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Influence of intra annual calibration methods in changing the preciseness of the obtainable information from DMSP-OLS NLT images

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Abstract

Intra-annual composition performing is important to make full use of the information derived from two satellites for the same year and to remove any intra-annual unstable lit pixels. According to the literature, two methods are used to intra-annual calibration of NLT images; the intra annual stable lit pixel identification and averaging method, and the intra annual lit pixel averaging method. In the literature, it was unable to find out any previous research that places attention to identify the most appropriate method for performing intra-annual calibration. Hence, aforementioned both methods were carried out in the study to identify the most appropriate method. In addition to that, it was unable to find out any research paper that places main attention to identify the relationship between DMSP-OLS NLT image data and Gross Domestic Products or electricity consumption of Sri Lanka. The most appropriate method for intra annual calibration of NLT images was identified by comparing the GDP and electricity consumption data that published by Sri Lanka government with the calculated GDP and electricity consumption data for Sri Lanka based on NLT images that calibrated based on aforementioned both methods separately. In the study it was identified a higher core relationship between DMSP-OLS NLT data and GDP as well as electricity consumption in Sri Lanka. However, it is better to perform the intra annual calibration based the intra annual stable lit pixel identification and averaging

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method (L method) rather than the intra annual lit pixel averaging method (Z method) for obtaining more reliable information on GDP and electricity consumption of Sri Lanka. Further, it was identified that accuracy of the Sum Of Digital Number Values (SODNV) based GDP estimation was higher than the Total Number of Lit Pixels (TNOLP) based estimation while the accuracy of the TNOLP based electricity consumption estimation was higher than the SODNV based estimation.

Keywords: Intra annual calibration; DMSP-OLS NLT image; GDP Sri Lanka

1. Introduction

Compare to general remote sensing satellite imagery, the potentiality of Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) Nighttime Lights Time-series (NLT) image products are relatively very high for observing global socio-economic activities (Zhao, et.al, 2015, Li, Zhao and Li 2016); in other words, NLT images can provide important foundation to estimate Gross Domestic Product (GDP), population, electric power consumption, greenhouse gas emission, poverty, and other socio-economic parameters (Li, Zhao and Li 2016).

After applying several systematic corrections for DMSP/OLS nighttime light imagery of 21 countries in the America, Elvidge et al (1997), have identified a higher coefficient of determination between light-emitting area and GDP. He et al (2013) have established a linear regression model between saturated corrected DN values of light images and electric power consumption in China. Letu et al (2016) have identified higher correlation coefficients of determination between stable light and electric power consumption of Japan, China, India, and some other Asian countries. According to their findings, the coefficient of determination for Japan was 0.8264.

Further, electric power consumption is a cause as well as a result of the economic development of a society and therefore, nighttime light is a representation of the economic development of the society. Shi, et al (2014) say that the total night time light data can better simulate GDP and electric power consumption statistics. Liu et.al (2012) have identified corrected NLT data has an ability to precisely explain the urban development and economic development of China. According to their findings, the corrected NSL data reflect the urban growth rate (10% per year) of China from 1992 to 2008. Further, the correlation coefficient of GDP and the total number of lit pixels (TNOLP) was greater than 0.68. Zhao et.al (2015) have identified the correlation between DMSP-OLS NLT image data and GDP growth rate and urban development pattern in China and USA from 1992 to 2008. Li, Ge and Chen (2013) have identified a linear correlation between GDP change rate and total nighttime light change rate in Zimbabwe. Elvidge et al (2014) have identified that DMSP time series could be used to map expansion in infrastructure, population, economic activity, and GDP.

However, on the one hand, several limitations in DMSP-OLS/NLT images such as relatively low spatiotemporal resolution, absence of onboard calibration, lack of inter-satellite calibration, lack of records of in-flight gain changes, limited 6 bit quantization of digital number, light saturation in highly populated urban centers (underestimation of digital number –DN- values), the blooming effect (overestimation of lit area) and limited accessibility to high quality daily OLS data (Huang, et al. 2014) reduce the reliability of the images. As a consequence of aforementioned limitations, following weaknesses can be identified in NLT image information (Liu, et.al, 2012, Zhao, et.al, 2015).

- Discrepancies between the sum of DN values (SODNV) derived from different satellites for the same year,
- Abnormal fluctuations in DN values for different years derived from the same satellite,

- discrepancies of the total number of lit pixels (TNOLP) between two satellites for the same year,
- abnormal fluctuations of the number of lit pixels of images derived from the same satellite for different year

On the other hand, several strategies have been developed to overcome some of these shortcomings too. For examples, Elvidge et al (2009), Hsu, et al (2015), and Liu et al(2012) have introduced several methods to inter-calibrate the NSL images; for solving the saturation effect, Hara et al (2004) and Letu et al (2012, 2016) have introduced a linear correlation method and a cubic regression equation model respectively. In addition to that, as discussed later in the paper, numbers of intra annual series correction methods have been adopted and introduced by many other researchers. However, a few researchers have placed attention on conducting comparative studies to identify the most appropriate method/methods for correcting aforementioned weaknesses. For example, Cao et al (2016) have placed attention on identifying the most appropriate regression model among the linear regression model and second-order polynomial regression model for an invariant area based inter annual calibration. Therefore, it is important to conduct comparative studies using several methods to identify the most appropriate method to calibrate and adjust the errors of NLT images for obtaining most reliable socio-economic/ demographic information from satellite images.

2. Objectives

Intra-annual composition performing is important to make full use of the information derived from two satellites for the same year and to remove any intra-annual unstable lit pixels. According to the literature, two methods are used to intra-annual calibration of NLT images; the intra annual stable lit pixel identification and averaging method, and the intra annual lit pixel averaging method.

Liu, et al (2012) have used the intra annual stable lit pixel identification and averaging method (hereafter, still referred to as L method). They have followed following steps to perform the enhancement.

- Identifying the intra-annual unstable lit pixels. In other words, if a lit pixel was detected by one of two satellites, the pixel was identified as an intra-annual unstable lit pixel;
- Replacing the DN values of intra-annual unstable lit pixel values with value of zero, hence in the step; some of stable lit pixels that have been recorded in one image would be identified as unstable lit pixels. Thus, the pixels could be named as missing stable lit pixels (Fig. 1);
- Replacing the DN value of each intra-annual stable lit pixel by averaging the stable lit pixels' DN values of two NSL images from the same year.

Zhao et al (2015) have performed the intra-annual calibration by averaging the DN values of two NLS images of same year (hereafter, still referred to as Z method). Hence, the resulted image of the method is consisted of both intra annual stable lit pixels as well as intra annual unstable lit pixels. However, it can be clearly identified that DN values of pixels would changed dramatically as indicates in Fig. 1.

In the Fig. 1, considerable differences can be identified in the lit area and the DN values of the resulted images of two intra-calibration methods and original images [for example see the changes of pixels (lit/unlit pixels and DN values) in the circles of F101994 and F121994 images and the changes after performing L method (A), and Z method (B)]. Some of the lit pixels in the F101994 image have been transformed into unlit pixels in the image 'A'; thus DN values of the pixels have been replaced with zero value. However, same pixels have been recognized as lit pixels in the image 'B' while DN values of the pixels have been decreased compared to the DN values of the same pixels in the F101994 image.

In the literature, it was unable to find out any previous research that places attention to identify the most appropriate method for performing intra-annual calibration. Hence, aforementioned both methods were carried out in the study to identify the most appropriate method. Therefore, hereafter, the images that were calibrated based on L method are referred to as 'L method image set (L-MIS)' and the images that were calibrated based on Z method are referred to as 'Z method image set (Z-MIS)'.

In addition to that, it was unable to find out any research paper that places main attention to identify the relationship between NLT image data and GDP or electricity consumption of Sri Lanka. Further, if it is possible to identify a higher correlation between GDP or electricity consumption statistics of Sri Lanka and NLT image data, it would helpful for planning Sri Lankan economy. Therefore, as a subordinate objective of the study, attention is placed to identify the correlation between DMSP-OLS NLT image data and GDP/electricity consumption of Sri Lanka.

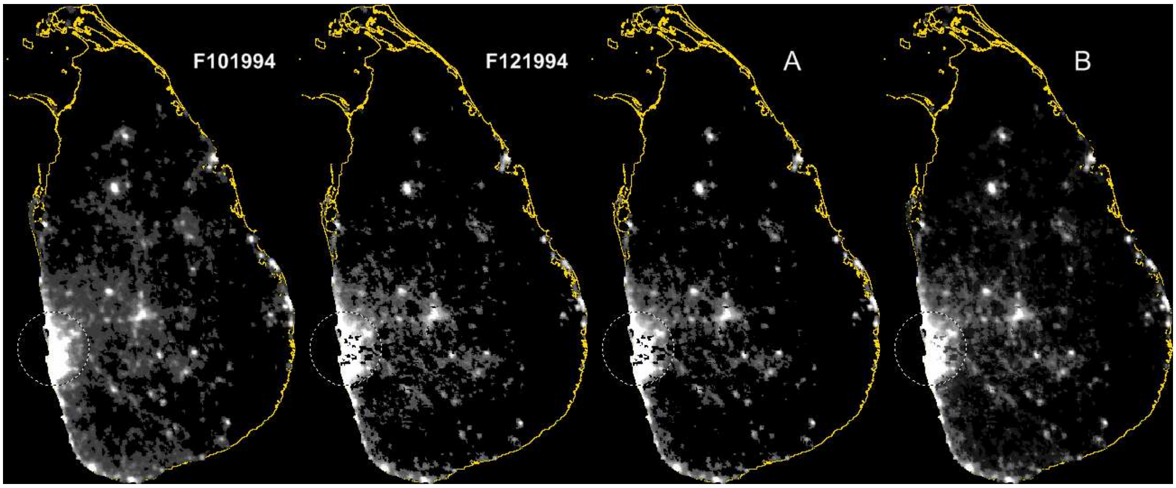

Fig. 1.Difference between Liu, et al adopted intra calibration method and Zhao et al adopted intra calibration method.

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3. Main and Ancillary Data

The main data were derived from National Oceanic and Atmospheric Administration’s National Geographic Data Center (NOAA-NGDC). Currently, the products of 34 satellite years (version 4) derived from six satellites (F10, F12, F14, F15, F16 and F18) from 1992 to 2013 are available for downloading from NOAA-NGDC website. It provides three kinds of annual average data; cloud free coverage, average visible and stable light. ‘Stable-light data cover cities, townships and other lasting light emissions, and background noise has been removed’ (Wu, et al. 2013: 7358). Therefore, in the study, stable light data from 1992 to 2013 were used as the main data.

Ancillary data include the Sri Lanka land boundary in shape file format, electricity production statistics and GDP statistics of Sri Lanka from 1992 to 2012. Electricity production statistics were derived from the web site of http://www.info.energy.gov.lk/ and GDP statistics were derived from the web site of https://countryeconomy.com/gdp/sri-lanka?year=2013.

4. Methodology

There are two types of lit pixels in an NLT image; real lit pixels (actually produced by the light of the earth surface) and fake lit pixels (produced by the existence of background lit pixels [blooming effect] or noises [irregularities or errors that occur in the sensor response and/or data recording and transmission] or inter-annual calibration process. Therefore, fake pixels should be corrected for obtaining precise information from NLT images.

In addition to that, there are two types of unlit pixels in an NLT image; real unlit pixels (produced due to unavailability or lack of light emitting from the earth surface [may be due to power failure or no electricity facilities]) and fake unlit pixels (produced due to noise effect as well as inter-annual calibration process).

The mixture of real pixels (lit and unlit) as well as fake pixels (lit and unlit) is one of the causes for discrepancies and abnormal fluctuations of the TNOLPs and the SODNVs. There are several methods have been developed by researchers to keep real pixels while removing fake pixels. Those methods can be categorized into several groups; inter-calibration methods, nonzero DN value correcting method, intra-annual calibration methods, and inter-annual series correction methods. Many of them were used in the study and the whole research process adopted in the study is depicted in the Fig. 2.

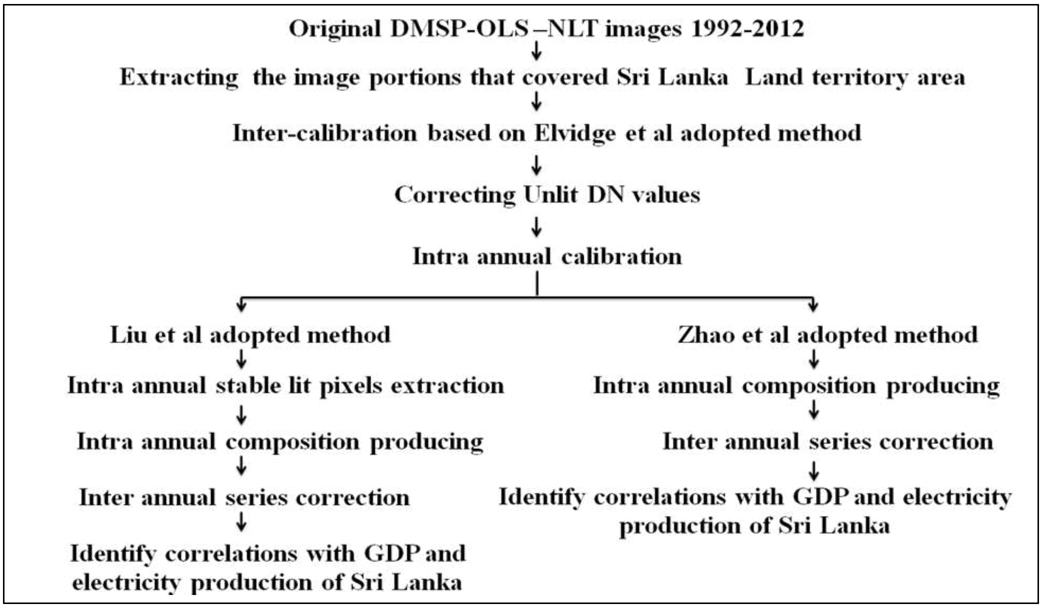

Fig. 2.Research methodology adopted in the study

4.1. Image Processing

4.1.1. Extracting the image portions covering the Sri Lanka land territory

The first step of the study was extracting the image portions that covered the Sri Lanka land territory area from the NLT global images. It was done by clipping each DMSP-OLS NLT stable light tif image using Sri Lanka boundary shape file. As a consequence of the extracting method, the booming effect occurred due to the ocean was removed.

However, as indicated in Fig. 3, the weaknesses that mentioned in the introduction section were identified in the images too. Therefore, to obtain reliable socio-economic information from the DMSP-OLS NLT images, those weaknesses should be solved.

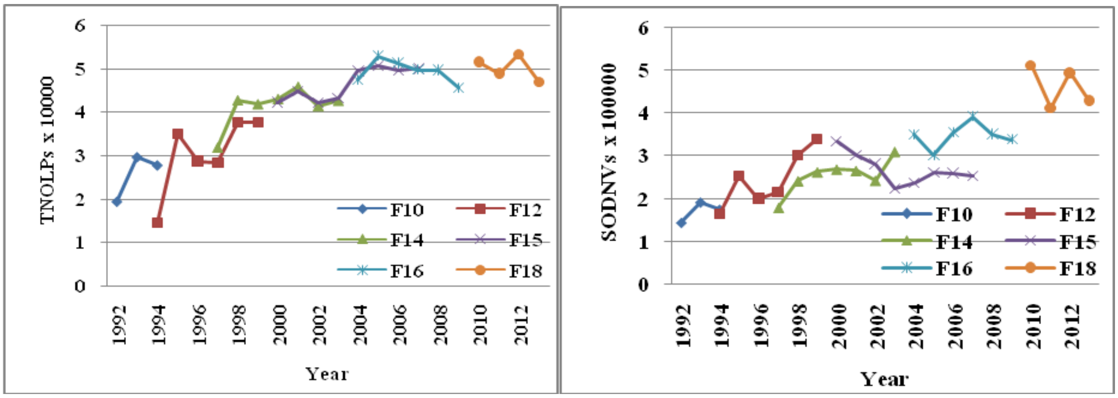

Fig. 3.The TNOLPs (left) and SODNVs (right) from NSL for Sri Lanka from 1992 to 2013 (without any calibration)

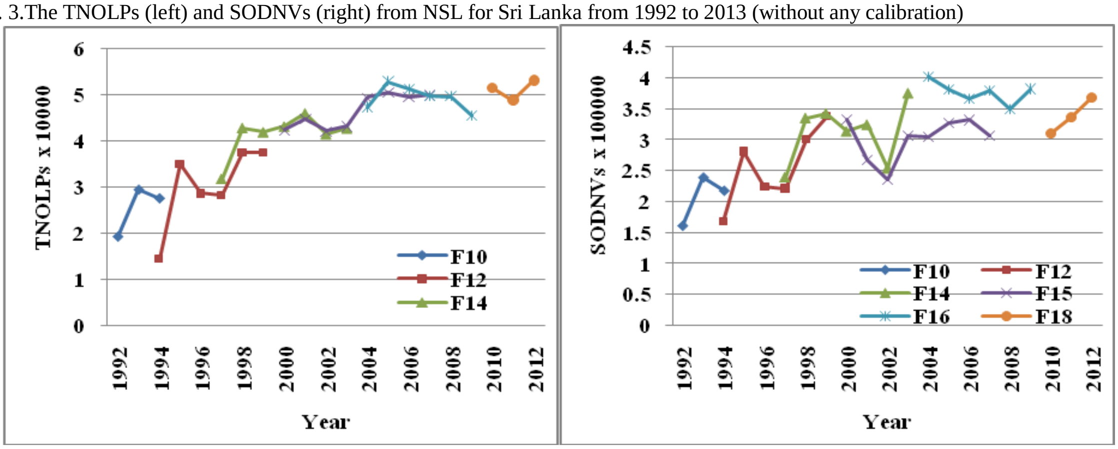

Fig. 4.The TNOLPs (left) and the SODNVs (right) from NSL for Sri Lanka from 1992 to 2012 after inter-calibration based on Elvidge et al developed method

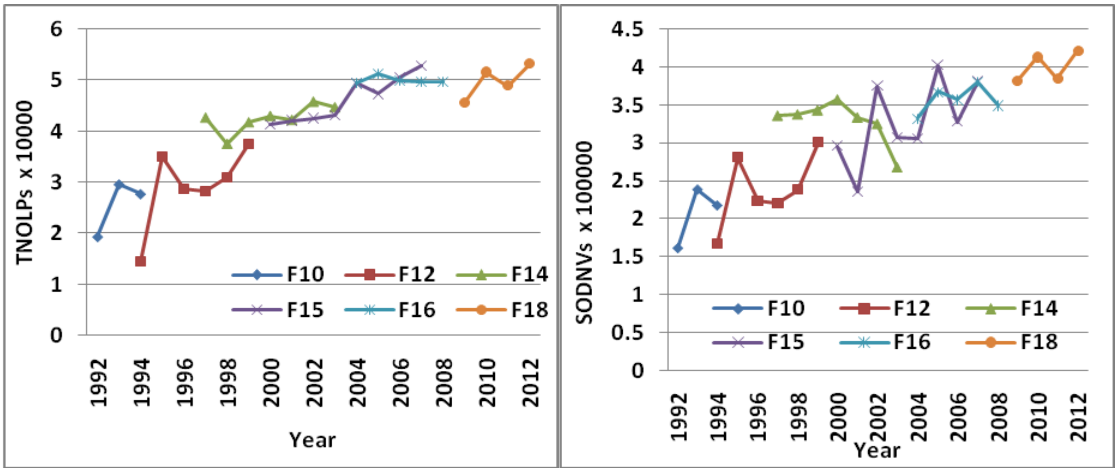

Fig. 5.Changes of the TNOLPs (left) and the SODNVs (right) after nonzero DN value correction

4.1.2. Inter-annual calibration

Here According to the literature, the invariant region method is applied to perform a comparative study between NLT images (Cao, et.al, 2016). Elvidge et al (2009) first inter-calibrated the global NSL data set by using the invariant region method. They have chosen Sicily, Italy as the invariant region. Subsequently, Liu et.al (2012) have also inter-calibrated Chinese NSL data set using a similar methodology. Both of the studies proposed a second order polynomial regression model to address the curvature in correction when DN values approached saturation in the NLT images (Cao, et.al, 2016). Hsu, et.al (2015) have developed a linear regression model for inter-calibration of the NLT images. However, as identified by Cao, et.al (2016) based on coefficient comparison of linear regression model and second order polynomial regression model, the second order polynomial regression model is superior to the linear regression model. Thus, in the study, inter-calibration was performed by using the same parameters that were developed by Elvidge et al (2014). Therefore, here, the step is not explained in details. As indicated in Fig 4, compared to the TNOLPs, the SODNVs of resulted images are changed dramatically due to the inter-calibration correction. It can be clearly identified in F14 and F18 of Fig. 4 (right).

4.1.3. Nonzero DN value correction

According to Zhao, et al (2015: 2041), 'many unlit pixels in original NLT image products have nonzero DN values due to the existence of background noise. Moreover, after inter-calibration, pixels with DN value 0 in original NLT image products have nonzero DN values because nonzero constants in quadratic polynomial regression equations were added to the pixels". Thus, by using equation 1, the nonzero DN values were converted to zero values as the 3rd step of the image preparation process. The changes of the TNOLP data and the SODNV data of resulted images are depicted in Fig 5. In the figure, two key points can be identified. First, the fluctuations of the TNOLPs and the SODNVs are still visible. The second, the overall growth pattern of the TNOLPs and the SODNVs are more visible than the previous stage of image preparation.

$$DN_{2012,i} = \begin{cases} DN_{2011,i} \ \text{if} \ DN_{2012,i} = 0 \ \text{and} \ DN_{2011,i} > 0 \\ DN_{2012,i}, \qquad \text{otherwise} \end{cases} \tag{5}$$

4.1.4. Intra-annual calibration

As noted above in the paper, L method places attention to filter only intra-annual stable lit pixels. However, as indicated in Fig. 6, after performing the L method to the inter-calibrated NLT images of 1994 and 1997 to 2007, it could able to be identified abnormal fluctuations and discrepancies in the intra-annual stable lit pixels and the DN values of the intra-annual stable lit pixels (except missing values). Further, it can be identified that if a pixel was not detected by both satellites, the pixel's DN value is replaced with the value zero. Hence, as indicated in Fig. 1 (A) and Fig. 6 (left, from F10 to F18) fake lit pixels as well as real lit pixels, which captured by only one satellite will be identified as intra-annual unstable lit pixels. Thus, in the Fig. 1 A, it can be identified zero values pixels in the core area of Sri Lanka economy as indicated in F121994 (see the inland area in the circle). On the other hand, as indicated in Fig. 1 (B) and Fig. 6 (left), after performing the Z method it was identified that all stable and unstable lit pixels have consisted in the resulted image. Further, the DN values have been slightly changed (Fig. 1, B). Moreover, a considerable difference between the TNOLPs and the SODNVs was identified/ calculated after performing L method and Z method separately (Fig. 7). The fluctuation of both of the TNOLPs and the SODNVs indicates the necessity of further correction.

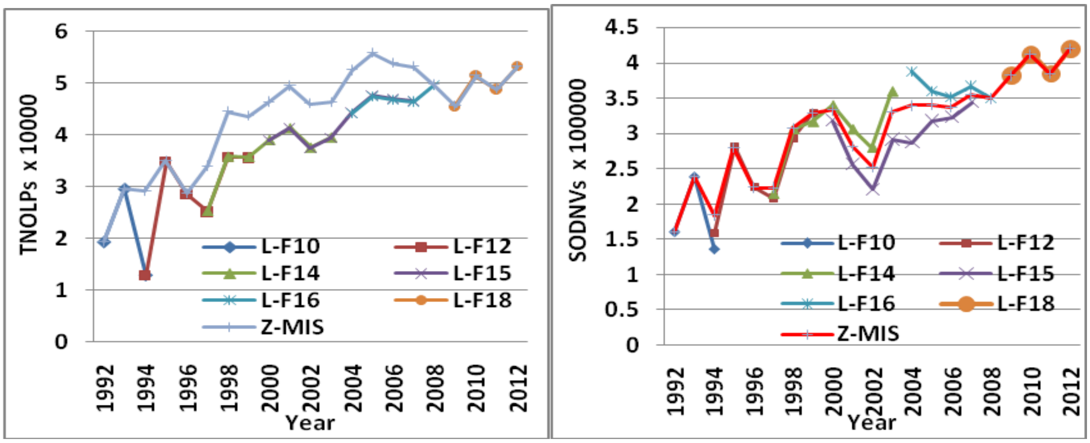

Fig. 6 Differences of the TNOLPs (left) and the SODNVs (right) after performing the intra annual calibration for Z-MIS and L-MIS

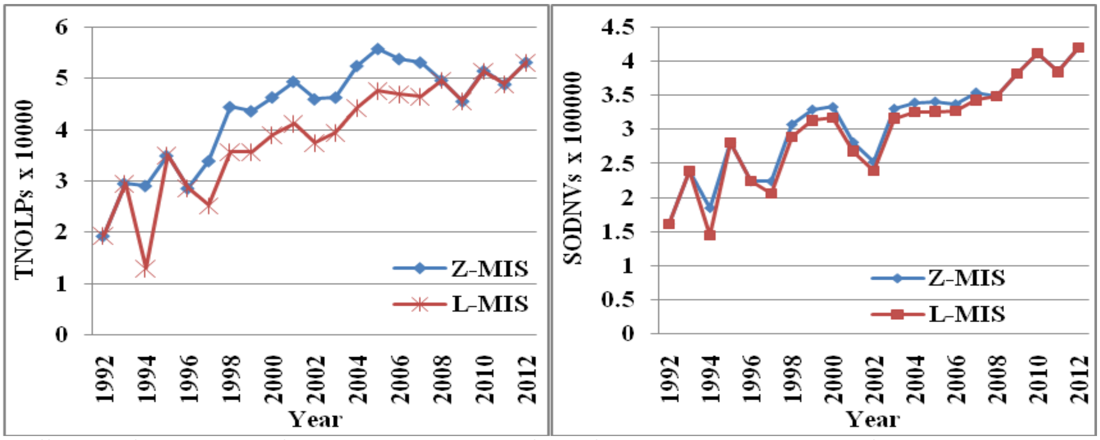

Fig. 7 Differences of the TNOLPs (left) and the SODNVs (right) after performing intra annual calibration for L and Z method image sets

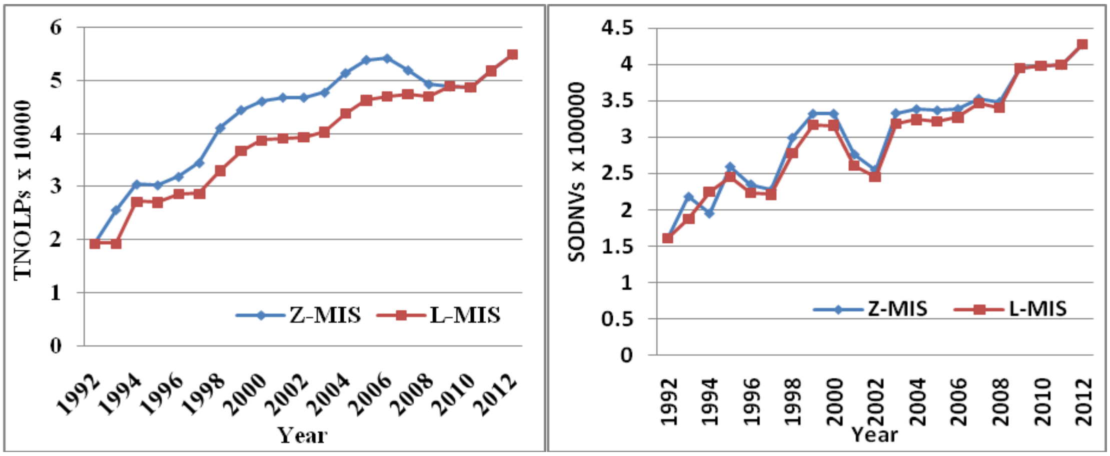

Fig.8 Differences of the TNOLPs (left) and the SODNVs (right) after performing all calibration and adjustments for L-MIS and Z-MIS

4.1.5. Inter-annual series correction

Numbers of inter-annual series correction methods can be identified in the literature. However, all of them have based on some assumptions. Liu et al (2012) have assumed that de-urbanization did not exist in China from 1992 to 2008 and therefore, decreases in lit area and DN values of pixels should not exist in the NLT images. Based on the assumption, they have adjusted all annual images using the equation 2 to guarantee that DN value of each pixel in an early annual image is not larger than in a later annual image.

$$DN_{n,i} = \begin{cases} DN_{n+1,i}, & \text{if } DN_{n,i} > DN_{n+1,i} \\ DN_{n,i}, & \text{if } DN_{n,i} \leq DN_{n+1,i} \end{cases} \tag{2}$$

where, ‘i’ represents the ‘i’th pixel in a NLT image, and ‘n’ represents a year between 1992 and 2007. Due to the continuous growth in GDP and no natural catastrophes (e.g. earthquake, tsunami, and warfare) occurred in Guangdong during the last thirteen years, Cao et al (2016) have made similar assumptions (equation 3) for filtering noise. According to them, the lit pixels detected in the earlier annual image would not be disappeared in the later annual image and therefore the DN values of the lit pixels should be maintained unless increased. Further, if the DN value of a pixel of a later annual image is smaller than an earlier annual image, the DN value of the pixel of the latter annual image should be replaced with the DN value of the pixel of the same geographical location of the earlier annual image.

$$DN_{n,i} = \begin{cases} 0, & \text{if } DN_{n+1,i} = 0 \\ DN_{n-1,i}, & \text{if } DN_{n+1,i} > 0 \text{ and } DN_{n-1,i} > DN_{n,i} \\ DN_{n,i}, & \text{otherwise} \end{cases} \tag{3}$$

Where, ‘i’ represents the ‘i’th pixel in a NLT image, and ‘n’ represents a year between 1992 and 2012. As assumed by Liu et al (2012) and Cao et al (2016), the above-mentioned methods can be applied only to continuous urbanization or economy growth appearing countries or regions. Further, Zhao et al (2015) have identified the inapplicability of Liu et al (2012) adopted method for comparative studies, especially for comparing rapid economic growth and urbanization existing countries such as China and de-urbanization existing countries such as the USA. As identified by Zhao et al (2015), the DN values of some pixels in earlier annual images would be decreased if Liu et al (2012) adopted inter annual series correction method is applied; it may lead to early annual images’ DN values being smaller than their actual DN values. Thus, Zhao et al (2015) have applied Liu et al (2012) adopted method (equation 2) as well as second steady increase adjustment method using equation 4 separately. Then, to make adjusted DN values close to their actual DN values, the first and the second steady increase adjusted images’ DN values have been averaged.

$$DN_{n,i} = \begin{cases} DN_{n-1,i}, & \text{if } DN_{n,i} < DN_{n-1,i} \\ DN_{n,i}, & \text{if } DN_{n,i} \leq DN_{n-1,i} \end{cases} \tag{4}$$

where, ‘i’ represents the ‘i’th pixel in a NLT image, and ‘n’ represents a year between 1992 and 2012. After that, they have employed gridded population data to further improve the NLT image data of China and USA based on following rules.

- If during a certain period, population increase in a region, business and brightness of nighttime lights should also be increased in the region. Hence, if the argument correct, steady increase in DN value method is applied.

- If during a certain period, population does not increase, the DN values of the pixel should be revaluated to those on the inter-calibrated NLT images.

However, as a developing country in the world, Sri Lanka was unable to maintain continuous or stable economic growth over her independence period. Further, from 1987 to 2008 Sri Lanka suffered from civil war. During this war period, LTTE terrorist blasted bombs at many of economically important places such as the central bank of Sri Lanka, Katunayaka international airport, Sri Lanka petroleum cooperation etc. Moreover, Sri Lanka government placed many attentions to solve the civil war by discussing with the terrorist group in several times, for example in 1994 and 2001. Nevertheless, the piece periods had very short life times. As a consequence of the civil war, Sri Lanka government could not conduct an island-wide population and housing census after 1981 to 2011. In addition to that, Sri Lanka lost about 50000 of people's lives due to Tsunami disaster in 2004. Apart from that, some parts of the country suffer from flood hazard and some other parts suffer from drought hazard in some years. In such circumstances, application of aforementioned inter-annual series correction methods for filtering noise of intra-annual calibrated NLT images would create unreliable results.

The main objective of the inter-annual series correction is to add missing lit pixel values and to remove the noise/fake lit pixels values from annual NLT images to obtain the reliable information. Hence, every annual image should be corrected based on other annual image/images. Except 1992 and 2012 images, all annual images can be corrected based on two annual images that besides them. However, in the study, 2012 annual image was adjusted for inter-annual series correction by assuming that the lit pixels in 2011 annual image cannot be disappeared in 2012 annual image (equation 5).

$$DN_{2012,i} = \begin{cases} DN_{2011,i} \text{ if } DN_{2012,i} = 0 \text{ and } DN_{2011,i} > 0 \\ DN_{2012,i}, \quad \text{otherwise} \end{cases} \tag{5}$$

Then, using equation 6, the inter-annual series correction was performed for all annual images from 1992 to 2012 of L-MIS and Z-MIS. According to the correction method, the DN values of the pixels of the resulting inter annual images are characterized by three annual images [the selected annual image (n) the earlier annual image (n-1), and the later annual image (n+1)].

- If any geographical location that was recorded as an unlit pixel (DN=0) in both earlier (n-1) and later (n+1) annual images should be recorded as an unlit pixel in the resulting inter annual image.
- If any geographical location that was recorded as a lit pixel in both earlier (n-1) and later (n+1) annual images and as a unlit pixel in selected annual image (n) should be recorded as a lit pixel by averaging the DN values of the same geographical location of both earlier and later annual images.
- The rest of geographical locations of the resulting image should be recorded with the DN values of the pixels of the same geographical location in the selected annual image (n).

$$DN_{n,i} = \begin{cases} \dfrac{(DN_{n-1,i} + DN_{n+1,i})}{2}, & \text{if } DN_{n-1,i} > 0 \text{ and } DN_{n+1,i} > 0 \\ o, & \text{if } DN_{n-1,i} = 0 \text{ and } DN_{n+1,i} = 0 \\ DN_{n,i}, & \text{otherwise} \end{cases} \tag{6}$$

where, 'i' represents the 'i'th pixel in a NLT image, and 'n' represents a year between 1992 and 2012. Several differences and similarities emerged in the TNOLPs and the SODNV of resulted two image sets after performing the inter-annual series correction (Fig. 8). Although discrepancies of the TNOLPs between satellites were dramatically disappeared (especially in L-MIS), there is a considerable difference between the TNOLPs of Z-MIS and L-MIS. In addition to that, relatively smooth and increasing linear pattern was identified in TNOLPs for L-MIS. Abnormal fluctuations in DN values for inter annual images was slightly changes. A common pattern was identified in the distribution of SODNV for both data sets. However, a slight deviation was identified between two lines.

5. Findings of the Study

After performing the correction process separately for L-MIS and Z-MIS, regression analysis was done for identifying the correlations between socio-economic statistics (GDP and electricity consumption) of Sri Lanka with the data obtained from corrected NLT images. Then, based on the regression equations, the electricity consumption and GDP estimations for Sri Lanka were calculated. Then standard error-SE- (the difference between actual statistics and the estimated statistics) were calculated. Summary of the calculations is indicated in Table 1. Based on the tables, a higher correlation between socio-economic statistics (GDP and electricity consumption) and corrected NLT images-based data can be identified. However, correlations of GDP and electricity consumption statistics with the L-MIS based TNOLPs/SODNVs data (Table 1, Fig. 9 & Fig. 10) were very high than Z-MIS based TNOLPs/SODNVs data.

As indicated in Fig. 11, lit pixel area as well as the brightness of pixels (DN values) of Sri Lanka has been increased during 1992 and 2012. However, as indicated in Fig. 12, the correlation between the electricity consumption and TNOLPs is higher than the electricity consumption and the SODNV of inter/intra calibrated and interannual series corrected images.

However, on the other hand, it can be identified that correlation between the GDP of Sri Lanka and the SODNVs is higher than the co-relationship between GDP and the TNOLPs (Table 1, Fig. 13). Furthermore, if consider the both, R2 value and error value (the difference between actual GDP statistics and the estimated GDP data based on the SODNVs/TNOLPs), exponential regression model is superior (R2 = 0.8678 & SE = 0.634128 US$ billions) than linear (R2 = 0.7723 & SE = ± 0.898583 US$ billions) and power (R2 = 0.8075 & SE = 0.799614 US$ billions) regression models for estimating the GDP of Sri Lanka.

Table 1 Correlations of electricity consumption and GDP of Sri Lanka with TNOLPs and SODNVs of L-MIS and Z-MIS at the end of image preparation process

Type of correlation		SODNVs		TNOLPs	
		L-MIS	Z -MIS	L-MIS	Z -MIS
Correlations between electricity consumption and NLT image data					
Linear	Equation	0.0297X-2711	0.0294X-2872.5	0.2142X-2121.2	0.1924X-2163
	R^2	0.8881	0.8529	**0.9240**	0.7317
	Error (GWh)	±760.545725	±872.067085	**±626.665062**	±1177.621331
Exponential	Equation	$1256e^{5E\text{-}06X}$	$1199e^{5E\text{-}06X}$	$1349e^{4E\text{-}05X}$	$1242.8e^{4E\text{-}05X}$
	R^2	0.9000	0.8857	**0.9757**	0.8542
	Error (GWh)	**±764.575045**	±811.112508	±828.097941	±1818.9822408
Power	Equation	$0.0001X^{1.4224}$	$0.0001X^{1.4131}$	$0.011X^{1.2512}$	$0.0092X^{1.2535}$
	R^2	0.8933	0.8615	**0.9310**	0.8073
	Error (GWh)	±735.757297	±954.115297	**±615.050242**	±1191.267812
Correlations between GDP and NLT image data					
Linear	Equation	2E-05X-3.4242	2E-05X-3.3748	0.0001X-2.6081	0.0001X-1.9690
	R^2	**0.7723**	0.7042	0.6991	0.4282
	Error (US$ billions)	**± 0.898583**	±0.95101	±1.937778	±1.421082
Exponential	Equation	$0.3028^{7E\text{-}06X}$	$0.2985^{7E\text{-}06X}$	$0.3688e^{5E\text{-}05X}$	$0.3995e^{4E\text{-}05X}$
	R^2	**0.8678**	0.8149	0.8506	0.6119
	Error (US$ billions)	**±0.634128**	±0.718308	±0.73125	±1.392295
Power	Equation	$1E\text{-}10X^{1.9035}$	$2E\text{-}10X^{1.8497}$	$1E\text{-}07X^{1.5989}$	$4E\text{-}07X^{1.4779}$
	R^2	**0.8075**	0.7450	0.7674	0.5664
	Error (US$ billions)	**0.799614**	0.895562	1.24988	1.311671

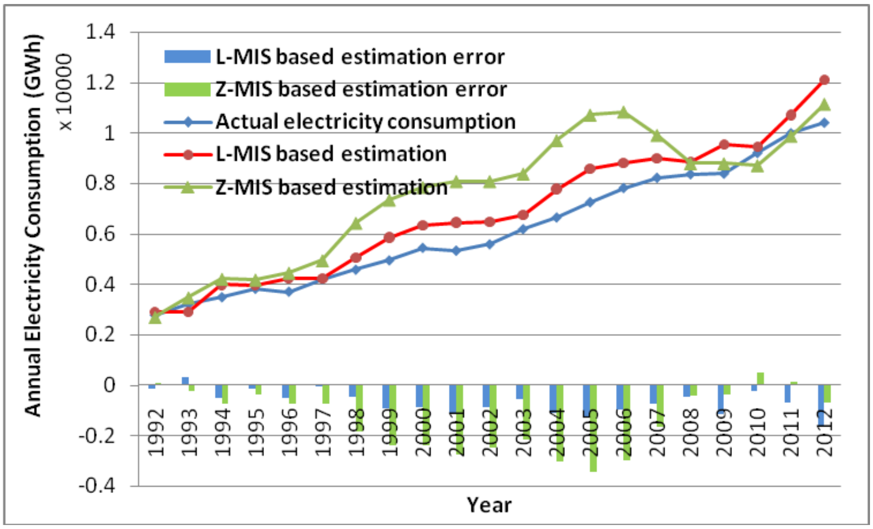

Fig. 9 Differences of annual electricity consumption of Sri Lanka and estimated electricity consumption based on SODNVs of NLT images and exponential regression model after performing whole correction process for L-MIS and Z-MIS

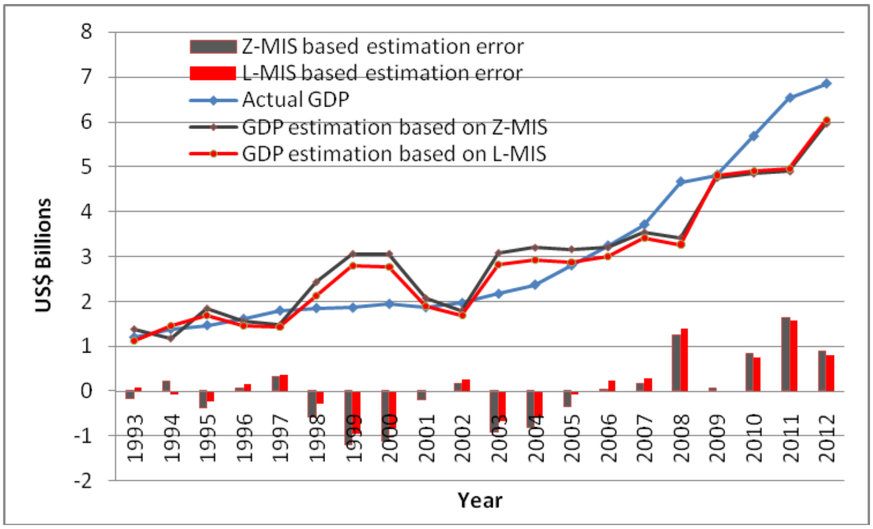

Fig. 10 Differences of actual GDP of Sri Lanka with the estimated GDP based on SODNV of NLT images and exponential regression models after performing whole correction process for L-MIS and Z-MIS

6. Conclusions and Recommendations

Based on the findings of the study, several conclusions can be made. First, there is a higher correlation between accurately corrected NLT image data and socio-economic statistics of Sri Lanka. Second, compared to linear and power regression models, the exponential regression model can more preciously identify the relationship between NLT image data and socio-economic statistics. Third, for obtaining more reliable information on GDP and electricity consumption of Sri Lanka, it is better to perform the intra annual calibration based the intra annual stable lit pixel identification and averaging method (L method) rather than the intra annual lit pixel averaging method (Z method). Fourth, the accuracy of the TNOLP based electricity consumption estimation is higher than the SODNV based estimation. Further, If consider the R^2 values, exponential regression model is superior (R^2 = 0.9757) than linear (R^2 = 0.9240) and power (R^2 = 0.9310) regression models for estimating the electricity consumption of Sri Lanka (Table 1). However, if consider the standard error-SE- (the difference between actual electricity consumption statistics and the estimated electricity consumption data based on the SODNV/TNOLPs), power regression model is more batter (SE = ±615.050242) than linear (SE = ±626.665062) and exponential (SE = ±828.097941) regression models for estimating the electricity consumption of Sri Lanka. Fifth, accuracy of the SODNV based GDP estimation is higher than the TNOLP based estimation. Therefore, it can be concluded that more attention has to be placed on evaluating the existing calibration/ adjustment methods to identify the most appropriate/reliable method/s.

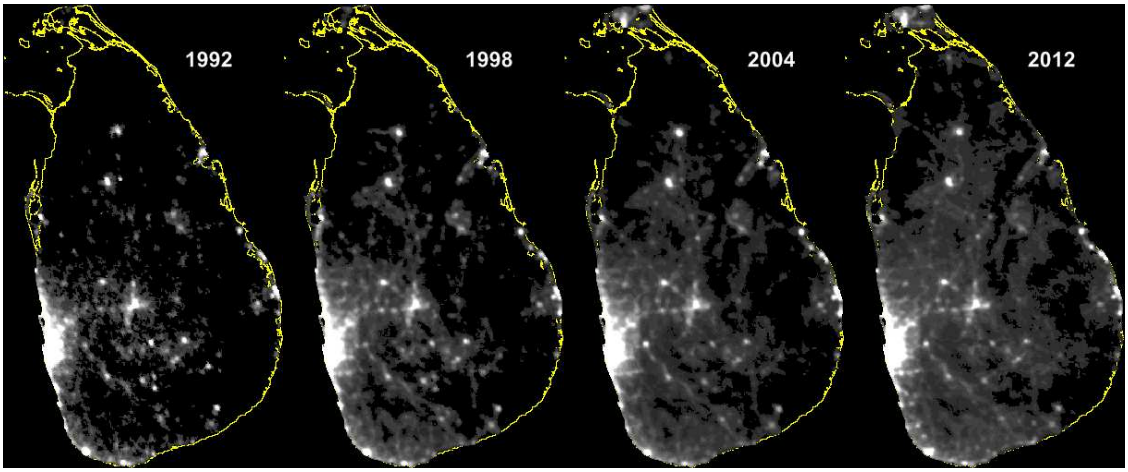

Fig. 11 Changes of lit pixels area of Sri Lanka for selected NLT images after performing whole correction process for L-MIS

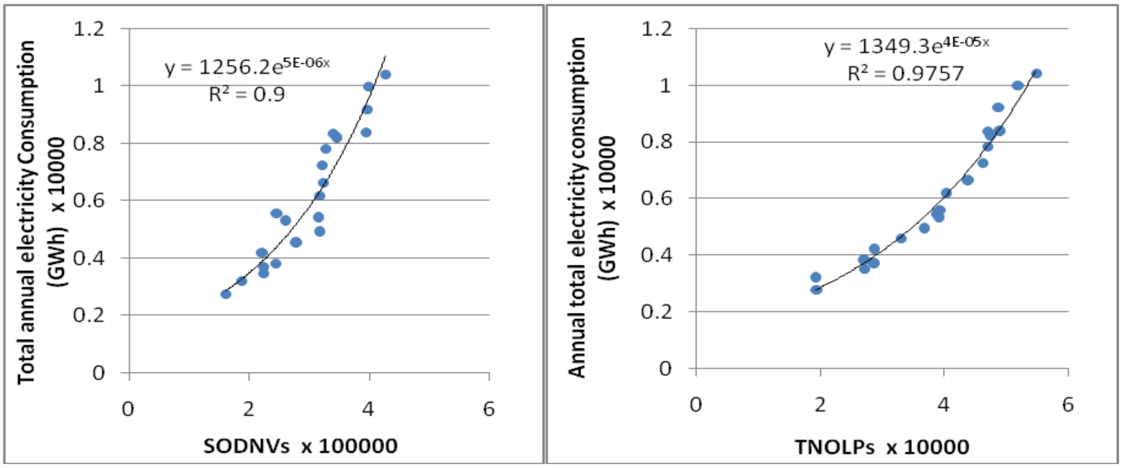

Fig. 12 Exponential correlation between the total annual electricity consumption and the SODNVs (left) and the TNOLPs (right) after performing the whole data preparation process for L-MIS

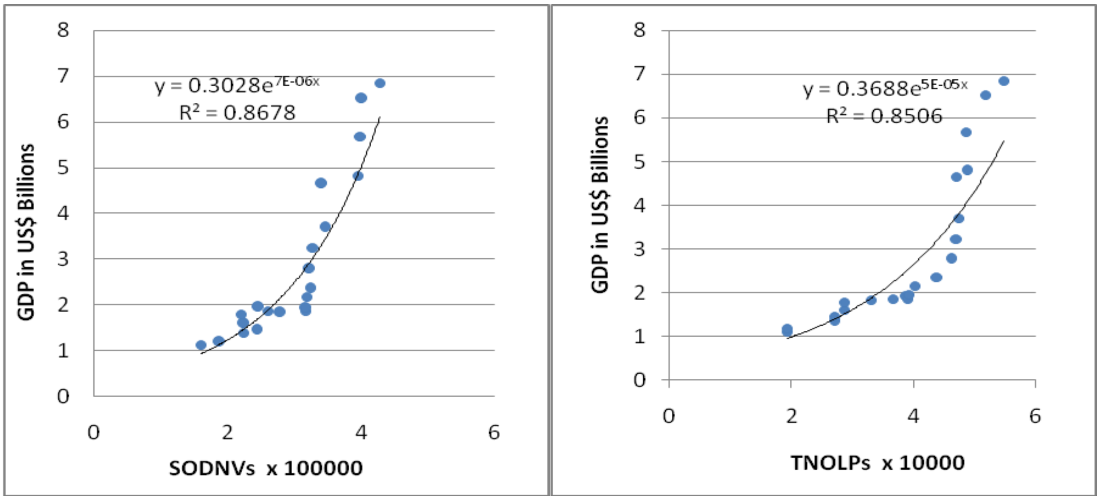

Fig. 13 Exponential correlation between GDP and the SODNV (left) and the TNOLPs (right) after performing the whole data preparation process for L-MIS

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