and they are shown in Table 1. From the five-number summary for UR, the variations of the four quarters were found 4.6, 2.3, 2.5 and 9.5 respectively, where the 4th. Quarter has the greatest variation of all. From the five-number summary for IR, the variations of the four quarters were found 7.84, 7.97, 7.64 and 6.21 respectively.

Table 1. Shows descriptive statistics for UR and IR variables

Variable	Mean	S.D	Skewness	Kurtosis	Min	Max	Q1	Q2	Q3
UR	10.89	3.94	.84	2.37	4.10	23.00	8.70	11.00	13.50
IR	27.55	8.91	-.01	-1.05	11.63	41.29	19.47	27.44	35.08

The values of spatial measures indicate how much and to what extent global clustering in studied variables is existed, how many local clusters are there, and where they are located. Table 2 shows global Moran's I, z -statistic, P -value, and permutation P -value for both variables UR and IR. Fig. 2a and 2b show visual insight for UR and its local Moran values respectively. Fig. 3a and 3b show visual insight for IR and its local Moran values respectively. Darkest shade corresponds to the highest quartile. These maps display geographical variation across governorates of Egypt. Based on visual inspection of UR and IR taken from Fig. 2a and Fig. 3a respectively, an overall worsening pattern (higher scores) was found in the eastern-northern and southern parts and in the western-northern and middle parts respectively. The suggestion of spatial clustering of UR that follows a visual inspection of mapping was confirmed as expected; accordingly, the null hypothesis of no spatial autocorrelation was rejected. The suggestion of spatial clustering of IR that follows a visual inspection of mapping was not confirmed. This finding was not expected for IR; accordingly, the null hypothesis of no spatial autocorrelation was not rejected.

Table 2. Shows global Moran's I, z -statistic, P -value and permutation P -value

Variable	Moran's I	z	P	Permutation P
UR	.25	2.63	.008	.005
IR	.03	.59	.56	.25

Two significant clusters in each of UR and IR were detected. Clusters of UR were located in the middle (Bani Swaif) and in the southern (Luxor) as shown in Fig. 2b. Clusters of IR were located in the eastern-northern (Port Said) and in the middle (Bani Swaif) as shown in Fig. 3b. Table 3 shows the name of governorate, UR, IR, local Moran's I_i for each of UR and IR and its corresponding p-value based on simulation study under standard normal distribution. The p-value in boldface was considered significant at .05 level.

The UR was not found associated with IR which is not expected. This is consistent with weak correlation .10 between UR and IR found by Allam (2003) in Egypt. Non-spatial Pearson correlation coefficient between UR and IR was found -.23, which is not significant with $P = .25$. The bivariate spatial correlation between UR and IR was found ($I_{xy} = -.19$), which is not significant with $z = -.97$ and $P = .98$ based on simulation study under standard normal distribution. Although, the correlation values are not significant, most probably its negative direction attributed to the quality of data set and to the measurement error. It was seen that Pearson coefficient is always over estimated when it is used in finding the spatial correlation. That is why, in investigating the bivariate spatial correlation, it is recommended to use spatial measures such as Wartenberg's (1985) measure.

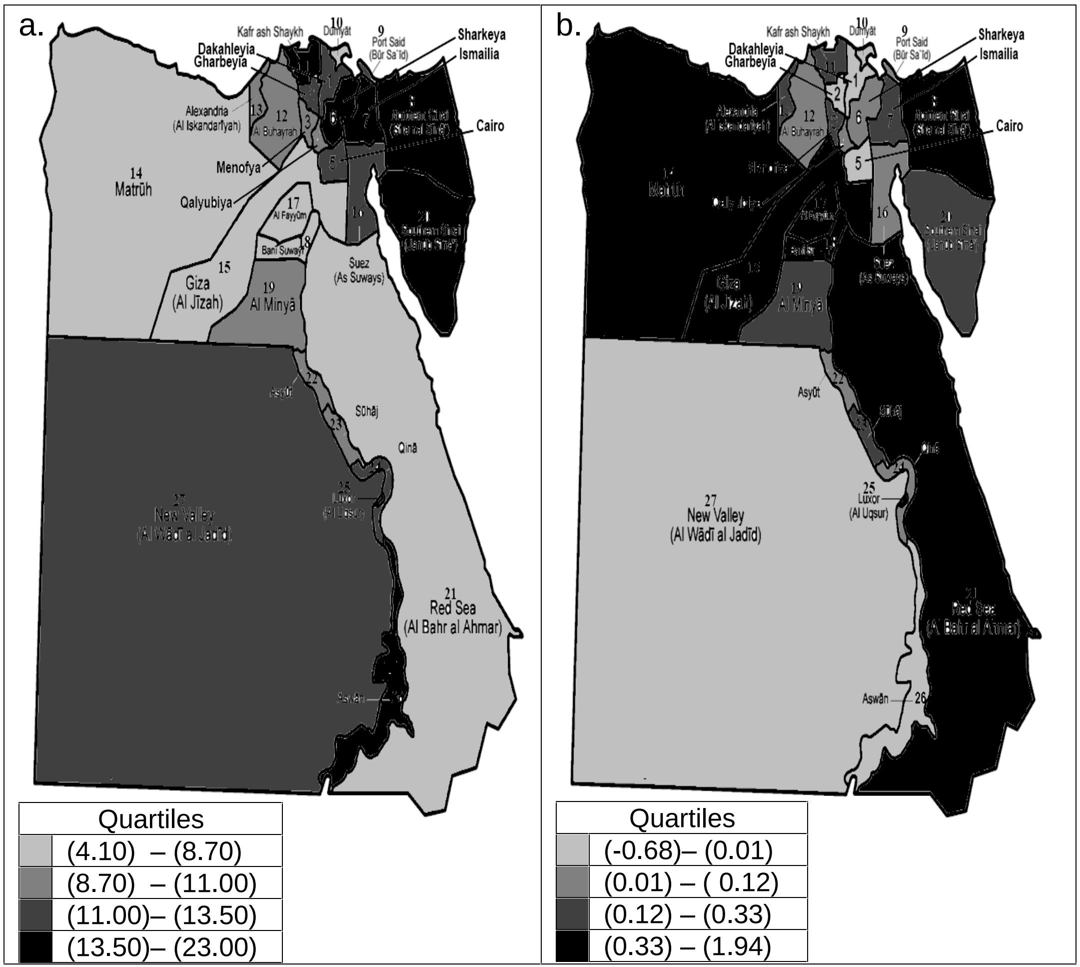

Fig. 2. Choropleth maps show: a. UR variable and b. its local Moran values

3.2 Discussion

This study, undertaken in Egypt, investigated the spatial autocorrelation of each of UR and IR, and the bivariate spatial correlation between them. Spatial global clustering and local clusters for UR and IR were examined based on global Moran's I and local Moran's I_i respectively. Bivariate spatial correlation between UR and IR was examined based on Wartenberg's measure. Such findings allow policy makers to better identify what types of resources are needed and precisely where they should be employed. The above framework revealed some noteworthy findings. After rejecting the null hypothesis for UR, concluding that there is a form of global clustering, it is of course, of interest to know the exact nature of this clustering. Are there hot-spot clusters? If so, how many hot-spots are there and where they are located? Also, is this clustering is associated with the clustering of IR?

The population size in the governorates is not equal. i.e., the rate of UR and IR did not express the absolute size of the problem. Several governorates were not observed visually as hot spots. But after considering the information of their neighbours, the pattern of their hot spots can be obviously seen. For example, governorates 7, 8, and 26 were found in IR; and governorates 14, 15, 17, 18, and 21 were found in UR.

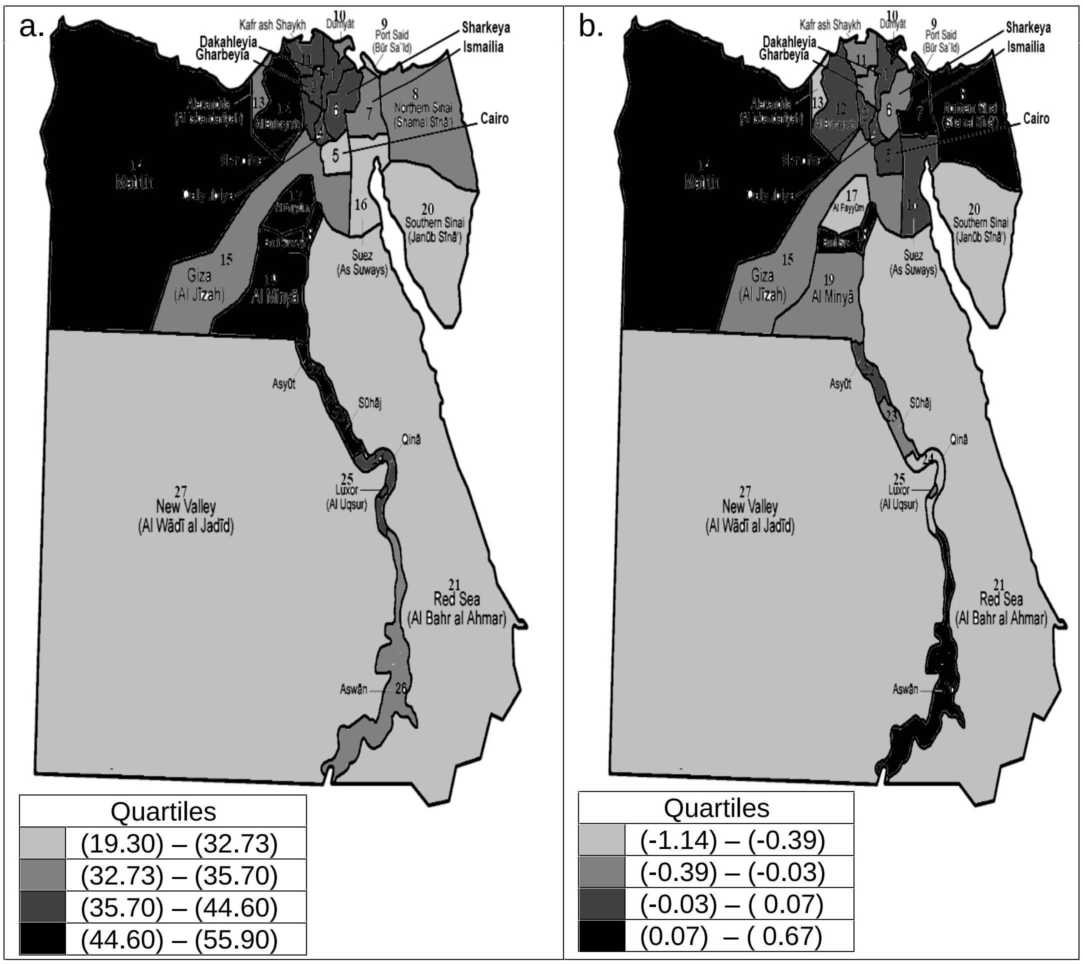

Fig. 3. Choropleth maps show: a. IR variable and b. its local Moran values

Maps provide powerful means to communicate data to others. Unlike information displayed in graphs, tables, and charts; maps also provide bookmarks for memories. In this way, maps were not passive mechanism for presenting information. Usually, in the spatial analysis and geographical mapping, small areas should be used such as districts, counties…etc. But, in this research governorates were used which considered somewhat larger than for example the districts because the data were not available for smaller areas. Most often the word 'neighbourhood' suggests a relatively small area surrounding individuals' homes. But researchers commonly make use of larger spatial area such as census tracts (Coulton et al., 2001). Often, the choice about neighbourhood spatial definition was made with respect to convenience and availability of contextual data rather than study purpose (Schaefer-McDaniel et al., 2010). Schaefer-McDaniel et al. (2010) stated that, researchers might utilize census data and thus rely on census-imposed boundaries to define neighbourhoods even though these spatial areas may not be the best geographic units for the study topic.

As noted by Waller and Jacques (1995), the test for spatial pattern employs alternative hypotheses of two types; the omnibus not the null hypothesis or more specific alternatives. Tests with specific alternatives include focused tests that are sensitive to monotonically decreasing risk as distance from a putative exposure source (the focus) increases. Acceptance of either types (the omnibus or a more specific alternatives) only demonstrates that some spatial pattern exist, and does not implicate a cause (Jacques, 2004). Hence, the existence of a spatial pattern alone cannot demonstrate nor prove a causal mechanism.

Table 3. Explains governorates, UR, IR, local Moran's I_i for each of UR and IR and its corresponding p -value (p -value in boldface was considered significant at .05 level)

ID	Governorate	UR	I_i	p	IR	I_i	p
1	Dakahleyia	12.00	-.02	.540	27.91	.00	.443
2	Gharbeyia	11.00	.00	.477	25.85	-.07	.617
3	Menofya	8.70	.21	.200	27.44	.00	.492
4	Qalyubiya	8.90	.01	.417	27.52	.00	.467
5	Cairo	11.00	.00	.460	19.10	.23	.159
6	Sharkeya	13.70	.11	.293	32.16	-.19	.740
7	Ismailia	14.00	.29	.130	22.83	.34	.106
8	North Sinai	14.10	.33	.204	24.22	.33	.204
9	Port Said	11.00	.02	.451	16.39	1.85	**.008**
10	Dumyat	7.50	-.68	.830	22.42	.31	.257
11	Kafr ash Shaykh	13.50	.31	.212	34.31	-.07	.586
12	El Buhayrah	9.30	.03	.513	36.66	.08	.423
13	Alexandria	10.20	.18	.287	19.47	-.36	.795
14	Matruh	5.60	.78	.130	35.08	.42	.243
15	Giza	8.30	.38	.101	27.11	.00	.602
16	Suez	11.80	.04	.349	17.14	.28	.120
17	El Fayyum	7.10	.40	.133	40.89	-1.75	.992
18	Bani Swaif	4.20	1.52	**.025**	40.54	1.62	**.020**
19	Al Minya	9.90	.30	.270	41.29	-.12	.801
20	Southern Sinai	15.40	.12	.327	11.63	-.21	.710
21	Red Sea	4.10	.41	.068	12.69	-.58	.944
22	Asyut	10.50	.01	.437	39.06	.06	.351
23	Sohaj	9.10	.22	.346	38.50	-.06	.787
24	Qina	11.70	.10	.470	34.77	-.38	.965
25	Luxor	23.00	1.94	**.002**	27.80	-.01	.496
26	Aswan	16.30	-.02	.737	23.00	.55	.213
27	New Valley	12.10	-.08	.772	18.17	-.71	.993

Anselin (1995) stated that indication of local pattern of spatial association may be in line with a global indication, although this is not necessarily be the case. It is quite possible that the local pattern is an aberration that the global indicator would not pick up, or it may be that a few local patterns run in the opposite direction of the global spatial trend. Local values that are very different from the mean (or median) would indicate locations that contribute more than their expected share to the global statistic. These may be outliers or high leverage points and thus would invite closer scouting. However, this is found in this research. Although global clustering in IR was not found significant, two local clusters were found significant. Spatial units were arbitrary subdivisions of the study region and people could move around from one area to another. That could be affected by UR and IR variability in areas other than the area they live in. i.e., the variability of UR and IR in the ith governorate was thought to be influenced and explained by the variability of UR and IR not just in the ith governorate but also in the neighbouring governorates.

The application of statistical techniques to spatial data faces an important challenge, as expressed in the first law of geography: “everything is related to everything else, but closer things are more related than distant things” (Tobler, 1979). The quantitative expression of this principal is the effect of spatial dependence. i.e., when the observed values are spatially clustered, the samples are not independent. UR and IR growth in governorate i generates UR and IR growth in governorate j. This mechanism of transmission causes a spatial autocorrelation of UR and IR growth. The obvious question after finding significant clusters in UR and IR is-why? Could this pattern be associated by the spatial pattern of other socioeconomic indicators such as the levels of household income or by the limitation of economic resources? However, further research regarding this bivariate spatial association between UR and IR and other socioeconomic indicators is required. It will be of our interest in the near future. This paper adds to the global body of knowledge on the utilization of spatial analysis to strengthen the research–policy interface in the developing countries such as Egypt.

It should be emphasized that UR and IR inequality problem cannot be overcome in the short-run; but long-term efforts are needed to tackle this problem. In turn, enabling the economy to create more job opportunities and establish new projects, especially in the governorates that found as hot spot clusters, means that the place of the problem is now clearly shown. Lack of investment in all levels of education and other life skills result in permanent life-long inequality problem. Finally, UR and IR studies should be conducted periodically in light of the changing of socioeconomic and political conditions.

Details presented in this research enables development actors to identify priorities, select fields and locate trends in designing national, regional, or sectorial policies. Moreover, this study provides civil society organizations, researchers, and citizens with a rich knowledge base of facts and analysis, offering information easy to understand and to apply. This knowledge can be used either in targeted initiatives, or as a tool for monitoring and assessing policies and methods. Most importantly, the research provides the information needed to both examine development strategies’ consistency with the actual situation, and to align priorities and develop them in accordance with the Egyptian people’s development needs.

As was not expected, spatial correlation between UR and IR was not found significant as was hypothesized by some studies. Most probably, much of job opportunities available in Egypt such as construction, carpentry, sewing, etc. do not need education or/and to be literate. Also, if the smaller analysis units such as districts were studied, may be different results are obtained. Although, this work was conducted as part of a wider study, its immediate implications are more for policy makers and practitioners than for researchers.

Policy which pays attention to area characteristics will reduce UR and IR variability. Consequently improves the prosperity in poor areas which in turn will improve health status. Indeed, the author agree with the statement stated by Allam (2003) that further efforts are required to meet the challenges related to participation in development, particularly in the areas of high illiteracy and unemployment.

To reduce the risk of unemployment in Egypt like other developing countries, efforts should focus on generating growth and deregulating labor markets rather than on expanding current labor market programs. Interventions that create opportunities for the poor people and reduce vulnerability should have priority over traditional social assistance interventions.

4. CONCLUSION

Conclusions are comprehensive in at least five aspects. First, based on visual inspection of mapping, high level of UR and IR were concentrated in eastern-northern and southern parts and in western-northern and middle parts respectively. Second, several governorates were not observed visually as hot spots. But after considering the information of their neighbours, the pattern of their hot spots can be obviously seen. Third, global clustering was found in UR, but was not found in IR. Two governorates were found to be local clusters in each of UR and IR in eastern-northern, middle, and southern governorates. The opposite was the case for those with low UR and IR were seen in some northern and southern parts. Forth, from negative local Moran values, looking at local variation, some governorates represented as areas of dissimilarity in each of UR and IR. These governorates with low UR or IR were surrounded by governorates with high UR or IR, or vice versa. Fifth, spatial correlation between UR and IR was not found significant. In summary, the present study supports the hypothesis of a spatial inequality in each of UR and IR at the governorate level that probably reflects the inequality distribution in several socioeconomic indicators across the governorates of Egypt. While results were specific to these data, the case study helps to identify general concepts for future studies.

The conclusions are important for both researchers and policy makers. Usually, policy makers are looking for the place of the problem which is shown in this study. Further research is required for researchers who looking for the variables correlated with UR and IR. The global clustering and local clusters found in this study are consistent with what found by previous studies. For example, the study conducted by Hooghe et al. (2011). But the non-significant correlation between UR and IR is not consistent with what found by previous studies. For example, the studies conducted in Egypt by El-Gamal (2012) and Wahba and Zenou (2005).

COMPETING INTERESTS

Author has declared that no competing interests exist.

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