《Chapter 4》Sustainable Development

Spatial Inequality in Myanmar during 1992- 2016: An Application of Spatial Statistics and Satellite Data

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Abstract The contribution of this study is twofold. Firstly, the relationship between the surveyed socio-economic condition in Myanmar and the density of Nighttime Light (NTL) observed by satellites has been verified. Specifically, this study has constructed the composite index representing the combination of sixteen socio-economic indicators by using Principal Component Analysis (PCA). It is found that this composite index is highly correlated with the density of NTL, and this result affirms the qualification of NTL as the proxy representing the stage of development in the spatial dimension, especially in the case of developing countries with limited availability of data. Secondly, this study has examined the nationwide inequality of stage of development in Myanmar during 1992-2016 by using series of NTL data observed and collected by DMSP/OLS and VIIRS-DNB satellites. The geographical cluster analyses using LISA (Local Indicators of Spatial Association) and Getis-Ord Gi* statistics have been conducted, identifying the single clustering development occurring in Yangon during 1992-2005 and the rapidly rising concentration of the second growth pole in the area of Naypyitaw after 2005. The computation of the Gini coefficient has also applied to NTL data, and the outcome indicates that inequality has been increasing since 2006. These results suggest the future development plan simultaneously emphasizing on both creating the stable growth and lowering the inequality across regions. It is additionally recommended that the establishment of special economic zones along the border would increase economic activities and concurrently mitigate the spatial inequality of development.

Keywords Myanmar, Remote Sensing, Nighttime Light, Spatial Statistics, Regional Development

JEL Classification E01, D30, R11

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1 Introduction

Since the year 2010, economic performance in Myanmar has improved steadily, and the income level across the population grew substantially. According to statistics produced by the United Nations and the World Bank, the nation’s per capita income nearly doubled between 2010 and 2014, rising from an estimated $800 per year to $1,200 over the four years period. With this improvement, Myanmar has been placed in the category of a lower-middle-income economy. According to the World Bank's report, poverty declined from 35.8% in 2004/05 to 23.3% in 2015. Also, urban poverty declined from 21.5% in 2004/05 to 9% in 2015[3]. Although there was a rising income level, Myanmar's middle-class population has been still a small percentage of the overall population. Moreover, most of the country’s citizens are still low-wage workers, primarily employed in agriculture. According to the 2013 census, only 0.5% of Myanmar’s population had all modern communication amenities at their homes, and 30.3% of the population had none of these items. Moreover, only 3.1% of the population owned an automobile, while nearly 39% owned a motorcycle or moped. With these development challenges, Myanmar government has been seeking the balanced growth strategies through managing inflation, encouraging savings, boosting domestic involvement in the formal banking industry, ramping up education and training throughout the country, together with the implementation of programs improving national communications and transportation infrastructure networks. However, according to some economic literature, there is a trade-off between higher economic growth and the improved regional equality, especially for countries in the early stage of development. Therefore, there will be a challenge for the government. Specifically, the balanced economic growth with an equal share of budget and investment seems inconsistent with high economic growth. Nevertheless, it is necessary for Myanmar government to reduce the income gap among regions/states and between urban and rural areas.

Most ASEAN countries have recorded the fairly high economic growth rates for the last several decades. It is important to learn how the geographical concentration of economic activity in these countries has changed during their rapid economic growth periods. However, since a lack of consistent and reliable data has limited the analysis of income inequality in Myanmar, there are a few studies on regional-level analysis of spatial inequality in Myanmar.

The purpose of this paper is to estimate regional income inequality in Myanmar, using a relatively new reliable and consistently available data namely the Nighttime Light (NTL) captured by satellites. According to the studies of Henderson et al. (2012) and Chen and Nordhaus (2011), the nighttime light data have recently been used as a proxy for income and growth. Therefore, this paper concentrates mainly on

3 https://www.worldbank.org/en/country/myanmar/publication/myanmar-poverty-assessment-2017-part-one-examination-of-trends

the potential of using light data in estimating regional inequality. Specifically, based on these challenging backgrounds, this paper has two main objectives. First, this paper verifies the possibility of using the NTL data as the proxy representing the socioeconomic condition. Second, this study examines the pattern of spatial inequality using the NTL data and methods of geographical cluster detection.

The structure of this paper is organized as follows. Section 2 presents the related literature. Section 3 discusses the details of data used. Section 4 describes theoretical backgrounds of research methodologies applied in this study. Section 5 discusses computational results and main findings. Lastly, section 6 concludes the key findings and suggests the future development of this study.

2 Related Literatures

Many studies on income inequality have been developed for the past six decades initiated by Kuznets (1955) which uncovered the forces behind the evolution of inequality and Mincer (1958) which quantified the effect of human capital accumulation on personal income distribution. These studies have been broadening insights on the conceptual and empirical difficulties associated with income inequality. Williamson (1965), by examining twenty-four countries with both cross-section and time-series data, found that regional income inequality increases in the early stage of development but gradually decreases as the economy matures. Based on these pioneering studies, this paper follows two main analytical frameworks as outlined in the following sections.

2.1 Principal Component Analysis (PCA) and the poverty index

The development of indicator representing poverty and inequality has been initiated by the theoretical framework introduced by Sen (1985), Sen (1993) and Sen (1999). Based on their mathematical capabilities to represent the main components of data, methods of PCA and factor analysis have been adopted by Lelli (2001), Sallu et al. (2010), Roche (2008), Islam (2013) and Berman et al. (2014) in their formulations of indices identifying the socioeconomic status. In the asset-based poverty analysis, Montgomery et al. (2000) adopted the simple method of equal weight to all assets in order to construct the asset-based index. Subsequently, Filmer and Pritchett (2001), McKenzie (2005) and Vyas and Kumaranayake (2006) applied PCA to an estimation of asset-based poverty index in the case of India, Mexico, Brazil, and Ethiopia, respectively. As stated in Hoque (2014) the PCA has become the standard method of constructing the poverty and socioeconomic index in recent literature. Particularly, the computed value of the first Principal component (PC1) has been conventionally used as the index in poverty and socioeconomic analyses.

2.2 Nighttime Light (NTL) data and economic development research

Regional income inequality is not merely an adverse effect of economic growth. Indeed, theoretical studies in spatial economics generally agree that these two phenomena have a circular causation.

Specifically, economic growth can induce spatial agglomeration and vice versa. Hence, the economic growth is geographically uneven because some regions have more advantage in doing business than others. For example, workers and firms tend to concentrate in developing regions where they seek higher wages and larger markets. Simultaneously, this spatial concentration is the source of positive externalities caused by labor pooling and knowledge spillover. With this pattern, it is possible to provide the physical and institutional infrastructures efficiently with the limited resources. Thus, it is conventionally concluded that economic agglomeration enhances economic growth.

As earlier introduced, the economic agglomeration is generally a beneficial force. Kudo and Kumagai (2012) stated that it is important to avoid excessively emphasizing on regional equality, especially in the very early stages of economic development. Otherwise, uniform distribution of limited development resources is likely to result in "equally poor". In terms of a spatial structure of economic activities, Kudo and Kumagai (2012) indicated that Thailand is a typical "one-polar" country while Vietnam is clearly a "two-polar" nation. In addition, their work proposed the spatial development strategy of Myanmar; whether it would lead to either the case of one-polar or two-polar growth poles.

Baumont et al. (2001) stated the basic principle of spatial econometrics in regional economic growth studies. The principle is that regional data can be spatially ordered since similar regions tend to cluster and that econometric models must take into account the fact that economic phenomenon may not be randomly distributed on an economically integrated regional space. Mapa et al. (2006) introduced a measure of neighborhood effect in their intra-country growth regression models. Anselin and Griffith (1988) constructed the spatial autoregressive model, which also included the neighborhood effect into the growth regression.

The recent studies conducted by Tilottama et al. (2013), Michalopoulos and Papaioannou (2014), Mellander et al. (2015), Addison and Stewart (2015), Souknilanh et al. (2015) and Ebener et al. (2005) used NTL as a proxy for income per capita. They found that measures of light are significantly correlated with both national and sub-national values of GDP. According to these publications, it is possible to formulate mechanisms through which NTL can measure regional inequality. Specifically, Elvidge et al. (2009) stated that *"areas with higher population counts in developing countries would be poorly lit and therefore have higher percentages of poor people"*, implying the significant correlation between the density of NTL and income per capita. Thus, the regions that are poorly lit are likely to have a low income per capita and hence less wealthy.

Typically the relationship between NTL and economic activity is determined by coefficients derived from regression analyses using ground data and nighttime light satellite imagery (Ghosh et al., 2010). Thus, the official data for per capita income growth by the whole country can be obtained. However, the data of per capita income growth by region is unavailable in the case of Myanmar. Therefore, Kudo and Kumagai (2012) applied NTL as an alternative method to estimate the distribution of GDP in Myanmar at a district level. The first two highest values are found in Yangon and Mandalay because Yangon, Mandalay, and Naypyitaw are located in these two states/regions. Although Yangon and Mandalay are main economic centers, Naypyitaw has newly been established as the capital city in 2005.

3 Data

3.1 Satellite data

The data of satellite-observed nighttime lights have been widely used in scientific research since the public availability of the global data sets collected by the Defense Meteorological Satellite Program (DMSP). These publicly available data are electronically transformed into the Geographic Information System (GIS) maps that indicate the location and intensity of artifcial lighting as observed from space. With widespread scientific applications, Huang et al. (2014) and Li et al. (2016) conducted systematic reviews covering 144 and 84 published papers, respectively, and topics of these published research works range from the fields of socioeconomics, demographics, regional development, light pollution, marine science, epidemiology to the study of natural humanitarian disasters.

To maximize the temporal coverage of data, this study used the NTL data captured by both DMSP/OLS and the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB) satellites. Particularly, satellites under the DMSP/OLS program provide the global data covering the period of 1992-2013, and the VIIRS/DNB satellite produces the global data of 2014-present. It is noted that the original purpose of DMSP satellites was for meteorological analysis, specifically the detection of the nighttime clouds. Consequently, the Earth's surface detection of nighttime lights, illuminating from human activities, is the intended features. However, their applications have been constantly broadening, yielding the extensive understanding in many fields of studies.

3.1.1 NTL data obtained from DMSP/OLS (1992-2013)

The Defense Meteorological Satellite Program (DMSP) has been established and administrated by the United States Air Force. All satellites under this program have been orbiting around the Earth and utilizing Operational Linescan System (OLS) for detecting changes on the Earth's surface. The DMSP's NTL data has been produced by processing the raw data with cleansing and correction techniques. The outcomes, which are the annual data series, are publicly available in GIS Raster format. Specifically, in the Raster data file, each pixel, approximately the geographical coverage of a square kilometer, represents the magnitude of illumination with the scale of 0-63. Since DMSP is the long-term program, there have been a series of satellites launched and utilized over decades. Table 1 exhibits the list of satellites capturing the density of NTL in each year. It is noted that there are cases of overlapping sources of data, i.e. more than one satellite providing the data, in a particular year[4]. Therefore, the calibration is required in order to integrate the overlapping data into a single standardized series.

4 The annual data are available at www.ngdc.noaa.gov/eog/dmsp/downloadV4composites.html.

3.1.2 NTL data obtained from VIIRS-DNB (2014-2016)

The Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB) has been launched and employed jointly by NASA and the National Oceanic and Atmospheric Administration (NOAA). As the follow-on producer of NTL data, the VIIRS-DNB incorporates many improved features, including the finer spatial resolution, the lower detection limits, the wider dynamic range, the finer scales of light density, and in-flight calibration (Schueler et al. 2013).

Table 1 Available data sets of DMSP's global NTL maps and their identification codes

Year / Satellite no.	F10	F12	F14	F15	F16	F18
1992	F101992					
1993	F101993					
1994	F101994	F121994				
1995		F121995				
1996		F121996				
1997		F121997	F141997			
1998		F121998	F141998			
1999		F121999	F141999			
2000			F142000	F152000		
2001			F142001	F152001		
2002			F142002	F152002		
2003			F142003	F152003		
2004				F152004	F162004	
2005				F152005	F162005	
2006				F152006	F162006	
2007				F152007	F162007	
2008					F162008	
2009					F162009	
2010						F182010
2011						F182011
2012						F182012
2013						F182013

Source: www.ngdc.noaa.gov/eog/dmsp/downloadV4composites.html

Hence, VIIRS-DNB has been serving as both the continuation and the improvement of producing the nighttime light data[5].

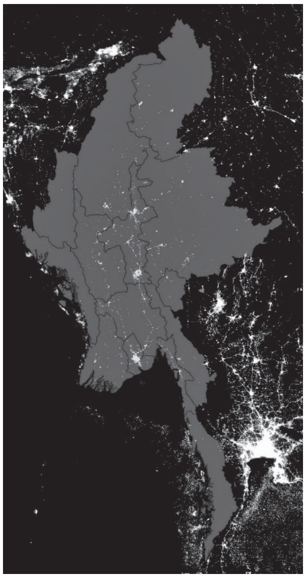
Figure 1 and 2 illustrate the outcomes of merging the raw NTL data of 2016 with the maps of first-level and third-level administrative states/regions of Myanmar, respectively. Figure 3 shows the result of transforming the raw NTL data into NTL index representing the average light density per square kilometer.

As previously stated, in some years, the data of DMSP/OLS include multiple sources. This paper applied the method introduced by Handerson et al. (2012) to calibrate the data. Figure 4-6 illustrate some of the outcomes which are smoothened time series of NTL index of a particular state/region. These

5 The monthly global data are now available at https://www.ngdc.noaa.gov/eog/viirs.html.

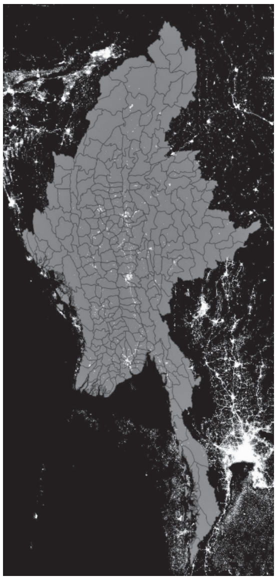
figures show that compared to Madaly and Ayeyarwady, the density of Yangon has the highest magnitude due to the cumulative increment over years.

Fig.1 Nighttime Light data (2016) merged with the map of first-level administrative states/regions of Myanmar



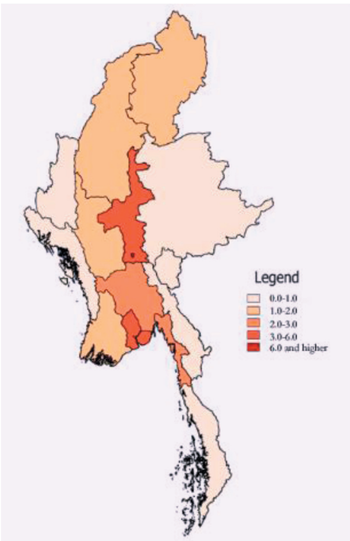
Source: Authors' calculation

Fig.2 Nighttime Light data (2016) merged with the map of third-level administrative states/regions (Township) of Myanmar



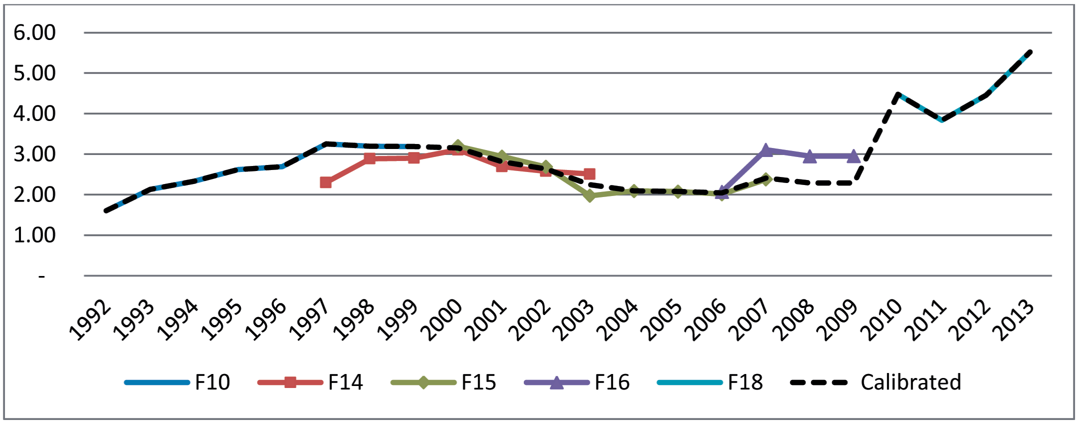
Source: Authors' calculation

Fig.3 Nighttime Light Index (2016) based on the classification of first-level administrative states/regions of Myanmar



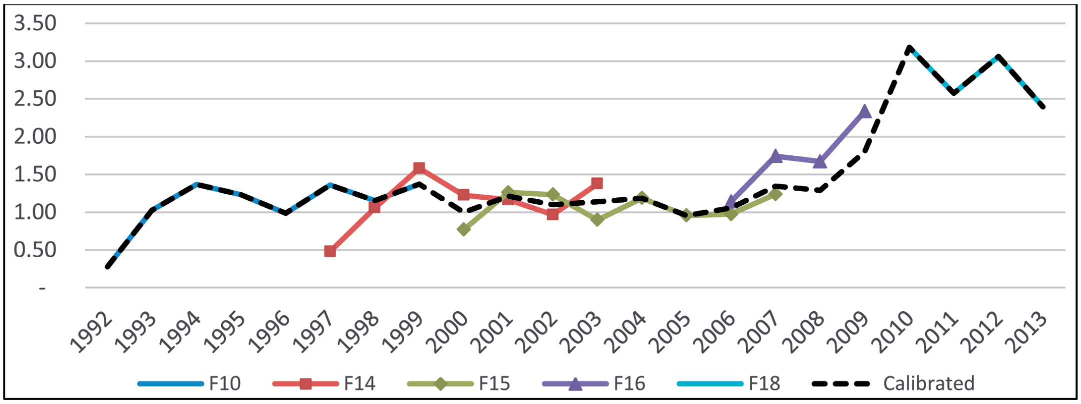
Source: Authors' calculation

Fig.4 Raw data and the calibrated annual NTL index of Yangon



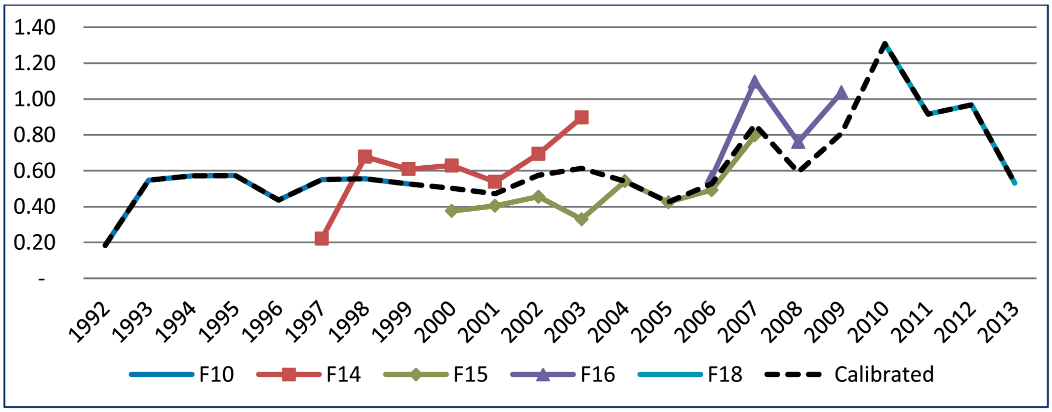
Source: Authors' calculation

Fig.5 Raw data and the calibrated annual NTL index of Mandalay



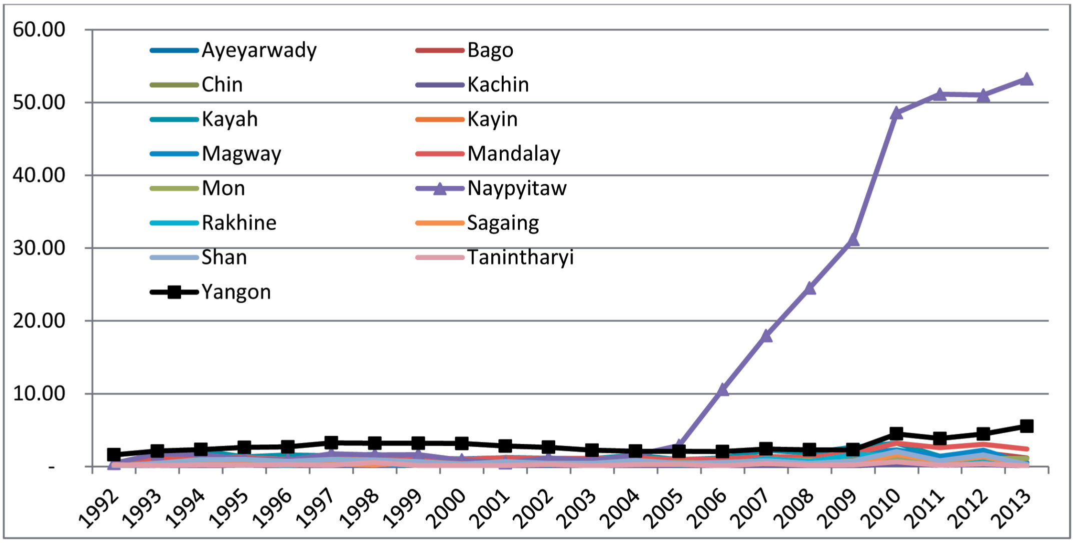
Source: Authors' calculation

Fig.6 Raw data and the calibrated annual NTL index of Ayeyarwady



Source: Authors' calculation

Fig.7 The calibrated annual NTL indices of all first-level administrative states/regions

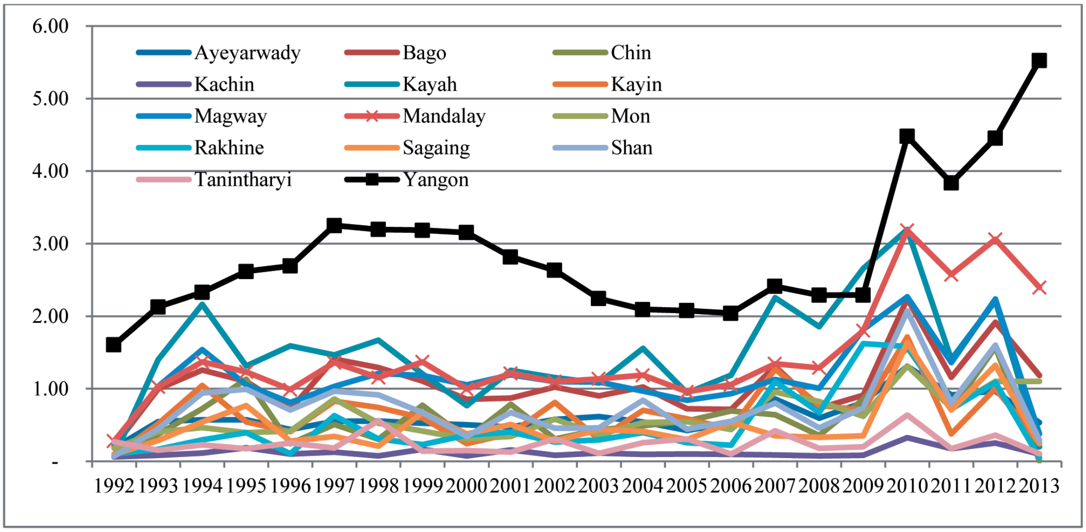


Source: Authors' calculation

Fig. 7 shows the time series of NTL index obtained from DMSP/OLS of all states/regions. Specifically, each series indicates the average density of light per km2. Since the average light density of Naypyitaw has grown rapidly after 2005, Figure 8 excludes that of Naypyitaw in order to exhibit the detailed variation of NTL indices of other states/regions. Based on using the identical dataset, Figure 7 obviously illustrates the substantial growth of the NTL density of Naypyitaw, exhibiting its steady expansion influenced by the government's policy of building the alternative growth pole. Also, this change has motivated the main research objective of this paper applying the spatial statistical tests on the obtained remote-sensing data in order to scientifically identify this geographical evolution.

Figure 8 shows the significance of Yangon and Mandalay as indicated by their magnitudes of NTL density still higher than others', affirming their continuous roles as the historical and economic hubs.

Fig.8 The calibrated annual NTL indices of all first-level administrative states/regions (excluding Naypyitaw)



Source: Authors' calculation

Table 2 Survey data and sources

	Variable	Description	Source
1	Consumption_20_pct	Consumption of 20-percent lowest income household	IHLCA Survey 2009-2010
2	Avg_HH_Size	Average household size	IHLCA Survey 2009-2010
3	Demgrph_Depend_Ratio	Demographic dependency ratio	IHLCA Survey 2009-2010
4	Avg_Land_Agri_HH	Average land owned by an agricultural household	IHLCA Survey 2009-2010
5	Landless_Rate_Agri	The ratio of households not owning the land	IHLCA Survey 2009-2010
6	Access_to_Credit_Agri	The ratio of agri household access to credit	IHLCA Survey 2009-2010
7	Access_to_Credit_Non_Agri	The ratio of non-agri household accessible to credit	IHLCA Survey 2009-2010
8	LF_Participation_Rate	Labor force participation rate	IHLCA Survey 2009-2010
9	Unemploy_Rate	Unemployment rate	IHLCA Survey 2009-2010
10	Underemploy_Rate	Underemployment rate	IHLCA Survey 2009-2010
11	Literacy_Rate	Literacy rate	IHLCA Survey 2009-2010

12	Net_Enroll_Primary	Net enrollment in primary school	IHLCA Survey 2009-2010
13	Net_Enroll_Secondary	Net enrollment in secondary school	IHLCA Survey 2009-2010
14	Access_to_Primary	Accessibility to secondary education	IHLCA Survey 2009-2010
15	Access_to_Secondary	Accessibility to primary education	IHLCA Survey 2009-2010
16	Total_Gov_Expediture	Total government expenditure	Subnational Governance in Myanmar Discussion Paper Series (2013-2014)

3.2 Survey data

In this study, most of the survey data were obtained from the official publications of Integrated Household Living Conditions Assessment (IHLCA) project, jointly conducted by the Government of the Republic of the Union of Myanmar, UN, and other national and international agencies. The project aimed at surveying the nationwide status of living conditions. The first survey was undertaken during 2004-2005 and the second phase was conducted during 2009-2010. The data of the second phase were utilized in this study in order to provide the most recent characteristics of nationwide socioeconomic conditions.

4 Research Methodology

4.1 Principal Component Analysis

Principal Component Analysis (PCA) is the quantitative method reducing the dimension of data while retaining the majority of information. In this study, the main objective of applying PCA was to construct the new indicator which is an aggregate index representing the main socio-economic condition of each region/state in Myanmar. Mathematically, PCA is the transformation of data generating the new set of uncorrelated components. Each is the linear weighted combination of original variables.

As shown in equation (1), for the original data containing the set of variables $X_1, X_2, ..., X_p$.

$$\begin{aligned} PC_1 &= a_{11} X_1 + a_{12} X_2 + \dots + a_{1p} X_p \\ PC_2 &= a_{21} X_1 + a_{22} X_2 + \dots + a_{2p} X_p \\ &\vdots \\ PC_p &= a_{p1} X_1 + a_{p2} X_2 + \dots + a_{pp} X_p , \end{aligned} \qquad (1)$$

where a_{pp} identifies the weight for the p-th principal component and the p-th variable. The coefficient of the first Principal component $a_{11}, a_{12}, ..., a_{1p}$ are the outcome of optimizing the variance of PC_1 subject to the constraint of $a_{11}^2 + a_{12}^2 + \dots + a_{1p}^2 = 1$. Particularly, PC_1 is the new component representing the majority of variance of original data. PC_2 is the second principal component which is completely uncorrelated with PC_1 (i.e. orthogonal to PC_1) obtained under the constraint of $a_{21}^2 + a_{22}^2 + \ldots + a_{2p}^2 = 1$. PC_2 represents the additional variance of original data with the explanatory power lower than that of PC_1. The subsequent Principal components marginally explain the variance of original data, and each principal component is uncorrelated to others. Hence, these subsequent principal components explain the smaller and smaller orthogonal proportions of variance of the original data. As a result of orthogonal decomposition, the summation of all principal components yields the 100 percent of the variance of the original data.

Following Hoque (2014), the selection of principal components for formulating the reduced data is based on the magnitude of the eigenvalue of each component. Conventionally, the eigenvalue of 1.0 is used as the threshold, identifying the significant degree of contribution to the variance of data. Then the data is transformed by using a linear weighted combination of significant principal components, yielding the data with reduced dimensions. In the last step, the PC_1 (i.e. the first Principal component) was selected as the single index representing the major variation of the socio-economic condition. The final outcome is the ground truth for validating the association between the NTL index and the actual socio-economic condition in each state of Myanmar.

4.2 Spatial Cluster Analysis

4.2.1 The Getis-Ord Gi* statistics

Developed by Getis and Ord (1992), the Getis-Ord G_i^* statistics is the quantitative method for identifying the degree of spatial concentration. The outcome can indicate both cases of spatial clustering of high-value (i.e. the "hot spot) and that of low-value (i.e. the "cold spot"). The mathematical representation is shown in equation (2).

$$G_i^* = \frac{\sum_{j=1}^{n} w_{ij} X_j}{\sum_{j=1}^{n} X_j} \qquad (2)$$

where G_i^* = the Getis-Ord G_i^* statistics; w_{ij} = the spatial weight matrix; and n = number of spatial units

Getis and Ord (1992) also included the standardized G_i^* statistics that are asymptotically normally distributed. Therefore, this enables the computation of p-value, indicating the statistically significant level of the obtained G_i^* statistics. The statistical significant value of G_i^* shows the area-specific concentration of high values (i.e. the "hot spots") that is above is statistically expected value. Also the case of "cold spot" is the region with the concentration of value specifically lower than the statistically expected one.

4.2.2 Local Indicators of Spatial Association (LISA) analysis

Introduced by Anselin (1995), Local Indicators of Spatial Association (LISA) is the alternative method for examining the degree of spatial dependencies. Particularly, LISA concentrates on the heterogeneity of correlation over the geographical dimension with the computational outcome of location-specific statistics. Hence, the obtained statistics identify the statistical significance of the similarity around the specific location. The spatial clustering of high-value areas is defined as “hot spot”. On the other hand, the regions having the significant association of low-value are called “cold spot”. It is noted that both classifications of clustering are cases of positive correlation. Unlike other indicators of spatial clustering statistics, LISA also identifies the case of a statistically significant negative correlation. This case, i.e. the spatial outliers, indicates the statistically significant dissimilarity between the core area and its neighbor. The mathematical representation of *Local Moran I* (i.e. *LISA*) is shown in equation (3).

$$Local\ Moran\ I_i = \frac{(x_i - \bar{x}) \sum_j w_{ij}(x_j - \bar{x})}{s_i^2}, \tag{3}$$

where $S_i^2 = \frac{\sum_j (x_j - \bar{x})^2}{(n-1)}$; w_{ij} = the spatial weight matrix; n = number of spatial units; and $\bar{x}$ = an average of x_{ij}

Mathematically, the computation of LISA is very similar to that of the correlation coefficient. Specifically, LISA indicates the correlation between the characteristics of area i and that of its neighbor. It is noted that the spatial weight matrix (w_{ij}) is a key component in this calculation, identifying the boundary of a neighborhood of area i. The outcome of the computation also includes the statistics of p-value, exhibiting the statistically significant level of the obtained value of the degree of correlation.

5 Discussion of Results

Following the sequence of objectives of this study, the results obtained from the Principal Component Analysis (PCA) were exhibited and discussed in section 5.1. Based on the key findings of section 5.1, the outcomes of spatial clustering analysis were illustrated and examined in section 5.2.

5.1 Socio-economic index obtained from Principal Component Analysis

As previously stated, the first task of this paper is to verify the association between the socioeconomic condition and the magnitude of nighttime light captured by satellites. Sixteen socioeconomic indicates collected during 2009-2013 were the main variables for the Principal Component Analysis (PCA). As introduced in section 4.1, the outcomes of PCA are principal components. Each principal component is the weighted combination of all variables, while the eigenvalue of each principal component represents its degree of contribution to the total variance. Table 3 and Figure 9 exhibit the first outcome of applying PCA on the dataset of sixteen variables, identifying that the first to the fourth Principal components significantly contribute to the variation of all data. Table 4 shows the second outcome of PCA which are weights for formulating each principal component.

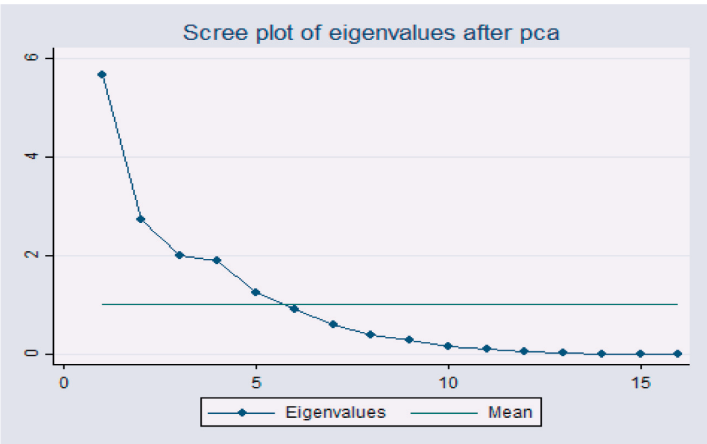
Following Hoque (2014), this study used the first Principal component as the main single index representing the socioeconomic condition. The validation of the correlation between the computed first Principal component and the NTL index was conducted. Specifically, Figure 10 shows that there exists a significant positive relationship between the computed first Principal component and the NTL index with the correlation coefficient of 0.870. This finding quantitatively supports the use of NTL index as the proxy of the stage of socioeconomic development, yielding the subsequent outcomes of spatial inequality and clustering analysis as discussed in the next section.

Table 3 Principal components/correlation obtained from PCA

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	5.6425	2.92294	0.3527	0.3527
Comp2	2.71956	0.719056	0.17	0.5226
Comp3	2.0005	0.095196	0.125	0.6477
Comp4	1.90531	0.653587	0.1191	0.7667
Comp5	1.25172	0.344706	0.0782	0.845
Comp6	0.907013	0.315278	0.0567	0.9017
Comp7	0.591735	0.215095	0.037	0.9386
Comp8	0.37664	0.103483	0.0235	0.9622
Comp9	0.273157	0.130431	0.0171	0.9793
Comp10	0.142725	0.0297035	0.0089	0.9882
Comp11	0.113022	0.0647011	0.0071	0.9952
Comp12	0.0483209	0.0205166	0.003	0.9983
Comp13	0.0278043	0.0278043	0.0017	1
Comp14	0	0	0	1
Comp15	0	0	0	1
Comp16	0	.	0	1

Source: Authors' calculation

Fig.9 The Scree plot of eigenvalues obtained from PCA



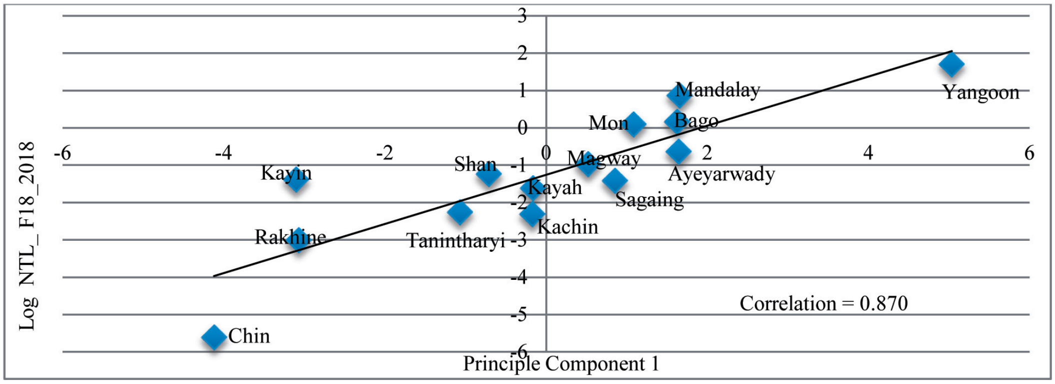
Source: Authors' calculation

Table 4 Principal components (eigenvectors) obtained from PCA

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7	Comp8	Comp9	Comp10	Comp11	Comp12	Comp13
Consumptio~t	-0.192	0.1647	0.1256	-0.4392	0.3734	0.1949	-0.0656	0.4375	-0.183	0.3439	0.2849	0.0262	-0.0832
Avg_HH_Size	-0.3529	0.0455	-0.0369	0.321	-0.089	0.0604	0.1347	0.3122	0.2948	0.2408	-0.0231	-0.0353	0.0202
Demgrph_De~o	-0.378	0.0956	-0.0222	0.0409	-0.0449	0.0846	0.3736	-0.3099	-0.141	0.3173	0.202	0.4247	0.3664
Avg_Land_A~H	0.3375	-0.1133	0.2575	0.066	0.015	0.0147	-0.1624	-0.1665	0.6634	0.329	0.3997	0.1589	-0.048
Landless_R~i	0.2965	-0.3381	0.2415	0.0013	0.1682	0.0921	0.0957	0.0504	-0.2369	-0.1145	-0.0555	0.3943	0.2376
Acces~t_Agri	0.3362	-0.087	-0.0435	-0.0477	0.272	-0.1647	0.5669	-0.2014	-0.1082	0.1682	-0.085	0.0616	-0.3143
Acces~n_Agri	-0.2191	-0.2944	0.4112	-0.097	0.081	0.1749	0.2863	-0.229	0.0011	-0.1875	0.288	-0.6168	0.0675
LF_Partici~e	0.1168	-0.0003	-0.3795	-0.1121	-0.0559	0.791	0.1541	0.0063	0.1848	-0.3125	0.0988	0.1352	-0.1012
Unemploy_R~e	-0.0246	-0.2721	-0.0734	0.5439	0.2907	-0.0503	0.2227	0.4496	0.086	-0.163	0.0687	-0.0017	0.1721
Underemplo~e	-0.2236	0.2686	-0.0116	-0.1872	0.4835	-0.313	0.0688	-0.0373	0.3323	-0.4994	0.1025	0.2263	-0.1189
Literacy_R~e	0.2522	0.0745	0.4336	-0.2173	-0.2233	0.0297	0.1319	0.4716	0.0137	-0.0849	-0.0896	0.0904	0.0924
Net_Enr~mary	0.2153	0.4681	-0.0033	-0.1272	-0.1633	-0.1008	0.28	0.0018	0.1916	-0.1247	-0.0238	-0.1622	0.5739
Net_Enr~dary	0.1698	0.455	0.0684	0.2939	-0.1274	0.0377	0.3201	0.0942	-0.1323	0.0793	0.1582	-0.1216	-0.4442
Access_~mary	0.2727	0.1525	-0.2151	0.0568	0.534	0.1671	-0.1233	-0.0545	0.0188	0.2979	-0.218	-0.3388	0.2941
Access_~dary	0.1089	0.3345	0.2561	0.4156	0.1405	0.1455	-0.328	-0.1614	-0.3364	-0.2145	0.3399	0.0862	0.0769
Total_Gov~re	0.2088	-0.1649	-0.4823	-0.131	-0.1502	-0.3115	-0.0044	0.167	-0.1788	-0.0285	0.6347	-0.1087	0.1212

Source: Authors' calculation

Fig.10 A relationship between the NTL index and the first principal component (PCA index)



Source: Authors' calculation

5.2 Spatial Cluster Analysis of Development using NTL index

As introduced in section 3.3, there were two methods of detecting spatial clustering. Figure 11 and 12 illustrate the first set of result showing the clustering pattern of NTL index using the data of 1992. Both figures clearly indicate the cluster of a high density of high NTL index in the area of Yangon, i.e. technically the area of "hot spot". This indicates the only urbanization in that area. Results obtained from both spatial detection methods also identify that there was the cluster of "cold spot" in the northern region of Myanmar, indicating the low density of urbanization in that area.

Figure 13 and 14 illustrate the situation in 2004. Compared to that of 1992, the spatial distribution had slightly changed. There was still the main urbanization in the area of Yangon. Also, there was a statistically significant high density of NTL in the area of Mandalay. In addition, the coverage of cold spot area, i.e. the statistically low density of urbanization, had declined. After 2004, the spatial distribution of urbanization has been continuously evolving. In the case of 2016, Figure 15 and 16 illustrate the raising significant density of urbanization in Naypyitaw. Specifically, in addition to the existing concentration in Yangon, both spatial statistical results obtained from Getis-Ord Gi* statistics and LISA confirm the newly detected "hot spot" in the area of Naypyitaw. Interestingly, Mandalay has no longer been the statistically significant "hot spot", affirming the rapidly emerging significance of Naypyitaw as the alternative zone of concentrated activities.

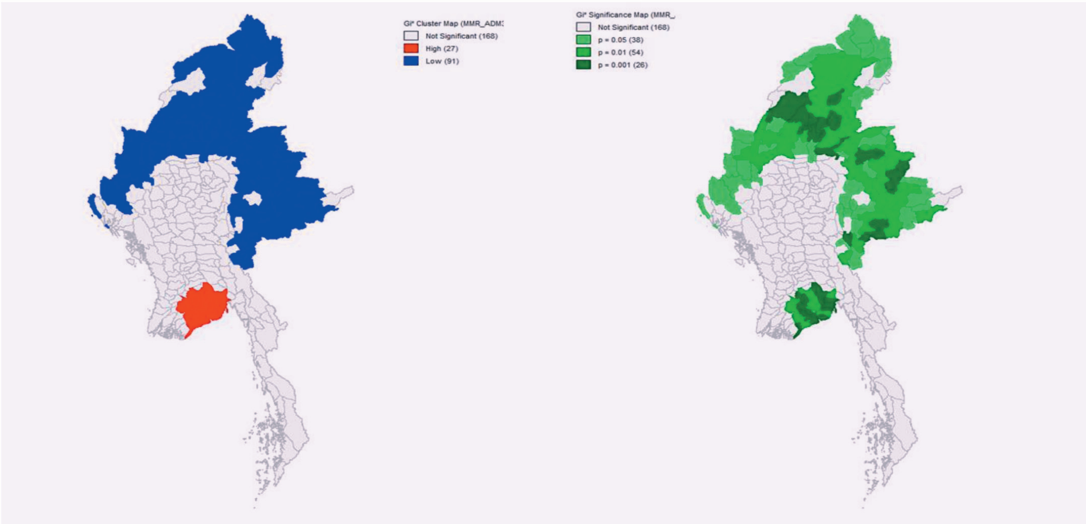
In addition to applying the spatial statistical methods for detecting the geographical distribution of socioeconomic inequality, this paper also quantified the degree of inequality by using the conventional Gini coefficient. The calculation was undertaken by using the annual data set of NTL index[6]. As exhibited in Figure 17, the computed series of NTL-based Gini coefficients indicate that spatial inequality was improved during 1993-2004. However, the geographical distribution of urbanization development has been widened as identified by the continuously increasing Gini coefficients. This rising spatial inequality is mainly caused by the rising density in Naypyitaw as previously shown in Figure 7, Figure 15 and 16. These outcomes provide the recent evidence of dual growth poles corresponding to the hypotheses initially suggested by Kudo and Kumagai (2012) regarding the possibilities of regional development and city agglomeration in the case of Myanmar. Moreover, these statistically significant results imply that the infrastructure investment in Naypyitaw would allow the higher mutual benefits of agglomeration and economic expansion. However, there is also the trade-off between the expected benefit and the widening spatial inequality of socioeconomic development.

Based on these empirical findings, the continuous urbanization and expansion of Naypyitaw are twofold. First, it would transform the country into the new development path functioning based on the multiple growth poles. This would allow more opportunities for labors and businesses to locate both their economic activities and accommodation. Second, however, the intended emphasis on expanding Naypyitaw has led to the nationwide widening gap of development. In addition, the increasing spatial inequality might worsen the problems of poverty and income inequality. Hence, the expansion of infrastructure development aimed at the socioeconomic improvement should be implemented in order to stimulate economic growth in other states/regions. Particularly the development in regions/states located along the border such as that between Myanmar and Thailand can be initiated through the promotion of special economic zones simultaneously stimulating the expansion of economic activities and bridging the inequality gap of development. In addition, these proposed special economic zones would mitigate the emigration problems, allowing more opportunities for Myanmar workers to stimulate the local economy via the increasing income and higher consumption capability. Furthermore, the regional development in the western region, e.g. Chin and Rakhine, should be initiated with the high priority because of their lagging

6 These computed results exhibit the contribution of NTL as an alternative source of data providing the finer spatial resolution at regional and sub-regional levels, which would potentially enable the extensive analysis on development in the case of Myanmar and other developing economies whose data are limited

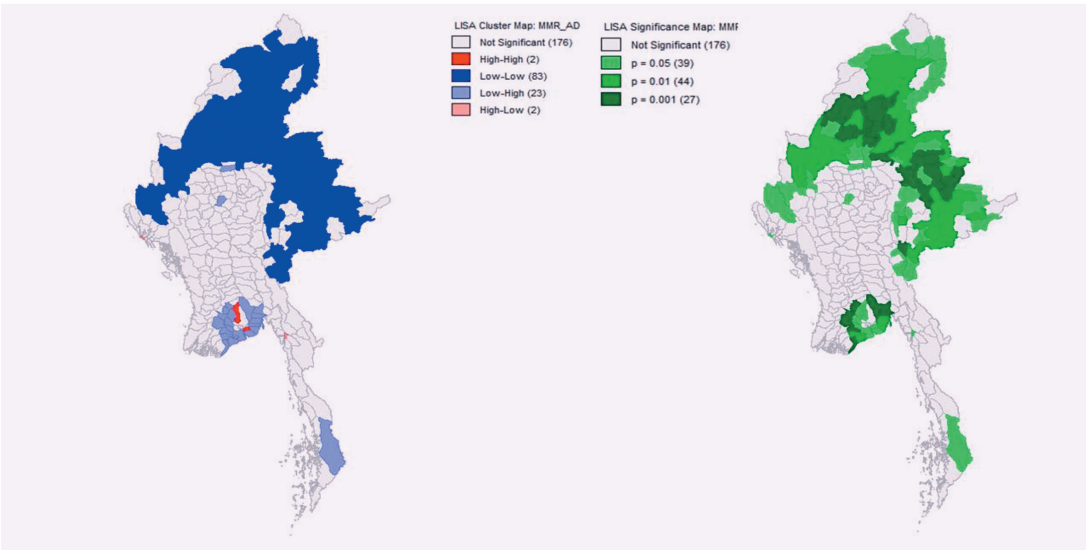
stage of development. The locational advantage of both states/regions would be the potential strategic economic corridor enabling the connectivity and expansion of trade and investment in the cross-region and international trades.

Fig.11 The cluster map obtained from Getis-Ord Gi* statistics (NTL index of 1992)



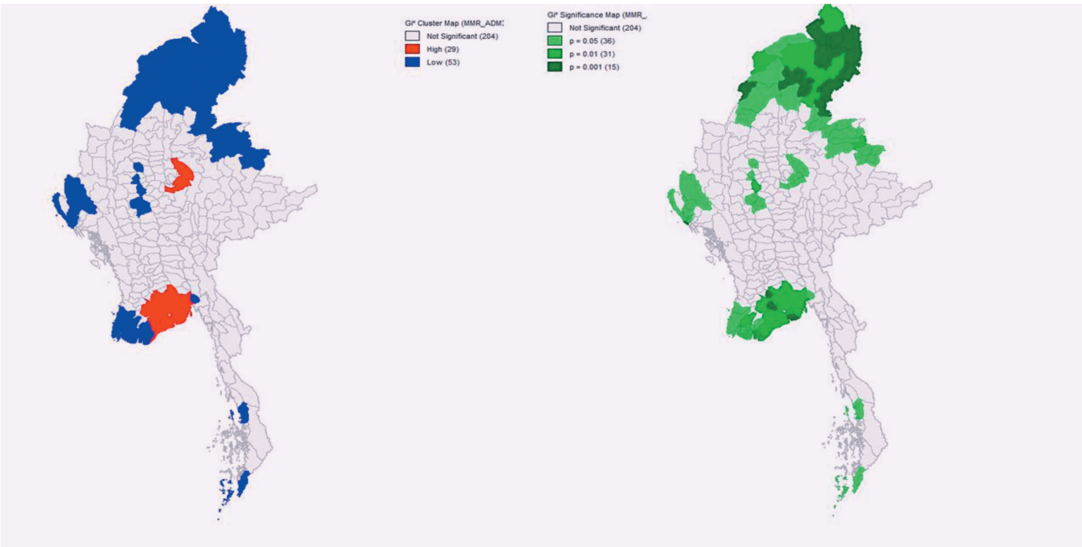
Source: Authors' calculation

Fig.12 The cluster map obtained from LISA (NTL index of 1992)



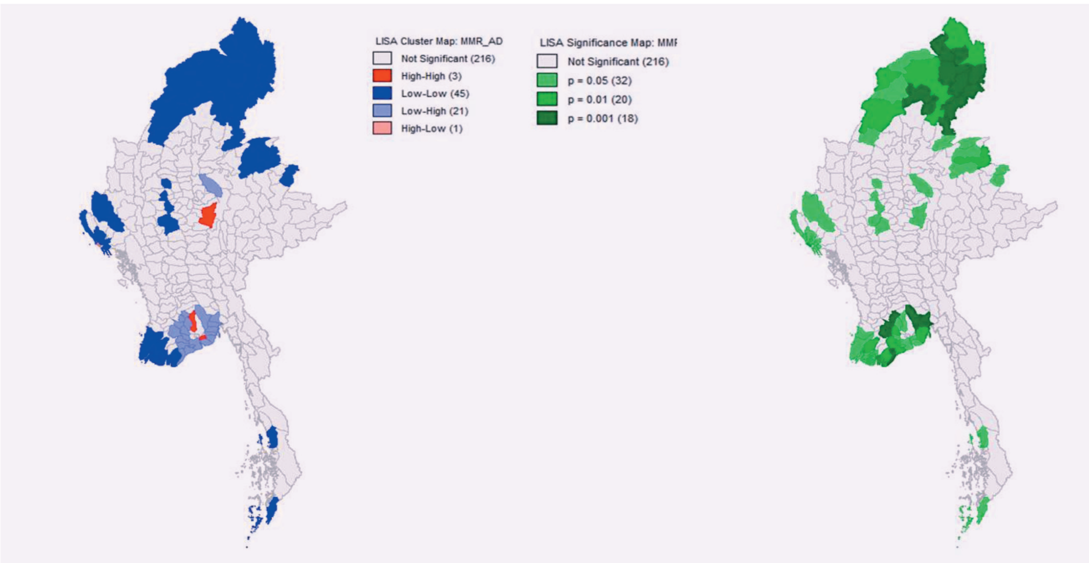
Source: Authors' calculation

Fig.13 The cluster map obtained from Getis-Ord Gi* statistics (NTL index of 2004)



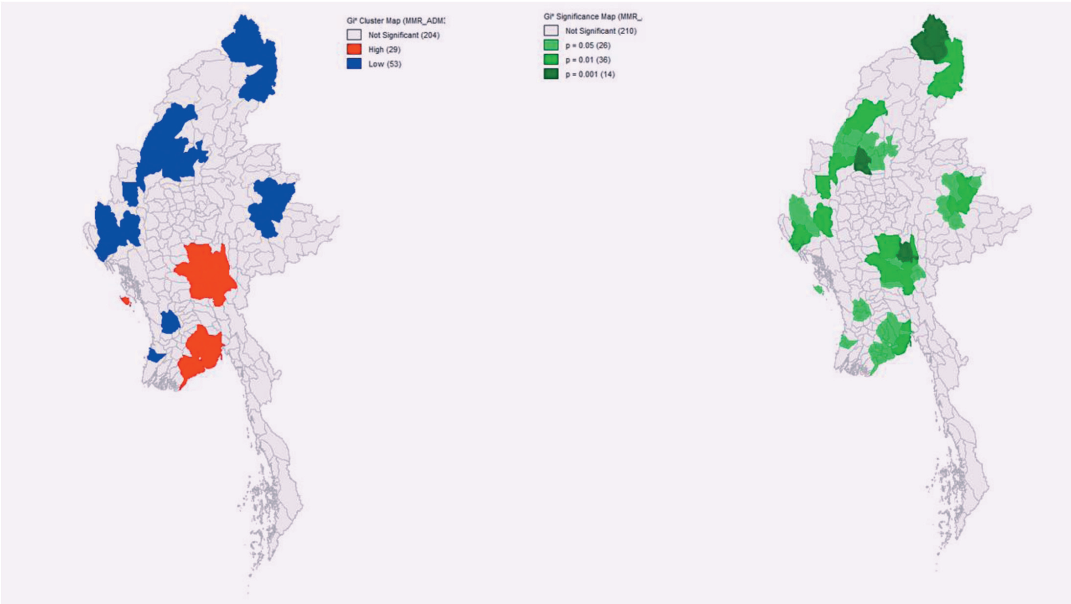
Source: Authors' calculation

Fig.14 The cluster map obtained from LISA (NTL index of 2004)



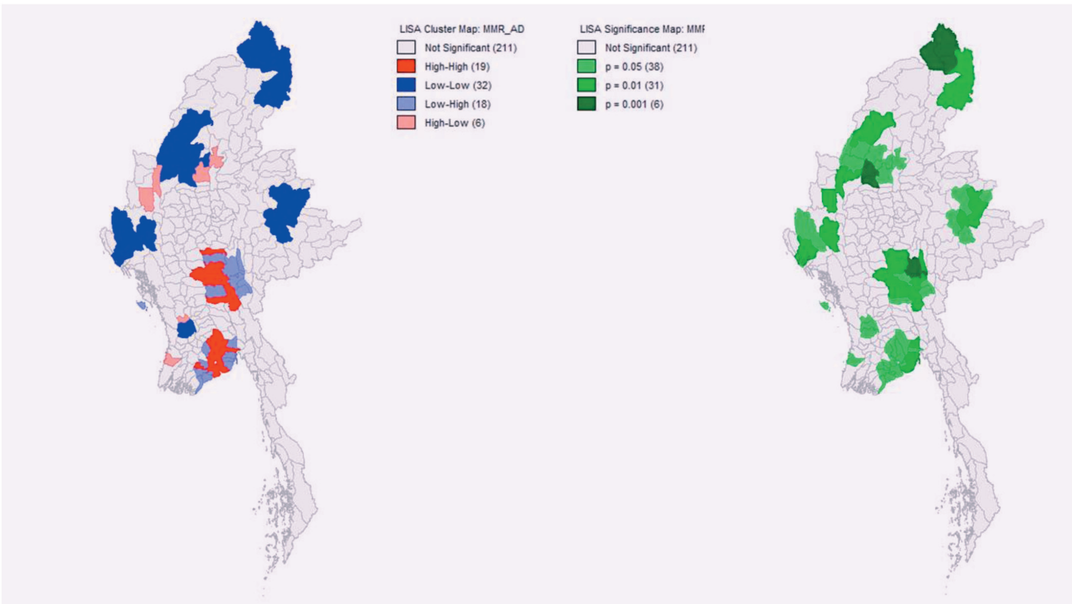
Source: Authors' calculation

Fig.15 The cluster map obtained from Getis-Ord Gi* statistics (NTL index of 2016)



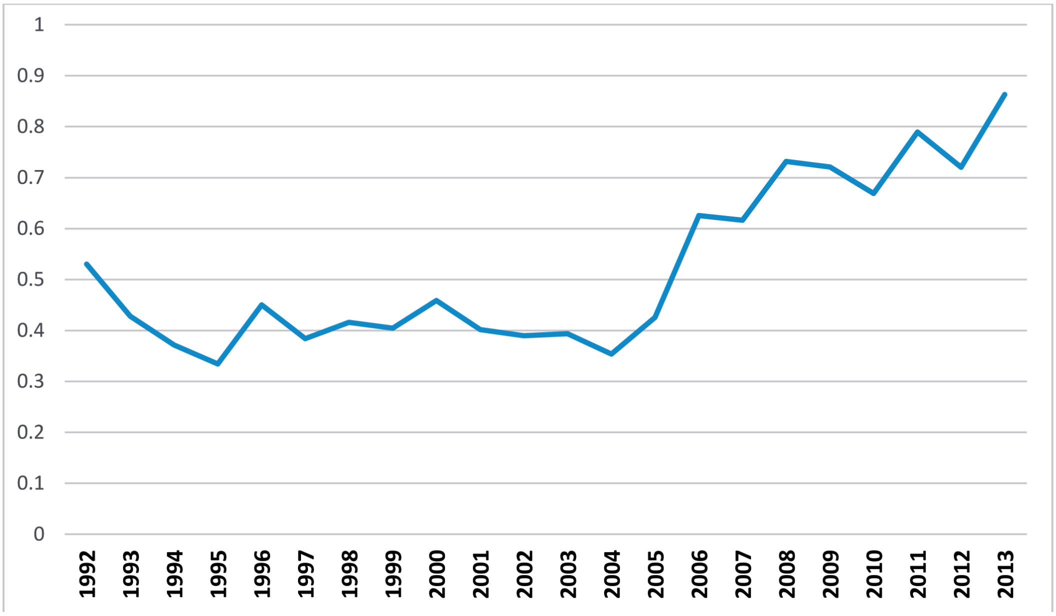
Source: Authors' calculation

Fig.16 The cluster map obtained from LISA (NTL index of 2016)



Source: Authors' calculation

Fig.17 The NTL-based Gini coefficients



Source: Authors' calculation

6 Conclusions

This study has two research objectives. First, it is shown that the single index representing the socioeconomic condition can be formulated by applying PCA on survey data. Further, this formulated index is highly correlated with the NTL index. Hence, the NTL index can also be utilized as the proxy indicating the status of the socioeconomic condition. Second, spatial inequality was analyzed using two methods of spatial cluster detection. The obtained results show that Myanmar has been gradually transforming from the centralized growth pattern to the case of multiple growth poles. Specifically, this transformation has been driven by the concentration of infrastructure investment in Naypyitaw. The formation of multiple growth poles would enable the expansion of economic growth and social development. On the other hand, the gap in spatial inequality has been widened. Therefore, additional development programs should be implemented such as the special economic zones located at the border. The development of such projects would concurrently induce the economic expansion and bridge the gap of spatial inequity.

The constraints of data unavailability have been the major problem in conducting this research. The analysis can be deepened and broadened with additional data having the higher spatial resolution and the longer inter-temporal coverage. In addition, the alternative techniques of calibrating NTL data should be applied in order to verify the robustness of results obtained from methods of spatial cluster detection. Also, the analysis of NTL-based Gini coefficient should be enhanced in order to mitigate the bias or the overestimation of values representing urbanized areas because some states/regions are mainly the mountain terrains naturally constraining habitation. Furthermore, additional details of related private and public development projects should be incorporated in the future analysis in order to identify the relationship between the initial effects of infrastructure investment and the subsequent outcomes of urban density and increasing agglomeration force. Likewise, with the improved availability of data, it is possible to construct a hybrid indicator incorporating both remote-sensing data and the ground survey representing the broader aspects of physical, economic and social conditions. This hybrid index would lead to a higher accuracy of cluster detection.

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