Regional Convergence and Spatial Dependence across Subnational Regions in ASEAN:
Evidence from Satellite Nighttime Light Data

Carlos Mendez\textsuperscript{a} · Felipe Santos-Marquez\textsuperscript{b}

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Abstract Satellite nighttime light data are increasingly used for evaluating the performance of economies in which official statics are non-existent, limited, or non-comparable. In this paper, we use a novel luminosity-based measure of GDP per capita to study regional convergence and spatial dependence across 274 subnational regions of the Association of South East Asian Nations (ASEAN) over the 1998-2012 period. Specifically, we first evaluate the usefulness of this new luminosity indicator in the context of ASEAN regions. Results show that almost 60 percent of the differences in (official) GDP per capita can be predicted by this luminosity-based measure of GDP. Next, given its potential usefulness for predicting regional GDP, we evaluate the spatio-temporal dynamics of regional inequality across ASEAN. Results indicate that although there is an overall (average) process of regional convergence, regional inequality within most countries has not significantly decreased. When evaluating the patterns of spatial dependence, we find increasing spatial dependence over time and stable spatial clusters (hotspots and coldspots) that are located across multiple national boundaries. Taken together, these results provide a new and more disaggregated perspective of the integration process of the ASEAN community.

Keywords convergence · spatial dependence · satellite nighttime light data · luminosity · subnational regions · ASEAN

JEL Classifications R10 · R11 · O57

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1 Introduction

Economic integration is a central priority of the development agenda of the Association of Southeast Asian Nations (ASEAN). As suggested by the experience of other economic communities, such as the European Union, achieving economic integration goes hand in hand with the reduction of income disparities across countries as well as subnational regions within countries. Economic growth in ASEAN, however, has not been fully inclusive when considering the large income disparities that remain across countries and subnational regions of the ASEAN community. For example, the GDP per capita in Singapore is more than 13 times larger than that of Cambodia, Laos or Myanmar. Thus, it may seem that much needs to be done to close the income disparities within an economic community that has been on the quest for regional integration since 1967.

Given that the ASEAN community is conformed by only ten countries, many previous studies are largely constrained by a small sample size problem. This constrain is particularly binding for the analyses of economic convergence and spatial dependence, which typically require a larger sample size to correctly infer the evolution of economic disparities over time and space. To increase the sample size, one could try to evaluate economic disparities among subnational regions instead of countries. A major difficulty, however, is the availability and comparability of regional data for developing countries.

In an attempt to overcome these data issues, economists have been using satellite nightlight data as proxy for economic activity. This approach has proved useful for evaluating the performance of economies in which official statistics are non-existent, limited, or non-comparable. Motivated by the progress in this area of research, the aim of this paper is to evaluate the dynamics of convergence and spatial dependence across the subnational regions of the ASEAN community. In particular, we use the new regional income dataset of Lessmann and Seidel (2017) that has been constructed based on satellite nighttime light data. This dataset covers 274 ASEAN regions over the 1998-2012 period, and thus it provides a much larger sample size for evaluating convergence and spatial dependence.

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1 These are Indonesia, Malaysia, Philippines, Singapore, Thailand, Brunei, Laos, Myanmar, Cambodia and Vietnam.
In this paper, we first provide an overview of relationship between night-light luminosity intensity and GDP per capita for a sample of ASEAN regions where official GDP data is available. Results indicate that almost 60 percent of the differences in (official) GDP per capita can be predicted by a luminosity-based measure of GDP per capita. Next, we use luminosity-based GDP per capita as a proxy for regional income and evaluate the spatio-temporal dynamics of regional inequality across the entire sample of 274 ASEAN sub-national regions over the 1998-2012 period. Results indicate that although—on average—there is regional convergence, regional inequality has not significantly decreased within most countries. Finally, we evaluate patterns of global and local spatial dependence across regions and countries. Results indicate increasing spatial dependence over time and the existence of stable spatial clusters beyond national borders.

The results of this paper contribute to the literature of regional convergence and spatial dependence in ASEAN in three fronts. First, we use a novel luminosity-based measure of GDP per capita to study the dynamics of convergence across a large sample of subnational regions in ASEAN. Second, to the best of our knowledge, this is the first study that systematically compares—within-country—regional convergence for nine ASEAN countries. Third, also to the best of our knowledge, this is the first study that evaluates spatial dependence and spatial clusters for multiple countries in ASEAN.

The rest of the paper is organized as follows. Section 2 provides an overview of the related literature. Section 3 describes the luminosity data and the methods of regional convergence and spatial dependence. Section 4 presents the results in three parts: usefulness of luminosity-based GDP data, regional convergence patterns, and spatial dependence patterns. Section 5 discusses related policy implications. Lastly, section 6 offers some concluding remarks.

2 Related literature

To avoid confusion of terms, it is important to distinguish the difference among official GDP, luminosity intensity, and luminosity-based GDP. Lessmann and Seidel (2017) first estimate an econometric model that summarizes the relationship between GDP and luminosity intensity using a relatively small sample for which official GDP data is available. Second, based on this model, they carry out an out-of-sample prediction of GDP for a large number of subnational regions. This out-of-sample prediction is refereed as luminosity-based GDP.
2.1 Measuring economic activity using satellite nighttime light data

Satellite nighttime light data are increasingly used for evaluating the performance of economies in which official statistics are non-existent, limited, or non-comparable (Chen and Nordhaus 2011; Nordhaus and Chen 2015; Henderson et al 2012; Lessmann and Seidel 2017; Mveyange 2018). Across countries, Henderson et al (2012) show a strong and largely significant relationship between changes in nighttime light intensities and economic growth. The interpretation of this strong relationship is simple: most economic activities that take place at night require light. Thus, one can expect that the higher a country’s luminosity intensity at nighttime, the higher its level of economic activities. Ultimately, these differences in economic activities will also reflect differences in production capacity and income levels.

Henderson et al (2012) and Chen and Nordhaus (2011) also emphasize the usefulness of satellite nighttime light data at both subnational and supra-national levels. As a result, a growing number of papers have been using satellite nighttime light data to uncover new and interesting patterns. For instance, Henderson et al (2012) find that coastal areas do not grow faster than non-coastal areas in sub-Saharan Africa. Alesina et al (2016) construct a new measure of ethnic inequality (based on nighttime luminosity) and find a strong inverse relationship between this measure of inequality and the level of development across subnational regions. Mveyange (2015) uses night lights data as proxy for subnational income in Africa. He finds increasing regional inequality between 1992 and 2003 and decreasing inequality between 2004 and 2012.

Lessmann and Seidel (2017) is one of the most comprehensive studies that uses satellite nighttime light data for understanding income differences within subnational regions in the world. They first use luminosity intensity data to predict regional GDP per capita within 180 countries over the 1992–2012 period. Based on this luminosity-based GDP, they study worldwide regional convergence and find that approximately 67 to 70 percent of all countries have reduced their subnational disparities, in other words, they have experienced within-country (sigma) convergence. They also find an N-shaped relationship between regional inequality and economic development. Finally, using cross-country data, they study the determinants of regional inequality and find that natural resources, transportation costs, trade openness,
aid, federalism and human capital are significantly correlated with regional inequality.

2.2 Testing for economic convergence

Standard neoclassical growth theory predicts that when economies share common technological and institutional environments, less developed regions would tend to grow faster than more developed ones. As a result, a catch-up (convergence) process would take place and regional inequalities would tend to diminish (Abreu 2019). In the growth and development literature, this inverse relationship between the initial level of development of an economy and its subsequent growth rate is known as beta convergence (Barro and Sala-i Martin 1992; Sala-i Martin 1996; Magrini 2004).

A large number of studies have documented the existence of beta convergence in different contexts: countries, regions, industries, and firms. In particular, seminal contributions to the regional convergence literature, such as those of Barro and Sala-i Martin (1991, 1992), have pointed out that the estimated speed of convergence is surprisingly similar across multiple studies in the US, Japan, and Europe. A common finding has been that regional economies have tended to converge at a speed of two percent per year. This speed of convergence implies that, relative to a convergence equilibrium, the average region would close 50 percent of its income gap in about 35 years.

There is a growing literature about income convergence among ASEAN countries. The results so far, however, appear mixed and inconclusive. For instance, Ismail (2008) finds evidence of convergence for five ASEAN countries during the 1960-2004 period. Similarly, Solarin et al (2014) finds signs of convergence between 1970 and 2009. In contrast, other authors, such as Park (2000) and Alavi and Ramadan (2008), indicate no evidence of income convergence.3

Given the small sample size in terms of the number of countries that belong to ASEAN, most previous studies have employed time series analyses to study cross-country convergence. Specifically, it has been common to use unit root tests to evaluate convergence, first in the context of the five

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3 Besides income variables, convergence of other measures is also common in the literature. For instance, Mishra and Smyth (2014) reports robust ASEAN convergence in energy consumption per capita over the 1971-2011 period. Chong et al (2017) studies the evolution of sectorial production differences and finds that the newest members of ASEAN are catching up with the old members.
foundering members of ASEAN and then in the entire ten-country sample. The evaluation of convergence across subnational regions of ASEAN not yet been explored due lack of comparable data. In this context, the new dataset of Lessmann and Seidel (2017) provides a unique opportunity to evaluate convergence within and among the subnational regions of ASEAN and other supranational associations in the world (Breinlich et al 2014).

2.3 Evaluating spatial dependence

New economic geography theories emphasize that the dynamics of regional inequality have a spatial nature (Krugman 1998, 2011; Schmutzler 1999). This is largely due to the spatial concentration of economic activity and the diffusion of spillover effects beyond administrative borders. To start an evaluation of regional dynamics that could be reflecting any (or both) of these two spatial processes, an exploratory analysis of spatial dependence is highly recommended (Anselin et al 2007; Anselin 1999, 1995). In particular, global and local analyses of spatial association are useful for testing the hypothesis of spatial dependence and for identifying the location of spatial clusters and outliers.

Anselin et al (2007) emphasize that exploratory spatial data analysis (ESDA) methods can be particularly useful for maximizing the informational content of newly available subnational databases. These methods provide a basis for a spatially explicit policy that may be able to address the needs of individual regions more effectively than non-spatial analyses. Also, as software for spatial analysis continues to improve and new databases continue to emerge, there will be increasing opportunities to better monitor socio-economic activities within and between geographical units.

A central component of ESDA is the notion of spatial dependence. At its basic level, it refers to a phenomenon in which attribute similarity (for instance, similar values of income per capita across regions) is matched with locational similarity (that is, observations are located in geographical proximity). From a measurement standpoint, spatial dependence is commonly evaluated based on global and local indicators of spatial autocorrelation (Anselin (1995)). On the one hand, indicators of global spatial autocorrelation are helpful for evaluating the existence of an overall pattern of spatial clustering. On
the other, local indicators of spatial autocorrelation are helpful for identifying the specific location of clusters and outliers.

To the best of our knowledge, we could not find any study that evaluates spatial income dependence across multiple ASEAN countries. It seems evident that study of spatial dependence across the subnational regions of ASEAN is highly constrained by the availability of comparable income data. However, studies for the subnational regions of individual countries are relatively more abundant. In particular, complex geographies such as those of Indonesia and Philippines are frequently evaluated through the lens of global and local indicators of spatial autocorrelation.⁵

3 Data and methods

This section describes the data and methodologies to evaluate spatio-temporal dynamics across the subnational regions of the ASEAN community. In the context of the research objectives, Figure 1 provides a workflow overview of the data and methods described in this section. We first describe the luminosity dataset in the context of ASEAN subnational regions. Next, we describe two methodologies to study regional convergence. Finally, we describe two methodologies to study spatial dependence.

<table>
<thead>
<tr>
<th>Research objectives</th>
<th>Research questions, methods, and workflow</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Evaluate the usefulness of luminosity data in the context of ASEAN subnational regions</td>
<td>(A) Data description - How to measure regional GDP using luminosity data? - Luminosity intensity vs luminosity-based GDP. Which one is better?</td>
</tr>
<tr>
<td>2. Evaluate the temporal dynamics of regional inequality using luminosity-based GDP per capita</td>
<td>(B) Data analyses - Beta convergence analysis: Is the luminosity-based GDP per capita of poor regions growing faster than that of rich regions? - Sigma convergence analysis: Is the overall dispersion of luminosity-based GDP per capita decreasing over time?</td>
</tr>
<tr>
<td>3. Evaluate the spatial dynamics of regional inequality using luminosity-based GDP per capita</td>
<td>- Global spatial autocorrelation: Is there an overall pattern of spatial clustering in luminosity-based GDP per capita? Is spatial dependence increasing over time? - Local spatial autocorrelation: Where is location of hotspots and coldspots (spatial clusters)?</td>
</tr>
</tbody>
</table>

Fig. 1: Research workflow: Objectives, questions, data, and methods

⁵ For instance, Rinaldi et al (2010) and Miranti and Mendez (2020) study the spatial dependence patterns of the human development index across provinces in Indonesia. For the Philippines, Salvacion (2020) studies spatial dependence of poverty rates across villages of the Marinduque Island; and Salvacion and Magcale-Macandog (2015) study spatial dependence of population growth in the same island.
3.1 Measuring regional GDP with luminosity data

A new luminosity dataset for a large sample of regions of the world has been originally assembled by Lessmann and Seidel (2017). These authors measure nighttime light intensities based on the satellite data from the U.S Air Force. Specifically, they use the satellite data that has been processed by the the Atmospheric Administration (NOAA) and the National Geophysical Data Center (NGDC). The scale of luminosity intensity is a number between 0 (no light) and 63 (full light) for every output pixel, which, at the equator, is approximately 0.86 square kilometers. The censoring of the of luminosity scale at 63 poses some problems for a few small rich areas. In case of Singapore, for instance, satellites are not able to identify within-country variation in luminosity. Thus, the subnational regions of Singapore are not included in this dataset.

In contrast to some previous studies, Lessmann and Seidel (2017) do not use luminosity intensity as a direct proxy for regional GDP. Instead, they first estimate an econometric model of the relationship between luminosity intensity and regional GDP for those countries in which subnational data are available. Next, given the estimated parameters of their econometric model and the availability of luminosity intensity data for a larger sample of subnational regions, they are able to estimate a luminosity-based measure of GDP per capita for 3,166 subnational regions of 180 countries over the 1992-2012 period.

Lessmann and Seidel (2017) provide estimates of luminosity-based GDP per capita for 3,166 first-level subnational administrations in 180 countries. Administrative boundaries data are from the Global Administrative Areas (GADM) project. Some examples of first-level subnational regions would be states, provinces, prefectures in the US, Indonesia, and Japan, respectively.

In this paper, we use the dataset of Lessmann and Seidel (2017) to study convergence and spatial dependence across the subnational regions of the Association of Southeast Asian Nations (ASEAN). After organizing this dataset in a way that is suitable for these two analyses, we end up with a dataset that covers 274 subnational regions of ASEAN for each year between 1998 and 2012. To briefly summarize this dataset, Table 1 provides some descriptive statistics for some selected years. In addition, Appendix B provides a list of the subnational regions of each country that is included in the dataset.
Table 1: Luminosity-based GDP per capita across 274 subnational regions of ASEAN

<table>
<thead>
<tr>
<th>Year</th>
<th>1998</th>
<th>2002</th>
<th>2007</th>
<th>2012</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>3,926</td>
<td>4,336</td>
<td>5,295</td>
<td>6,074</td>
</tr>
<tr>
<td>Std.Deviation</td>
<td>4,935</td>
<td>5,129</td>
<td>5,400</td>
<td>5,445</td>
</tr>
<tr>
<td>Min</td>
<td>562</td>
<td>702</td>
<td>1,054</td>
<td>1,263</td>
</tr>
<tr>
<td>Q1</td>
<td>1,899</td>
<td>2,078</td>
<td>2,527</td>
<td>2,891</td>
</tr>
<tr>
<td>Median</td>
<td>2,768</td>
<td>2,978</td>
<td>3,642</td>
<td>4,209</td>
</tr>
<tr>
<td>Q3</td>
<td>4,757</td>
<td>5,380</td>
<td>6,842</td>
<td>8,029</td>
</tr>
<tr>
<td>Max</td>
<td>49,808</td>
<td>50,754</td>
<td>51,215</td>
<td>47,855</td>
</tr>
<tr>
<td>MAD</td>
<td>2,571</td>
<td>2,693</td>
<td>2,737</td>
<td>2,824</td>
</tr>
<tr>
<td>IQR</td>
<td>2,856</td>
<td>3,299</td>
<td>4,303</td>
<td>5,118</td>
</tr>
<tr>
<td>CV</td>
<td>1.26</td>
<td>1.18</td>
<td>1.02</td>
<td>0.90</td>
</tr>
<tr>
<td>Skewness</td>
<td>5.77</td>
<td>5.40</td>
<td>4.48</td>
<td>3.70</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>41.97</td>
<td>37.68</td>
<td>28.09</td>
<td>19.87</td>
</tr>
<tr>
<td>Observations</td>
<td>274</td>
<td>274</td>
<td>274</td>
<td>274</td>
</tr>
</tbody>
</table>

Note: Q1 and Q3 stand for the first and third quartile of the distribution, respectively. MAD stands for the mean absolute deviation. IQR stands for the interquartile range. CV stands for the coefficient of variation.

Table 1 help us understand at least four initial features about the evolution of GDP per capita across subnational regions in ASEAN. First, indicators of centrality, such as the mean and median, consistently indicate that (luminosity-based) GDP per capita has increased over time, with a particular acceleration in more recent years. Second, there are large disparities in GDP per capita across subnational regions in ASEAN. In 2012, for instance, GDP per capita in the richest region of the sample was almost 38 times larger than that in the poorest region. Third, common indicators of dispersion, such as the standard deviation and the coefficient of variation, do not provide a conclusive answer on the evolution of regional disparities. On the one hand, the standard deviation would suggest that regional disparities have increased over time. On the other, the coefficient of variation would suggest a notable decrease. Forth, based on the skewness indicator, this inconclusive answer largely depends on the highly asymmetric shape the distribution of GDP per capita across subnational regions.

The descriptive statistics of Table 1 only provide an initial overview of the new dataset of Lessmann and Seidel (2017) in the context of ASEAN regions. In the next subsections we summarize two methodologies that will help us better understand the dynamics of regional convergence and spatial dependence. Taken together, an analysis of economic convergence and spatial de-

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6 To control for the effect of some very rich regions (mainly from Brunei), one can evaluate the dynamics of the interquartile range (IQR), which is less sensitive to extreme observations. From this perspective, regional disparities appear to have increased over time.
Evidence from Satellite Night-time Light Data

...dependence may prove useful for both designing and monitoring regional integration policies as one focuses on the time dimension of regional integration and the other focuses on the geographical location of regional clusters with high spatial dependence.

3.2 Measuring regional convergence

Following the classical convergence framework of Barro and Sala-i Martin (1991), the speed of regional convergence ($\beta$) can be estimated based on the following regression model:

$$
\frac{1}{t} \log \left( \frac{y_t}{y_0} \right) = \gamma - \frac{(1 - e^{-\beta t})}{t} \log y_0 + u_t,
$$

where $y_0$ is the initial level of income, $(1/t) \log \left( y_t/y_0 \right)$ is the average growth rate between time 0 and time $t$, $\gamma$ is a constant term, and $u_t$ is a random disturbance that represents unexpected changes in technologies, institutions or preferences.

In addition to the speed of convergence ($\beta$), a second parameter of interest, can be computed as

$$
\text{half-life} = \frac{\log 2}{\beta}.
$$

This second parameter, known as the “half-life” measure of convergence, measures the time that a representative economy would need to halve the distance between its initial position and its long-run equilibrium.

Despite the literature’s emphasis on the measurement of beta convergence, it has also been acknowledged that beta convergence is not a sufficient condition for the reduction of regional inequality over time (Quah 1993; Sala-i Martin 1996; Young et al 2008). As such, a complementary notion of convergence has been suggested. The concept of sigma convergence directly describes the (average) dynamics of the cross-sectional dispersion. As such, sigma convergence implies that the distribution of income across economies is becoming more equitable over time. From a measurement standpoint, analyses of sigma convergence commonly estimate the standard deviation of the log of GDP per capita and evaluate it at multiple periods of time. When a systematic reduction in the standard deviation is observed, then a process of sigma convergence is taking place.
3.3 Measuring spatial dependence

An analysis of global spatial dependence aims to test the hypothesis of spatial randomness and the existence of an overall pattern of clustering. From a measurement standpoint, it is commonly based on the Moran’s I statistic. In the context of a regional income analysis, this statistic describes the association of the income value at one location with the income values at neighboring locations (Anselin et al. 2007; Anselin 1995). For any time period $t$, the global Moran’s I statistic is defined as

$$I_t = \frac{N}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}} \left[ \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (X_i - \bar{X}) (X_j - \bar{X})}{\sum_{i=1}^{n} (X_i - \bar{X})^2} \right],$$

where $N$ is the number of regions under analysis, $w_{ij}$ is an element of a spatial weights matrix ($W$) that defines the neighborhood structure between each pair of regions, $X_i$ and $X_j$ are the income values of regions $i$ and $j$, respectively; and $\bar{X}$ is the average value of income.

When the Moran’s I is statistically different from zero, then the null hypothesis of spatial randomness can be rejected. Intuitively similar to a standard correlation coefficient, the numerical value of the Moran’s I statistic lies between plus and minus one. When its value is close to one, it indicates positive spatial autocorrelation. That is, evidence of an overall clustering pattern of similar values. On the other hand, when its value is close to minus one, it indicates negative spatial autocorrelation. That is, evidence of spatial dissimilarity, which at its limit it could be similar to a chessboard-like pattern where low values are surrounded by high values and vice versa.

An analysis of local spatial dependence aims to identify the location of spatial clusters and spatial outliers (Anselin et al. 2007; Anselin 1995). From a measurement standpoint, it is commonly based on the breaking up of a global statistic of spatial dependence. In particular, for the case of the Moran’s I statistic and in the context of a regional income evaluation, it potentially classifies regions into four groups. Regions with high income values surrounded by neighbors with high income values (that is, a high-high cluster). Regions with low income values surrounded by neighbors with low income values (that is, a low-low cluster). Regions with high income values surrounded by neighbors with low income values (that is, a high-low group). And regions with low income values surrounded by neighbors with high income values (that is, a low-high group). The first two groups (high-high and low-
low clusters) identify the location of spatial clusters (also known as hotspots and coldspots). The other two groups (high-low and low-high groups) identify the location of spatial outliers. For any time period \( t \), a local Moran’s statistic is defined for each region \( i \) as

\[
I_{it} = \left( \frac{X_i - \bar{X}}{m_o} \right) \sum_{j=1}^{n} w_{ij} \left( X_j - \bar{X} \right) \quad \text{with} \quad m_o = \frac{\sum_{i=1}^{n} (X_i - \bar{X})^2}{n},
\]

where the notation follows that of the previously described global Moran’s I.

4 Results

4.1 Luminosity intensity vs luminosity-based GDP: Which one is better?

There is a growing literature that uses luminosity intensity as a direct proxy for national and regional income (Alesina et al. 2016; Henderson et al. 2012; Mveyange 2018). However, compared to the national level, luminosity alone has less explanatory power at the regional level (Chen and Nordhaus 2011). Motivated by the relatively low explanatory power at the regional level, Lessmann and Seidel (2017) use additional indicators to compute a luminosity-based GDP per capita proxy. In addition to luminosity intensity, the econometric model to estimate luminosity-based GDP includes country-level GDP per capita, number of top and dark coded pixels of satellite scans at the regional level, number of regions within a country, overall size of a country, interaction between country size and number of regions, country-group fixed effects, country fixed effects, regional fixed effects, and satellite configuration fixed effects. Based on these variables and a sample of 5,258 regions from 81 countries, these authors are able to explain 76 percent \( (R^2_{\text{within}}) \) of the actual differences in GDP per capita across subnational regions. Compared to the initial 33 percent fit of luminosity alone, the model with additional variables predicts much more accurately the actual differences in GDP per capita across regions.

In this section, we re-evaluate the findings of Lessmann and Seidel (2017) in the context of the subnational regions of ASEAN. First, using a simple polled regression model, we evaluate the relationship between GDP per capita and luminosity intensity in those ASEAN regions where official data on re-
Fig. 2: Relationship between GDP per capita and luminosity intensity in a sample of ASEAN regions


Results indicate that only 40 percent of regional GDP per capita differences are explained by luminosity intensity differences (see Figure 2).

Second, using the same econometric model and data, we evaluate the relationship between GDP per capita and luminosity-based GDP. This second variable, as previously explained, has been constructed by Lessmann and Seidel (2017) using luminosity intensity and additional control variables. Results indicate that 59 percent of regional GDP per capita differences are explained by luminosity-based GDP differences (see Figure 3).

Overall, the results for the ASEAN sample are consistent with those reported by Lessmann and Seidel (2017) for the global sample. Compared to the initial 40 percent fit of luminosity alone, luminosity-based GDP predicts regional GDP is available and comparable. Results indicate that only 40 percent of regional GDP per capita differences are explained by luminosity intensity differences (see Figure 2).

For this analysis, regional GDP data are from Gennaioli et al (2013).

See Section 2.2.1 of Lessmann and Seidel (2017) for further details about the econometric specification and control variables.
Fig. 3: Relationship between GDP per capita and luminosity-based GDP per capita in a sample of ASEAN regions


much more accurately (59 percent fit) the actual differences in GDP per capita across ASEAN regions. Thus, in the following subsections, we use luminosity-based GDP per capita as the main variable for the analysis of regional convergence and spatial dependence.

4.2 Convergence across subnational regions in ASEAN

Figure 4 shows the results of sigma convergence for a balanced panel dataset of 274 ASEAN regions over the 1998-2012 period. Using two alternative indicators of dispersion, the standard deviation and the coefficient of variation, a similar pattern is observed: on average, across all ASEAN regions, disparities in luminosity-based GDP per capita have systematically declined over time. In 1998, for instance, the standard deviation was 0.82; by 2012 it decreased to 0.67. The convergence dynamics—at the ASEAN community level—show a smooth downward tendency for most of the entire period. Only in the 2008-
2012 sub-period, we can observe some fluctuations. A further investigation, beyond the scope of this paper, could evaluate to what extent regional disparities in ASEAN are affected by global shocks such as the 2008-2009 global financial crisis.

Fig. 4: Sigma convergence within the entire ASEAN community

Notes: The dashed line is an observed measure of regional dispersion. SD stands for standard deviation and CV stands for coefficient of variation. The solid line and its associated confidence interval indicate a predicted measure of regional dispersion, which has been estimated using a local nonparametric regression. Each indicator is computed for every year, using a panel dataset of 274 first-level sub-national ASEAN regions. Singapore is not included in the sample.

The convergence dynamics at the community level appear to be hiding weaker patterns of convergence within countries. The first two columns of Table 2 report standard deviations of luminosity-based GDP per capita for each of the nine ASEAN countries in 1998 and 2012. Statistical significance is evaluated based on a dispersion ratio test, where the null hypothesis is that the value of the ratio of the two standard deviations is equal to one. The most striking finding is that, at the ASEAN community level, there is a statistically significant convergence (see the dispersion ratio: 1.22***). However, within each country, convergence is not statistically significant.

To confirm this weak pattern of convergence within countries, statistical significance is re-evaluated based on the slope coefficient of a linear regression between the standard deviation and a time index. From this analysis, only Brunei, Indonesia, Vietnam, and Malaysia show a statistically significant reduction in inequality. In contrast, the decrease in inequality in Thailand, Philippines, Laos, and Cambodia is not statistically significant. Of particular interest is the case of Myanmar, as it is the only ASEAN country that shows a statistically significant divergence. Taken together, these findings indicate
Table 2: Sigma convergence within the countries of ASEAN

<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Brunei</td>
<td>0.1990</td>
<td>0.1746</td>
<td>1.14</td>
<td>-0.0020***</td>
</tr>
<tr>
<td>Thailand</td>
<td>0.1373</td>
<td>0.1258</td>
<td>1.09</td>
<td>-0.0007</td>
</tr>
<tr>
<td>Indonesia</td>
<td>0.1985</td>
<td>0.1852</td>
<td>1.07</td>
<td>-0.0010***</td>
</tr>
<tr>
<td>Philippines</td>
<td>0.1727</td>
<td>0.1662</td>
<td>1.04</td>
<td>-0.0008</td>
</tr>
<tr>
<td>Vietnam</td>
<td>0.1286</td>
<td>0.1249</td>
<td>1.03</td>
<td>-0.0009***</td>
</tr>
<tr>
<td>Malaysia</td>
<td>0.1550</td>
<td>0.1522</td>
<td>1.02</td>
<td>-0.0005*</td>
</tr>
<tr>
<td>Laos</td>
<td>0.1422</td>
<td>0.1399</td>
<td>1.02</td>
<td>-0.0001</td>
</tr>
<tr>
<td>Cambodia</td>
<td>0.1758</td>
<td>0.1783</td>
<td>0.99</td>
<td>-0.0011</td>
</tr>
<tr>
<td>Myanmar</td>
<td>0.1551</td>
<td>0.1633</td>
<td>0.95</td>
<td>+0.0010*</td>
</tr>
<tr>
<td>Total ASEAN</td>
<td>0.8212</td>
<td>0.6741</td>
<td>1.22***</td>
<td>-0.0110***</td>
</tr>
</tbody>
</table>

Note: The dispersion of (log) luminosity-based GDP per capita has been measured using the standard deviation. Statistical significance is evaluated based on a dispersion ratio test, where the null hypothesis is that the value of the ratio of the 1998-2012 standard deviations is unity. The slope coefficient is from a linear regression between the standard deviation and time index. *, **, *** indicate significance at the 10%, 5%, 1% level respectively.

that masked behind the overall (average) convergence pattern of the ASEAN community, there is still a high degree of regional heterogeneity within countries.

Figure 5 further illustrates the dynamics of regional convergence within each country. Two new findings emerge from this figure. First, the dynamics of convergence show a highly non-linear behaviour. In particular, countries such as Laos, Myanmar, and the Philippines exhibit waves of convergence followed by waves of divergence, and vice versa. Second, with the exception of Myanmar, a reduction in regional inequality is taking place since the mid 2000s.

In Figure 6 the relationship between the (luminosity-based) growth rate of GDP per capita and the initial GDP per capita is shown for the 274 ASEAN regions. On average, it appears that the poorest regions are growing faster than the richest ones. In order to evaluate the statistical significance of this relationship, linear regressions are performed both at the entire ASEAN community level and within each country. The speed of regional convergence is recovered from the slope of the regression described in Equation 1 and the "half-life" time of convergence (in years) is computed using Equation 2. All these results are reported in Table 3.
Fig. 5: Sigma convergence within ASEAN countries

Notes: The dashed line is an observed measure of regional dispersion. SD stands for standard deviation. The solid line and its associated confidence interval indicate a predicted measure of regional dispersion, which has been estimated using a local nonparametric regression.
Evidence from Satellite Night-time Light Data

Fig. 6: Beta convergence within the entire ASEAN community

Notes: The solid line and its associated confidence interval indicate the fit of a linear regression.

For all ASEAN regions (last row in Table 3), it can be concluded that there is beta convergence, with a highly significant coefficient and a half-life time of convergence of 41.8 years. Interestingly, the speed of convergence is around 2%, which is commonly reported in the literature of regional convergence in the US, Japan, and Europe (Barro and Sala-i Martin 1991).

Table 3: Beta convergence within the countries of ASEAN

<table>
<thead>
<tr>
<th>Country</th>
<th>Beta coefficient</th>
<th>Speed of convergence</th>
<th>Half-life(years)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brunei</td>
<td>-0.12*</td>
<td>0.009</td>
<td>73.2</td>
</tr>
<tr>
<td>Thailand</td>
<td>-0.12***</td>
<td>0.009</td>
<td>79.3</td>
</tr>
<tr>
<td>Indonesia</td>
<td>-0.08***</td>
<td>0.006</td>
<td>120.0</td>
</tr>
<tr>
<td>Philippines</td>
<td>-0.10**</td>
<td>0.007</td>
<td>92.6</td>
</tr>
<tr>
<td>Vietnam</td>
<td>-0.07</td>
<td>0.005</td>
<td>132.5</td>
</tr>
<tr>
<td>Malaysia</td>
<td>-0.02</td>
<td>0.002</td>
<td>420.9</td>
</tr>
<tr>
<td>Laos</td>
<td>-0.20</td>
<td>0.016</td>
<td>42.6</td>
</tr>
<tr>
<td>Cambodia</td>
<td>-0.13</td>
<td>0.010</td>
<td>68.1</td>
</tr>
<tr>
<td>Myanmar</td>
<td>0.00</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Total ASEAN</td>
<td>-0.21***</td>
<td>0.017</td>
<td>41.8</td>
</tr>
</tbody>
</table>

Note: The beta coefficient is the coefficient of a linear regression given by equation 1, the speed of convergence can be recovered from the beta coefficient and the half-life is calculated using equation 2. *, **, *** indicate significance at the 10%, 5%, 1% level, respectively.

The patterns of beta convergence within countries are much weaker and most of them are not statistically significant. For example, countries such as
Regional Convergence and Spatial Dependence in ASEAN

Brunei, Thailand, Indonesia and Philippines present significant coefficients and half-lives that range between 79 and 120 years. The speeds of convergence associated with those coefficients are around half of the one reported for the entire ASEAN community. For the other countries, they either show non-significant coefficients or very slow speeds of convergence.

One more outstanding finding can be drawn from the results of Table 3. It seems that the richest ASEAN members are experiencing within-country convergence, while most of the poorest members show no signs of (statistically significant) within-country convergence. Nevertheless, Malaysia is an exception to this pattern. It is the only relatively rich country in ASEAN that shows no signs of significant (within-country) regional convergence. If anything, its very slow speed of convergence would imply that even after 421 years, the average Malaysian region would only close 50 percent of its luminosity-based GDP per capita gap.

Although previous convergence studies in ASEAN have focused on country-level data, the regional-level results of this paper may help clarify some inclusive debates. Consistent with the results of Ismail (2008) and Solarin et al (2014), in this paper we find evidence of convergence when we evaluate all subnational regions independently of their country of origin. Within some countries (Cambodia, Laos, Malaysia, and Vietnam), however, beta convergence is not statistically significant. Moreover, the subnational regions of Myanmar show clear signs of sigma divergence. Thus, these within-country results appear more consistent with the findings of Park (2000) and Alavi and Ramadan (2008) who report no evidence of income convergence.

4.3 Spatial dependence across subnational regions in ASEAN

In order to explore spatial patterns, a shapefile of ASEAN regions is used. Moreover, in order to calculate spatial autocorrelation statistics, a spatial weight matrix is also needed. To create this matrix, the queen contiguity criteria is standard in the literature. However, in the sample of ASEAN regions many island-regions are included and in some instances the distance between them

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9 At this point, it is worth mentioning that the luminosity-based GDP per capita for Vietnam is given at the economic area level (8 areas). However, such areas are not formally the first administrative level. The first administrative level for Vietnam includes 58 provinces and 5 municipalities and for this reason the shapefile used in this paper includes provinces and municipalities. In order to use this type of shapefile, it is assumed that the data at the economic area level can also be assigned to each province that is within that economic area.
can be relatively large. For example, using a distance band, the minimum distance for all regions in ASEAN to have at least one neighbor was found to be 697 km. This band seems appropriate for an archipelago like Indonesia, however, this distance band can leave some regions in Thailand or Cambodia with as many as 150 neighbors.

In order to assign neighbors to all locations it is preferred to consider a set number for each region, a criteria which is known as the k-nearest neighbors approach. When considering the sub-sample of all regions in ASEAN that have at least one land bordering region, the mean of the number of neighbors is 4.52. Rounding up this number to 5, it seems plausible to use the 5 nearest neighbours as the criteria for computing the spatial weights matrix.

Using equation 3, the value for the global Moran’s I is computed for each year of the sample period. In Figure 7 the Moran’s I scatter plots are shown for the initial and final year of the sample. Overall, for all years, this statistic is highly significant and within a small range: $0.780 \leq I \leq 0.794$. In addition, global spatial autocorrelation shows an increasing tendency from 2008 (Figure 8). In this graph, the Moran’s statistic for the luminosity-based GDP per capita without log is also plotted. For this variable, the upward tendency in spatial dependency is more evident and it is present since 1998. Positive and significant values of the Moran’s I indicate that, on average, regions tend to be surrounded by neighbors with similar values. The existence of spatial clustering suggests that it is possible to perform spatial regressions when evaluating beta convergence, this type of analysis is left for future research.
In terms of the local analysis of spatial dependence, Figure 9 shows the location of spatial clusters (hotspots and coldspots) for the years 1998 and 2012. Regions in the choropleth maps are considered members of a cluster if the p-value of the local Moran’s I is lower than 0.01. On average, it seems that panels (a) and (b) are relatively similar, which means that there is a relatively high spatial persistence in terms of cluster size and membership.

Overall, low GDP clusters (coldspots) are located in Myanmar and Cambodia. In 1998, 9 out of the 14 regions of Myanmar belonged to a low GDP cluster, while 20 out of the 24 regions of Cambodia belonged to a low GDP cluster. Nevertheless, some regions escaped and some others joined these clusters. Over time the size of the low GDP clusters decreased from 34 to 30 regions. In the one hand, the six regions that are not longer part of the low GDP cluster in 2012 include three regions from Myanmar, two regions from southern Laos and one region from the coastal area of Cambodia. On the other hand, the two regions that became part of this type of cluster are located in the north of the Philippines.

High GDP clusters include regions from Thailand, Malaysia, Brunei and Indonesia. In the year 2012, 6 more regions joined these clusters. Interestingly,

10 The significance maps are reported in Appendix A.
all these newly joint regions are located in central Thailand. As this cluster grew in size, it also got closer to the border of south Myanmar. Thus, a new high-low GDP group was formed from a single region in that country.

The part of ASEAN near the equator line, where Brunei, Singapore and Malaysia are located, includes most of the regions in the high GDP cluster. All regions of Malaysia and Brunei are included, together with four regions in southern Thailand and five Indonesian regions. All these regions were part of the high GDP clusters both in 1998 and 2012.
Finally, as previously mentioned, clusters are not necessarily located within countries. Some clusters are formed on both sides of national boundaries. In 1998 and 2012, low-GDP clusters were composed by Cambodian and Lao regions; and the most proximate neighbors of this cluster include regions from Vietnam and Thailand.

Some of the high GDP clusters also spread beyond national boundaries. The regions in southern Thailand form a cluster with the Malaysian regions in the Malay Peninsula. In addition, in the island of Borneo, all regions of Brunei, two of Malaysia, and one region of Indonesia form another high GDP cluster.

5 Policy implications

Taken together, the previous results provide a new and more disaggregated perspective of the integration process of the ASEAN community. As suggested by the experience of other economic communities (for instance, the European Union), achieving economic integration goes hand in hand with the reduction of regional disparities across the members of the community. In addition, reducing regional disparities is central for achieving sustainable development. The importance of reducing inequality among and within countries is clearly stated in the declaration of the Sustainable Development Goals.

More specifically, the results of this paper could inform the design and monitoring of regional integration policies across the members of the ASEAN community in two fronts. First, in Figure 9, three persistent clusters of low income are identified. The low economic growth of the north-western regions of ASEAN should be a major concern for the integration and sustainability of the entire ASEAN community. Given the spatial configuration of the clusters, targeted policies at the cluster level policies may prove useful. In particular, investment spillovers from the subnational regions of Thailand (the fourth richest country in ASEAN) could play a role in enabling the development of neighboring lagging regions.\textsuperscript{11}

Second, continuous monitoring and evaluation of the scope by which inequality has been reduced both within and among countries is crucial to for the sustainable development of the ASEAN community. The importance of this task has already been singled out by the international community.

\textsuperscript{11} There is an expanding high-income spatial cluster in Thailand that has crossed the Myanmar border. In the near future, this spatial cluster could grow beyond the border with Cambodia
The goal of inequality reduction became the 10th goal of the Sustainable Development Goals (SDGs) adopted by all United Nations member states. A luminosity-based GDP per capita database appears to be a powerful tool for measuring the evolution of regional inequality. Currently, the database created by Lessmann and Seidel (2017) provides regional income data up to 2012. Extending the database for recent years, improving the specification of the prediction model, and including newly reported regional GDP may help increase its accuracy. A better prediction of regional GDP may help both researchers and policymakers alike to evaluate progress in inequality reduction across countries as well as subnational regions.

6 Concluding remarks

A large number of studies have evaluated income disparities and convergence patterns among ASEAN countries. Results, however, appear mixed and inconclusive as they largely depend on time frame and sample coverage. Given that the ASEAN community is conformed by only ten countries, many previous studies are largely constrained by a small sample size problem. This constrain is particularly binding for the analyses of economic convergence and spatial dependence, which typically require a larger sample size to correctly infer the evolution of economic disparities over time and space.

In an attempt to increase the sample size and infer the evolution of economic disparities over time and space, we use the new regional income dataset of Lessmann and Seidel (2017) that has been constructed using satellite night-time light data. This new dataset covers 274 subnational regions of the ASEAN community over the 1998-2012 period. Our main results are threefold. First, in the context of ASEAN related studies, the dataset of Lessmann and Seidel (2017) is useful in the sense that almost 60 percent of the differences in (official) GDP per capita can be predicted by a luminosity-based measure of GDP per capita. Next, the regional dynamics of this predicted GDP per capita measure suggest a pattern of regional convergence for the entire ASEAN sample. However, regional inequality has not significantly decreased within the majority of the individual countries of ASEAN. Third, there is an increasing degree of spatial dependence over time and some stable spatial clusters (hotspots and coldspots) are identified across multiple national boundaries.

As this is the first study that evaluates spatio-temporal dynamics using luminosity data across subnational regions in ASEAN, we only provided
an exploratory perspective using a classical convergence framework and a standard spatial dependence analysis. Although these two methodologies are complementary from a time-space analysis point of view, we did not fully integrate them in this paper. We leave this task for further research. In particular, from a spatial econometric perspective, one could evaluate to what extend spatial dependence accelerates or decelerates the speed of convergence.\textsuperscript{12} In addition, from a non-parametric distributional perspective, one could evaluate how spatial dependence affects the regional income distribution and its evolution.\textsuperscript{13}

\textsuperscript{12} See Rey and Montouri (1999) for one the seminal contributions in this line of research. More recent surveys are presented in Abreu et al (2005) and Rey and Le-Gallo (2009).

\textsuperscript{13} See Quah (1993) and Rey (2001) for two seminal contributions in this line of research. More recent surveys are presented in Rey (2015) and Rey (2019).
References


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Appendix

A  Significance map of the local Moran’s I

Fig. 10: Significance map for the local Moran’s I for log(luminosity based regional GDP pc)

(a) Significance map for 1998

(b) Significance map for 2012
### B List of ASEAN regions and luminosity-based GDP per capita in selected years

**Table 4: Brunei’s first-level subnational regions**

<table>
<thead>
<tr>
<th>Region</th>
<th>Year1998</th>
<th>Year2005</th>
<th>Year2012</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temburong</td>
<td>31781.15</td>
<td>31156.76</td>
<td>32577.63</td>
</tr>
<tr>
<td>Belait</td>
<td>33829.60</td>
<td>34450.44</td>
<td>33667.58</td>
</tr>
<tr>
<td>Tutong</td>
<td>38476.07</td>
<td>38117.24</td>
<td>38463.04</td>
</tr>
<tr>
<td>Brunei and Muara</td>
<td>49808.02</td>
<td>50506.77</td>
<td>47855.34</td>
</tr>
</tbody>
</table>

**Table 5: Cambodia’s first-level subnational regions**

<table>
<thead>
<tr>
<th>Region</th>
<th>Year1998</th>
<th>Year2005</th>
<th>Year2012</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mondol Kiri</td>
<td>561.93</td>
<td>905.92</td>
<td>1262.94</td>
</tr>
<tr>
<td>Steng Treng</td>
<td>562.22</td>
<td>906.39</td>
<td>1346.13</td>
</tr>
<tr>
<td>Preah Vihear</td>
<td>561.86</td>
<td>905.80</td>
<td>1355.45</td>
</tr>
<tr>
<td>Pouthisat</td>
<td>562.15</td>
<td>906.27</td>
<td>1399.25</td>
</tr>
<tr>
<td>Kampong Thm</td>
<td>562.08</td>
<td>906.15</td>
<td>1403.71</td>
</tr>
<tr>
<td>Kampong Chhnang</td>
<td>564.07</td>
<td>909.37</td>
<td>1424.54</td>
</tr>
<tr>
<td>Odar Mean Chey</td>
<td>564.13</td>
<td>957.98</td>
<td>1458.73</td>
</tr>
<tr>
<td>Kaoh Kong</td>
<td>630.61</td>
<td>994.87</td>
<td>1485.73</td>
</tr>
<tr>
<td>Prey Veng</td>
<td>564.37</td>
<td>909.86</td>
<td>1467.89</td>
</tr>
<tr>
<td>Kracheh</td>
<td>562.24</td>
<td>906.41</td>
<td>1476.75</td>
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<tr>
<td>Batdambang</td>
<td>621.49</td>
<td>1194.68</td>
<td>1524.35</td>
</tr>
<tr>
<td>Kampong Spe</td>
<td>563.54</td>
<td>908.53</td>
<td>1536.03</td>
</tr>
<tr>
<td>Kampaong Cham</td>
<td>632.41</td>
<td>1092.69</td>
<td>1573.94</td>
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<tr>
<td>Takev</td>
<td>565.10</td>
<td>1038.88</td>
<td>1596.73</td>
</tr>
<tr>
<td>Banteay Mearchey</td>
<td>646.17</td>
<td>1194.31</td>
<td>1616.53</td>
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<td>Krong Pailin</td>
<td>714.76</td>
<td>1091.25</td>
<td>1638.70</td>
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<td>Ratanokiri</td>
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<td>Kampil</td>
<td>564.40</td>
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<td>Siemreab</td>
<td>628.78</td>
<td>1203.06</td>
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<td>Svay Rieng</td>
<td>612.98</td>
<td>1133.93</td>
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</tr>
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<td>Kep</td>
<td>572.35</td>
<td>922.72</td>
<td>1936.53</td>
</tr>
<tr>
<td>Krong Preah Sihanouk</td>
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<td>1385.20</td>
<td>1963.50</td>
</tr>
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<td>Kandal</td>
<td>794.55</td>
<td>1336.04</td>
<td>2077.80</td>
</tr>
<tr>
<td>Phnom Penh</td>
<td>1204.38</td>
<td>1974.40</td>
<td>2901.71</td>
</tr>
</tbody>
</table>

**Table 6: Philippines’s first-level subnational regions**

<table>
<thead>
<tr>
<th>Region</th>
<th>Year1998</th>
<th>Year2005</th>
<th>Year2012</th>
</tr>
</thead>
<tbody>
<tr>
<td>Apayao</td>
<td>1534.53</td>
<td>1804.96</td>
<td>2099.36</td>
</tr>
<tr>
<td>Mountain Province</td>
<td>1866.14</td>
<td>1835.88</td>
<td>2104.62</td>
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<td>Aurora</td>
<td>1791.06</td>
<td>2271.67</td>
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<td>Abra</td>
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<td>No.</td>
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<td>----------</td>
</tr>
<tr>
<td>5</td>
<td>Romblon</td>
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<td>2300.35</td>
</tr>
<tr>
<td>6</td>
<td>Ifugao</td>
<td>1838.67</td>
<td>2127.23</td>
</tr>
<tr>
<td>7</td>
<td>Occidental Mindoro</td>
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<td>2488.83</td>
</tr>
<tr>
<td>8</td>
<td>Kalinga</td>
<td>1819.88</td>
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<td>9</td>
<td>Eastern Samar</td>
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<td>Northern Samar</td>
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<td>Sulu</td>
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<td>Tawi-Tawi</td>
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<td>Dinagat Islands</td>
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<td>Compostela Valley</td>
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<td>Zamboanga del Norte</td>
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Table 7: Thailand’s first-level subnational regions

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Table 8: Malaysia’s first-level subnational regions

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Data source: Lessmann and Seidel (2017)
### Table 9: Indonesia’s first-level subnational regions

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### Table 10: Vietnam’s first-level subnational regions

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