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Measuring Regional Inequality in the Andean Countries: A Multiple-Stage Nested Theil Decomposition Using Night Light Emissions

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Abstract

This paper examines inequality in the Andean countries using satellite-recorded nighttime lights and gridded population datasets from 2012 to 2021. We follow a multiple-stage nested Theil index decomposition method accounting for each country's lowest administrative divisions to enhance our understanding of how spatial dimensions contribute as primary sources of inequality and how these contributions vary across each country. The main findings reveal a decrease in overall inequality for the Andean region throughout the period (primarily driven by a decline in between-country inequality) and an increase in the relative importance of within-country inequality. In addition, there are spatial heterogeneities by country. Bolivia, Colombia, and Peru experienced a decline in wealth inequality over the past decade due to decreased disparities between provinces and less inequality within departments and provinces, respectively. In contrast, the inequality components in Ecuador and Venezuela exhibit a more balanced contribution to overall inequality. And, while Ecuador does not show a significant change in overall inequality during the period, the inequality increase in Venezuela is primarily driven by changes in the disparity between all geographic subgroups.

Keywords: Andean countries, decomposition, inequality, nighttime lights, Theil index

JEL Classification: C80, D63, E01, O15, O54, O57, Q40, R12

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1. Introduction

Since the early 2000s and until 2019, more than 45 million people have risen out of income poverty across Latin America and the Caribbean (LAC), of which about 15 million people lived in the Andean Region (Bolivia, Colombia, Ecuador, Peru, and Venezuela).[1] However, the COVID-19 pandemic widely dominated 2020 and caused severe impacts on socioeconomic indicators, pulling back growth forecasts and significantly increasing poverty-vulnerable populations and income inequality (Castilleja 2020; De la Cruz et al. 2020; Lanjouw and Tarp 2021; Andrian and Manzano 2023). As a result, about 48.3 million people in the Andean region suffered income poverty by 2021 (a fifth being extremely poor), 32 percent and 8 percent more than in 2012 and 2019, respectively.[2]

Poverty is closely related to regional inequality.[3] Economic and social opportunities are often unequally distributed across regions, and poverty tends to concentrate in areas with lower economic development and resource access. In many cases, these regions are rural areas (Rodríguez-Pose and Hardy 2015; Economic Commission for Latin America and the Caribbean, ECLAC, 2018; Kharas et al. 2020; Maldonado 2023), not densely populated and where agriculture is the primary source of income, and urban slums, weak and densely packed housing units where inhabitants have limited access to essential services (such as clean water, sanitation, education, and healthcare) and fewer job opportunities (Stampini et al. 2015). For example, about 38 percent of the rural population in the Andean region faced income poverty in 2021 (11.3 million people), while 31 percent were urban poor (37 million people). Regional inequality can also lead to migration as people move from poorer regions to more affluent ones in search of better opportunities. This situation may lead to

[1]For details, see the Economic Commission for Latin America and the Caribbean's Statistical Database (2022, January): https://statistics.cepal.org/portal/cepalstat/dashboard.html?lang=en. Due to data availability constraints for Venezuela, its poverty figures are based on the Venezuelan National Survey of Living Conditions and from Maldonado (2023).

[2]Venezuela influences these figures up, although the trend remains. Excluding Venezuela, 33.3 million people were income poor by 2021 (about 10 million of which were extremely poor), 10 percent more than in 2012 and 15 percent more than in 2019.

[3]Regional inequality refers to economic, social, or political disparities between different regions within a country or geographic area.

structural rather than contextual issues, a local brain drain, loss of economic activity, and uneven regional growth, further exacerbating poverty in the poorer regions and driving intergenerational transmission of poverty (Bird 2013).

Governments face a first challenge when addressing inequality in their countries: how to implement effective and efficient policy agendas to reach equality objectives? This is a fundamental and critical aspect of policy design. A first approximation to answering this question involves enhancing our understanding of how spatial dimensions contribute as primary sources of inequality. A better idea of a country's local dynamic may significantly influence the precision and effectiveness of initiatives tackling inequality, promoting inclusivity and participatory governance while considering the preferences and needs of specific geographic levels.

In this sense, this paper uses satellite-recorded nighttime lights and gridded population datasets to shed light on the appropriate geographical level for implementing initiatives to tackle inequality in each country within the Andean region. We measure inequality accounting for their lowest (smallest)-level administrative divisions and examine how it may have varied from 2012 to 2021. In the best scenario, the analytical approach involves decomposing inequality following a three-stage nested Theil index decomposition method using night light emissions as a proxy of economic wealth.[4] This study confirms a decrease in overall wealth inequality for the Andean region throughout the period (primarily driven by a decline in between-country inequality) and an increase in the relative importance of within-country inequality. It also identifies spatial heterogeneities by country, particularly in Venezuela, the only one in the Andean region where inequality increased.

Nighttime lights from satellite imagery are often used in regional analyses to track economic activity and economic development (Dai et al. 2017; Wang et al. 2019; Andrade-Núñez and Aide 2020; Gibson and Boe-Gibson 2021;

[4]Econometrician Henri Theil introduced the Theil decomposition method in the 1960s, based on the Theil index, an entropy measure of inequality. The decomposition considers both the inequality between groups and the inequality within groups. It involves partitioning the total variation in the dependent variable into different components, each representing a different factor's contribution to the overall variation.

Maldonado 2022; McCord and Rodriguez-Heredia 2022), and socioeconomic and political outcomes (Hodler and Raschky 2014; Bruederle and Hodler 2018; Ferreira 2018; Jagnani and Khanna 2020; Maldonado 2023). These studies rely on the assumption that night light emissions implicitly capture relevant information about spatial heterogeneity and human impact on a local level.

Regional inequality and light emissions are deeply interconnected. The availability and consumption of energy, such as electricity, is fundamental to modern living and a key input to industrial and trade activity, while its absence can be a significant constraint on income and development (Moss et al. 2020). Lights can also indicate inequality. Wealthier areas have more lighting at night, while poorer and more deprived areas have less. Moreover, urban areas concentrate electricity and energy infrastructure, emitting an intensity of light likely captured by sensors aboard satellites. In contrast, electrification is inferior in rural areas or agricultural regions, mainly because it is far from national grids, thus leading to less intense lighting (Keola et al. 2015; Ferreira 2018; Smith and Wills 2018; Maldonado 2023). In this sense, uneven light emissions across the territory may signaling different degrees of development and economic activities.

Conventional methods of measuring inequality typically incorporate data from national accounts, administrative records, household surveys, or a mix. However, these sources are susceptible to discrepancies in design and inconsistent accessibility (Dahl et al. 2011; Burkhauser et al. 2012; Deaton 2016; Carr and Wiemers 2018; Galimberti et al. 2023). For example, administrative data can have missing values or be outdated (Courtemanche et al. 2019), national accounts are not designed to generate poverty estimates, and surveys tend to under-sampling richer households likely due to forgetfulness, temporal misplacement, or misclassification (Deaton 2005; Lynn et al. 2012). Ayala et al. (2022) also confirm significant differences in the level and structure of inequality across administrative and survey data, particularly in the tails of the income distribution. Tax avoidance and evasion are also issues in administrative data. Tax records do not account for informal sources and may be limited by fiscal manipulation strategies and income reporting rules (Alstadsæter et al. 2019;

Galbraith 2019; Meyer and Mittag 2021).

Analyzing regional inequality based on alternative sources and methods may generate new outputs or complement existing results. A feasible but insufficiently exploited approach is to estimate light-based inequality measures. Geospatial source data have consistent coverage worldwide and are less prone to transitory income shocks. The intensity of light emissions can also reveal rural-urban territorial features (Zhao et al. 2019; Li et al. 2020), capture specificities beyond reported income (such as informal activities, access to electricity, and infrastructure), and act as independent novel data with predictive power to audit and reduce measurement errors from surveys and national accounts (Henderson et al. 2012; Nordhaus and Chen 2012; Chen 2016; Pinkovskiy and Sala-i-Martin 2016; Maldonado 2022; Martinez 2022).

Satellite imagery is slowly gaining ground as a proxy of income and wealth for estimating inequality in developed and developing countries. Mveyange (2015) found a significant positive relationship between regional inequality calculated through nighttime lights and income in Africa. Alesina et al. (2016) constructed measures of ethnic inequality using light data and the historical homelands of ethnolinguistic groups to examine its impact on contemporary development. Lessmann and Seidel (2017) also used luminosity data to estimate regional income inequality across 180 countries at the first subnational administrative level from 1992 to 2012. Their study revealed that predicted income is a more precise representation of real figures than nominal figures, which is crucial in assessing regional disparities. Weidmann and Schutte (2017) also demonstrated the accuracy of light data in predicting local economic wealth for 39 of the world's least-developed countries.

More recently, Galimberti et al. (2023), Weidmann and Theunissen (2021), and Andreano et al. (2021) have contributed to that growing literature. Galimberti et al. (2023) confirmed the superiority of using satellite data on nighttime lights and spatially distributed population data to measure economic inequality within developing countries. Weidmann and Theunissen (2021) focused on African countries and suggested that nighttime light can be an alternative to survey-derived data when estimating local disparities. Furthermore, Andreano et al. (2021) analyzed a panel of 20 countries in Latin America and the Caribbean at the first subnational administrative level between 2000 and 2013. Their findings suggest that nighttime lights could be a critical source of information for deriving spatially disaggregated and continuous-time calculations of inequality indices.

The contribution of this paper is threefold. First, there is a lack of studies using remote sensing data from satellite imagery to expose regional inequality accounting for multiple subnational levels in each Andean country. In fact, this study is the first to use satellite-recorded light data to study inequality, focusing solely on the Andean region. There are studies for each Andean country using light data but analyzing map urbanization dynamics and estimating economic or social indicators. Parés-Ramos et al. (2013) used nighttime lights to analyze spatial patterns of urban development between 1992 and 2009 in the major cities of Bolivia, Colombia, Ecuador, and Peru. We also came across a blog post by Andersen et al. (2023, January) presenting results of night light intensity by municipalities of Bolivia. In Ecuador, Cabrera-Barona et al. (2020) mapped urban representations of the Ecuadorian Amazon using a geospatial approach, and Mejía Juárez (2020) analyzed the evolution of urban uses using the magnitude and intensity of nighttime light data. In Peru, Seminario and Palomino (2022) estimated subnational GDP from 1993 to 2018. Zhang et al. (2020) carried out a spatiotemporal analysis relating light emissions with multiple variables to evaluate the socioeconomic crisis that suffers Venezuela, while Maldonado (2023) actually combined the absence of high intensity of lights and gridded population datasets to estimate 2000-2020 rural poverty rates at different geographic levels of Venezuela. Furthermore, satellite data as an alternative source is particularly important for analyzing developing countries, which are often limited or lack robust subnational indicators to diagnose regional disparities.

Second, this paper uses the latest consistently processed annual series of nighttime lights -version 2.1- collected by the Visible Infrared Imaging Radiometer Suite (VIIRS) instrument at its highest available spatial resolution (approximately 500 meters at the equator) from 2012 to 2021. Earlier studies on local inequality using satellite data often rely on yearly light imagery from the U.S. Air Force Defense Meteorological Satellite Program (DMSP)-Operational Linescan System (publicly available from 1992 to 2013); however, VIIRS data are superior to DMSP for mapping nighttime lights (Elvidge et al. 2013). VIIRS spatial resolution provides more detailed information than DMSP. In addition, unlike VIIRS data, DMSP sensors lack linearity, suffer from frequent saturation, and have no onboard calibration.[5] Therefore, results using VIIRS data ensure a gain in reliability and precision on subnational outcomes, keeping us (for a while) at the forefront of other studies on regional inequality.

Third, a comprehensive analysis of inequality measures requires considering both spatial and temporal dimensions (Khan and Siddique 2021). This paper accounts for both dimensions. Here, we analyze spatiotemporal heterogeneities at the lowest-level administrative divisions of each Andean country. This paper follows a multiple-stage nested Theil decomposition method covering ten years, 2012-2021. This approach allowed us to find noteworthy particularities. For example, the paper verifies a decline in wealth inequality over the past decade in Bolivia, Colombia, and Peru. It finds that Bolivia's reduction in inequality can be attributed to the decline in disparities between provinces. Similarly, Colombia experienced a decrease in inequality within departments, and Peru witnessed a decline within provinces. In contrast, the inequality components in Ecuador and Venezuela exhibit a more balanced contribution to overall inequality. And, while Ecuador does not show a significant change in overall inequality during the period, the inequality increase in Venezuela is primarily driven by changes in the disparity between all geographic subgroups.

As far as we know, recent studies have yet to apply multiple-stage nested geographic disaggregations for Andean countries, although some exercises exist for Chile and China. A decade ago, Paredes et al. (2012) empirically proposed a Theil decomposition for Chile at the regional, provincial, and county levels, assuming household incomes as the lowest level observations. In addition,Wu et al. (2018) analyzed inequality in research funding in China at the individual

[5]This means that assigned values of intensity of DMSP light data are not comparable from one year to another.

researcher level by university-institute subgroup.

The recent global policy agenda acknowledges the importance of including different levels of geography to understand multiple degrees of development within and among countries (Sachs et al. 2022). Reducing inequality is in ten out of 17 goals adopted by all United Nations (UN) member States in 2015 as part of the 2030 Agenda for Sustainable Development. Floerkemeier et al. (2021) further emphasize that inequality measures are sensitive to the choice of geographical scale. This study is a step towards promoting a spatial perspective for Andean countries, an approach that could play a vital role in achieving equitable development goals.

This paper could be beneficial for two main strands of inequality studies. First, it complements literature using geospatial data to measure national or subnational inequality (Lessmann and Seidel 2017; Gilliland et al. 2019; Haithcoat et al. 2021; Mirza et al. 2021; Rabiei-Dastjerdi and Matthews 2021; Puttanapong et al. 2022; Galimberti et al. 2023). Second, it also expands existing studies on inequality based on decomposition methods (Morduch and Sicular 2002; Akita 2003; Shorrocks and Wan 2005; Elbers et al. 2008; Paredes et al. 2012; Wu et al. 2018; Sinha et al. 2022).

The paper is structured as follows. Section 2 summarizes the analytical framework describing the conventional one-stage Theil decomposition method and its extension to the two-stage nested and three-stage nested Theil decomposition method. Section 3 describes the study area and data sources. Section 4 presents stylized facts of night light data for the sample and main results. Section 5 concludes.

2. Methodology

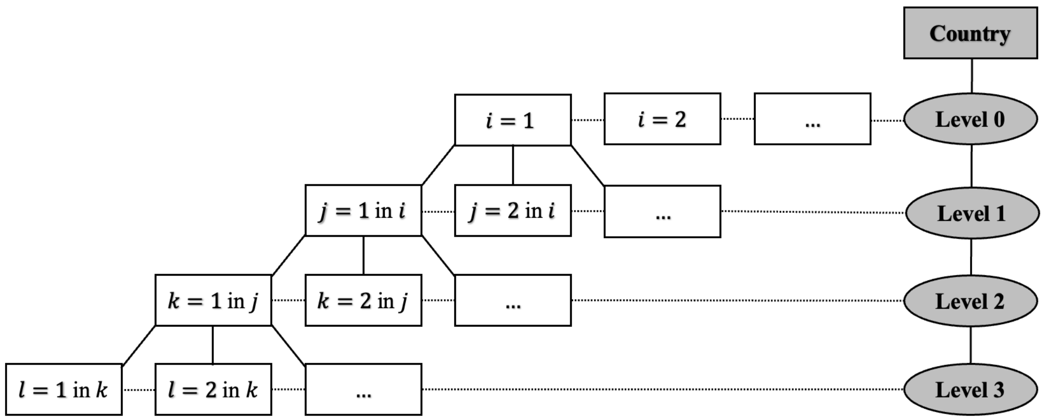
The Theil index[6] was designed to measure income and wealth disparity within a country. As indicated by Akita (2003), the index comprises two variants: the Theil T index, which employs income proportions as weights and tends to be more responsive to changes in more affluent areas, and the Theil L index, which

[6] Developed by Theil (1967) using principles of information theory.

uses population proportions and thus is particularly responsive to changes among poorer areas. Here, the framework is based on the Theil T index.

Figure 1 shows four layers of geographic levels and sublevels nested in a country, where the last layer (*Level* 3) contains the underlying unit l to measure regional inequality.

Figure 1: Four-Level Hierarchical Structure



The country-level Theil T index (overall inequality) will depend on the number of levels defined a priori for the hierarchical structure, such as T_1 is the Theil index assuming a one-level hierarchical structure, T_2 assuming a two-level hierarchical structure, T_3 for a three-level hierarchical structure, or T_4 for a four-level hierarchical structure. These are given by the following equations:

$$T_1 = \sum_i \left(\frac{Y_i}{Y}\right) Log \left(\frac{Y_i/Y}{N_i/N}\right) \tag{1}$$

$$T_2 = \sum_i \sum_j \left(\frac{Y_{ij}}{Y}\right) Log \left(\frac{Y_{ij}/Y}{N_{ij}/N}\right) \tag{2}$$

$$T_3 = \sum_i \sum_j \sum_k \left(\frac{Y_{ijk}}{Y}\right) Log \left(\frac{Y_{ijk}/Y}{N_{ijk}/N}\right) \tag{3}$$

$$T_4 = \sum_i \sum_j \sum_k \sum_l \left(\frac{Y_{ijkl}}{Y}\right) Log \left(\frac{Y_{ijkl}/Y}{N_{ijkl}/N}\right) \tag{4}$$

where Y is the total income at the country-level, Y_i is the total income of i (in *Level* 0), Y_{ij} is the total income of j (in *Level* 1) in i, Y_{ijk} is the total income of k (in *Level* 2) in j in i, Y_{ijkl} is the total income of l (in *Level* 3) in k in j in i, N is the total population at the country-level, N_i is the total population of i (in *Level* 0), N_{ij} is the total population of j (in *Level* 1) in i, N_{ijk} is the total population of k (in *Level* 2) in j in i, and N_{ijkl} is the total population of l (in *Level* 3) in k in j in i. Therefore, $Y = \sum_i Y_i = \sum_i \sum_j Y_{ij} = \sum_i \sum_j \sum_k Y_{ijk} = \sum_i \sum_j \sum_k \sum_l Y_{ijkl}$ and $N = \sum_i N_i = \sum_i \sum_j N_{ij} = \sum_i \sum_j \sum_k N_{ijk} = \sum_i \sum_j \sum_k \sum_l N_{ijkl}$.

The Theil index is additively decomposable, meaning that the overall national inequality can be expressed as the sum of within-groups and between-groups inequality components.[7] It quantifies the degree to which the structure in the distribution of income across groups deviates from the distribution of population across those same groups. When the structures are the same, there is an equal income distribution for all underlying units; thus, each group has the same share of income as its population share, and the Theil index equals zero (minimum value). Similarly, if a specific group has the same share of income and population, its relative contribution to the index is zero. On the other hand, the larger the index, the larger the inequality. Groups with higher shares of income relative to the population contribute positively to the Theil index, and those with lower shares of income than the population contribute negatively. By definition, the positive contributions will always be higher than the negative ones, so the index or its components will always be positive overall or zero.[8]

Let's consider a simplified case of a two-level hierarchical structure of a

[7] Theil indices satisfy convenient properties as a measure of regional income inequality: mean independence (the index remains unchanged if every group's income changes by the same proportion), population-size independence (the index remains unchanged if the population in each group changes by the same proportion), and the Pigou-Dalton principle of transfers (any income transfer from a richer to a poorer group that does not reverse their relative ranks in income reduces the value of the index). For details, see Bourguignon (1979), Shorrocks (1980), and Akita (2003).

[8] For guidance about intuitive interpretations and analytical applications of the Theil index, see Conceição and Ferreira (2000).

country, ignoring lower nested levels, where *Level* 1 encloses the underlying unit j. In this case, overall regional income inequality can be measured by Equation 2. If we define T_i to measure Theil T indices within i for *Level* 0 as

$$T_i = \sum_j \left(\frac{Y_{ij}}{Y_i}\right) Log \left(\frac{Y_{ij}/Y_i}{N_{ij}/N_i}\right) \tag{5}$$

then, the within-0 inequality component (T_{W0}) is a weighted average of Equation 5 using income shares as weights at the *Level* 0 as in Equation 6,

$$T_{W0} = \sum_i \left(\frac{Y_i}{Y}\right) T_i = \sum_i \left(\frac{Y_i}{Y}\right) \sum_j \left(\frac{Y_{ij}}{Y_i}\right) Log \left(\frac{Y_{ij}/Y_i}{N_{ij}/N_i}\right) \tag{6}$$

Noting that Equation 7 measures the between-0 inequality component (T_{B0}) of the country or the inequality between subgroups in *Level* 0,

$$T_{B0} = \sum_i \left(\frac{Y_i}{Y}\right) Log \left(\frac{Y_i/Y}{N_i/N}\right) \tag{7}$$

then, the Equation 2 can be decomposed into,

$$\begin{aligned} T_2 &= \sum_i \left(\frac{Y_i}{Y}\right) \sum_j \left(\frac{Y_{ij}}{Y_i}\right) Log \left(\frac{Y_{ij}/Y_i}{N_{ij}/N_i}\right) + \left(\frac{Y_i}{Y}\right) \sum_i \left(\frac{Y_i}{Y}\right) Log \left(\frac{Y_i/Y}{N_i/N}\right) \\ &= \sum_i \left(\frac{Y_i}{Y}\right) T_i + \sum_i \left(\frac{Y_i}{Y}\right) Log \left(\frac{Y_i/Y}{N_i/N}\right) = \sum_i \left(\frac{Y_i}{Y}\right) T_i + T_{B0} = T_{W0} + T_{B0} \end{aligned} \tag{8}$$

Equation 8 represents the conventional one-stage Theil decomposition.

We can also assume a three-level hierarchical structure, adopting k as the underlying unit in *Level* 2, to get a two-stage nested Theil decomposition.[9] In this case, overall regional income inequality can be measured by Equation 3.

By analogy, we can further decompose the Theil T indices of Equation 5 into,

[9] For details, see Akita (2003).

$$T_i = \sum_j \left(\frac{Y_{ij}}{Y_i}\right) T_{ij} + \sum_j \left(\frac{Y_{ij}}{Y_i}\right) Log \left(\frac{Y_{ij}/Y_i}{N_{ij}/N_i}\right) = \sum_j \left(\frac{Y_{ij}}{Y_i}\right) T_{ij} + T_{Bi} \quad (9)$$

where T_{Bi} represents the inequality between each j in i. And, if we define T_{ij} to measure Theil T indices within j in i for *Level* 1,

$$T_{ij} = \sum_k \left(\frac{Y_{ijk}}{Y_{ij}}\right) Log \left(\frac{Y_{ijk}/Y_{ij}}{N_{ijk}/N_{ij}}\right) \quad (10)$$

By substituting Equation 9 in Equation 8, and using Equation 10, we obtain Equation 11.

$$\begin{aligned} T_3 &= \sum_i \left(\frac{Y_i}{Y}\right) \left[\sum_j \left(\frac{Y_{ij}}{Y_i}\right) T_{ij} + T_{Bi}\right] + T_{B0} \\ &= \sum_i \sum_j \left(\frac{Y_{ij}}{Y}\right) T_{ij} + \sum_i \left(\frac{Y_i}{Y}\right) T_{Bi} + T_{B0} \\ &= \sum_i \sum_j \left(\frac{Y_{ij}}{Y}\right) T_{ij} + \sum_i \sum_j \left(\frac{Y_{ij}}{Y}\right) Log \left(\frac{Y_{ij}/Y_i}{N_{ij}/N_i}\right) + T_{B0} = T_{W1} + T_{B1} + T_{B0} \end{aligned} \quad (11)$$

where T_{B1} represents the inequality between subgroups in *Level* 1 (between-1 inequality component), and T_{W1} is a weighted average of the within-group j Theil indices T_{ij} (within-1 inequality component).

Furthermore, we can now assume the four-level hierarchical structure, where *Level* 3 comprises the underlying unit l. In this case, Equation 4 measures the overall regional income inequality, and we should now decompose the Theil T indices of Equation 10, obtaining thus Equation 12.

$$T_{ij} = \sum_k \left(\frac{Y_{ijk}}{Y_{ij}}\right) T_{ijk} + \sum_k \left(\frac{Y_{ijk}}{Y_{ij}}\right) Log \left(\frac{Y_{ijk}/Y_{ij}}{N_{ijk}/N_{ij}}\right) = \sum_k \left(\frac{Y_{ijk}}{Y_{ij}}\right) T_{ijk} + T_{Bij} \quad (12)$$

where T_{Bij} is the inequality between each k in j in i.

If we define T_{ijk} to measure Theil T indices within k in j in i for *Level* 2,

$$T_{ijk} = \sum_{l} \left(\frac{Y_{ijkl}}{Y_{ijk}} \right) Log \left(\frac{Y_{ijkl}/Y_{ijk}}{N_{ijkl}/N_{ijk}} \right) \tag{13}$$

Finally, by substituting Equation 12 in Equation 11, and using Equation 13, we have,

$$\begin{aligned}
T_4 &= \sum_{i} \sum_{j} \left(\frac{Y_{ij}}{Y} \right) \left[\sum_{k} \left(\frac{Y_{ijk}}{Y_{ij}} \right) T_{ijk} + T_{Bij} \right] + \sum_{i} \left(\frac{Y_i}{Y} \right) T_{Bi} + T_{B0} \\
&= \sum_{i} \sum_{j} \sum_{k} \left(\frac{Y_{ijk}}{Y} \right) T_{ijk} + \sum_{i} \sum_{j} \left(\frac{Y_{ij}}{Y} \right) T_{Bij} + \sum_{i} \left(\frac{Y_i}{Y} \right) T_{Bi} + T_{B0} \\
&= \sum_{i} \sum_{j} \sum_{k} \left(\frac{Y_{ijk}}{Y} \right) T_{ijk} + \sum_{i} \sum_{j} \sum_{k} \left(\frac{Y_{ijk}}{Y} \right) Log \left(\frac{Y_{ijk}/Y_{ij}}{N_{ijk}/N_{ij}} \right) \\
&\quad + \sum_{i} \sum_{j} \left(\frac{Y_{ij}}{Y} \right) Log \left(\frac{Y_{ij}/Y_i}{N_{ij}/N_i} \right) + T_{B0} = T_{W2} + T_{B2} + T_{B1} + T_{B0}
\end{aligned} \tag{14}$$

where T_{B2} is the inequality between subgroups in *Level* 2 (between-2 inequality component), and T_{W2} is the weighted average of the within-group k Theil indices T_{ijk} (within-2 inequality component). Equation 14 represents the three-stage nested Theil decomposition.

3. Study Area and Data

This paper carries out a multiple-stage nested Theil decomposition method to present wealth inequality results for Bolivia, Colombia, Ecuador, Peru, and Venezuela between 2012 and 2021. We use night light emissions as a proxy for wealth and their respective lowest-level administrative divisions as the underlying regional unit.[10]

[10] In this case, nighttime lights may directly reflect the built environment and infrastructure development, indirectly capturing the potential for wealth accumulation.

The geographic levels considered by country are given in Table 1 and correspond to a four-level hierarchical structure, except for Colombia, which has a three-level structure.

Table 1: Geographic Levels by Andean Country

Country	*Level* 0	*Level* 1	*Level* 2	*Level* 3
Bolivia	Region 3	Department 9	Province 112	Municipality 339
Colombia	Region 5	Department 32+1 (Capital District)	Municipality 1,122	
Ecuador	Region 4+1 (Non-delimited)	Province 24+1 (Non-delimited)	Canton 221+3 (Non-delimited)	Parish 1,040
Peru	Region 3	Department 24+1 (Constitutional Province of Callao)	Province 195+1 (Constitutional Province of Callao)	District 1,873
Venezuela	Region 9	State 23+1 (Capital District)	Municipality 335	Parish 1,134

Note: *Level* 0 corresponds to natural or physiographic regions (except political-administrative regions for Venezuela). The number of geographic levels may differ from official major administrative areas due to the availability of geospatial data.

We use shapefiles of subnational administrative boundaries from the United Nations Office for the Coordination of Humanitarian Affairs (OCHA) Common Operational Datasets to aggregate gridded data to divisions in *Level* 1, *Level* 2, and *Level* 3. In addition, we create regional divisions, *Level* 0, based on predefined physiographic features by country (or political-administrative regions for Venezuela). Adding *Level* 0 allows us to obtain more detailed inequality components while accounting for natural differences in land surface and climate, which lead to diversity, for example, in crops.

The Oak Ridge National Laboratory, ORNL (2023, February) provides the global population distribution data: LandScan Global Population database.[11] This is an ambient -average over 24 hours- gridded population data at 30 arc-second spatial resolution (approximately a cell area of 1x1 kilometers). Here, LandScan seems a suitable choice. Yin et al. (2021) conducted an accuracy assessment of four commonly used gridded population data products, including LandScan.[12] They concluded that LandScan performs best regarding spatial fineness and estimated errors. In this paper, we aggregate LandScan, adding it

[11]The files are freely available at the online repository of the ORNL: https://landscan.ornl.gov

[12]In particular, Yin et al. (2021) cross-compared global gridded population datasets such as the Gridded Population of the World (GPW), Global Human Settlement Population Grid (GHS-POP), WorldPop, and LandScan.

up throughout the different geographic levels by country.

Regarding the light emissions data, we use the newly consistently processed time series -version 2.1- of annual global low-light imaging data captured by the VIIRS Day/Night Band (DNB) onboard the Suomi National Polar-Orbiting Partnership satellite platform. The intensity of light is measured by the DNB radiance at night with unit: nano watts per square centimeter per steradian, $nW/(cm^2/sr)$. The Earth Observation Group of the Payne Institute for Public Policy at the Colorado School of Mines processes these light raster products, currently available from 2012 to 2021 (Earth Observation Group 2022, June).[13] Looking for pre-filtered spatially refined data, we use VIIRS annual masked average radiance products (Elvidge et al. 2021) at its highest spatial resolution of 15 arc-seconds or approximately 500 meters at the equator, which is particularly important when aggregating to a detailed-geographic level.

Using the latest VIIRS products has advantages. On the one hand, local studies using satellite light data often rely on older products, such as those from DMSP, publicly available from 1992 to 2013. VIIRS data outperform DMSP for mapping nighttime lights (Elvidge et al. 2013; Elvidge et al. 2017; Li et al. 2017; Levin et al. 2020). DMSP data have lower spatial resolution than VIIRS products, suffer from saturation, and have no onboard calibration.[14] Gibson and Boe-Gibson (2021) confirmed the DMSP data understate spatial inequality in, for example, the United States due to blurring and top-coding, while masked VIIRS products -version 2- perform better as proxies for local economic activity. Moreover, McCord and Rodriguez-Heredia (2022) found that nighttime lights strongly predict regional economic activity in seven countries, including Bolivia, Colombia, Ecuador, and Peru, using VIIRS data -version 2- from 2014 to 2019. Furthermore, we use version 2.1 as an upgrade of version 2, in which lit masks are updated, thus ensuring an improvement in the preprocessing. In

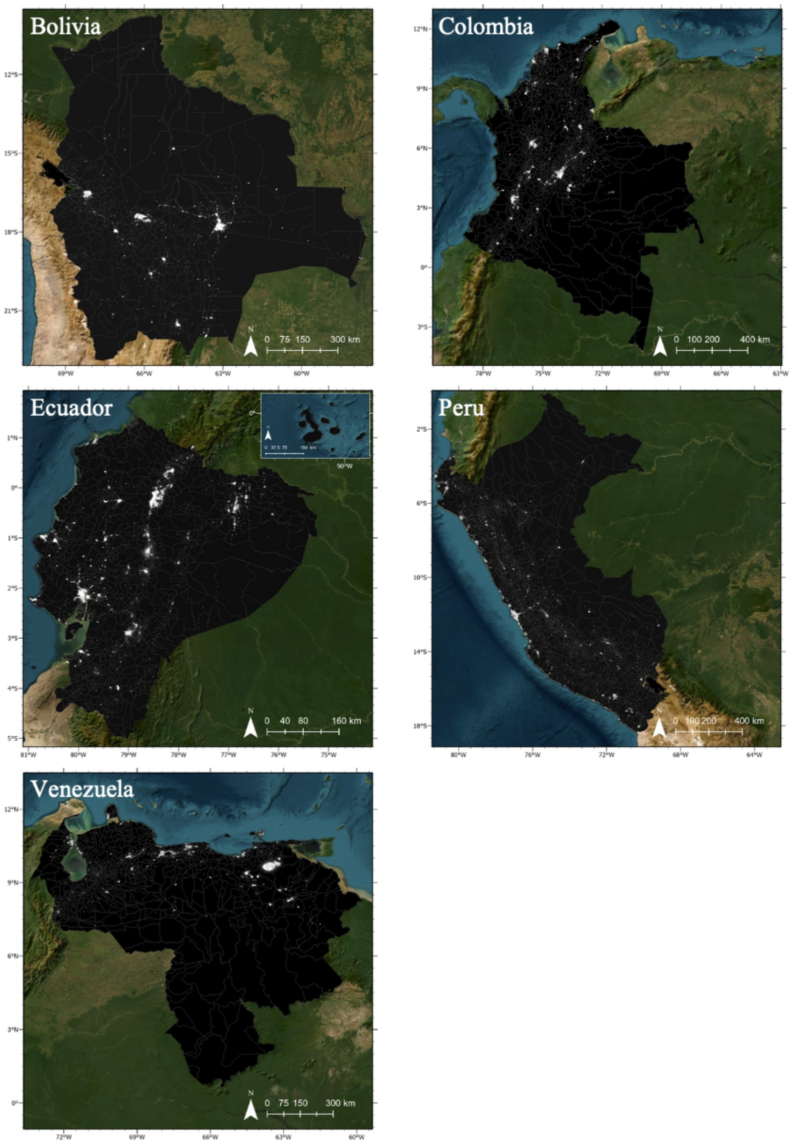
[13]VIIRS products are available since April 2012. The annual products are processed from monthly raw data; thus, the 2012 annual data only considers the period from April 2012 to December 2012.

[14]These differences are motivated by sensor variations in spatial resolution, spectral response, point of spread function, overpass time at night, and wider radiance range of the VIIRS.

this sense, this paper gains reliability and precision using VIIRS data to obtain subnational outcomes.

Figure 2 shows the spatial distribution of light data across each country and the divisions by lowest geographic level. At first glance, there are notable differences in light data distribution by country.

Figure 2: Nighttime Lights by Andean Country, 2021



Source: Earth Observation Group, Payne Institute - Colorado School of Mines. Note: The maps are presented in alphabetical order.

In Bolivia, the intensity of light is spatially evident mainly around the city of Cochabamba (in central Bolivia in a valley in the Andes), in Santa Cruz de la Sierra (the largest city and principal industrial center in the country located on tropical lowlands, and one of the fastest growing cities in the region), and in its capital La Paz and the adjacent city El Alto on the Altiplano highlands.

Colombia also denotes multiple spots of light from main cities such as Bogotá (the capital and the most populated city in the country), Medellín (the second-largest city in the central region of the country, surrounded by the Andes Mountains), Cali (main urban and economic center in southwest Colombia and third-largest city of the country), and Cartagena and Barranquilla in the north, Caribbean region, of the country.

Ecuador shows light concentration primarily through the Andean foothills from north to south (including its capital city, Quito), across its Pacific coastline, including Guayaquil (principal economic capital and port city), and in zones within the provinces of Orellana and Sucumbíos in the Amazon region in northeast Ecuador (territories containing multiple oil fields and relying primarily on exports of crude oil).

In Peru, light emissions are clearly visible throughout its vast coastline bordering the Pacific Ocean. A significant concentration of light comes from Lima (the capital and largest city in the desert zone of the central coastal part) and dispersed spots, especially in the south and south central of the country.

Venezuela shows the most intensity of night lights in its northern area, mainly across its Andean region and the Coastal (Caribbean) Mountain range, in the northeast of Los Llanos region (a widely extended flat central depression), and surrounding the Maracaibo Basin located in the northwestern corner of Venezuela in Zulia state. Now, the highest intensity of light directly comes from natural gas flaring located primarily on oil fields in three out of eight oil-producing Venezuelan states: Anzoategui, Falcon, and Monagas.[15] Satellite sensors can capture light reflected from intensive gas flaring activity. Treating

[15] In general, we can assume that Venezuela has eight oil-producing states: Anzoategui, Apure, Barinas, Delta Amacuro, Falcon, Guarico, Monagas, and Zulia; however, the highest intensity of light in the country comes from pixels in Anzoategui, Falcon, and Monagas.

gas flares as a measure of economic wealth could mislead the inequality outcomes. To reduce this concern, we masked and excluded a total of 19,913 pixels high light intensity pixels from those three states based on light distribution across their respective main urban cores. In particular, we use a state-specific cutoff value approach defined by the maximum urban core light intensity value unrelated to gas flaring across all the years, where values above the cutoff are flagged as light from gas flares in their respective state.[16]

Table 2: Summary Statistics (Pixel-Based), All Years

Country	Mean	Standard deviation	Minimum	Maximum	Observations
Bolivia					
Intensity of lights	2.0	14.0	0	100	52,240,480
Population (percent)	43.3	49.6	0	100	13,071,200
Population (count)	8.5	268.2	0	46,473	13,071,200
Colombia					
Intensity of lights	4.2	20.1	0	100	53,541,750
Population (percent)	45.7	49.8	0	100	13,419,930
Population (count)	35.7	748.3	0	92,873	13,419,930
Ecuador					
Intensity of lights	10.7	31.0	0	100	12,009,920
Population (percent)	62.8	48.3	0	100	3,019,180
Population (count)	53.5	644.5	0	46,214	3,019,180
Peru					
Intensity of lights	3.7	18.8	0	100	61,169,180
Population (percent)	46.3	49.9	0	100	15,315,360
Population (count)	20.5	465.1	0	63,485	15,315,360
Venezuela					
Intensity of lights	8.2	27.4	0	100	43,138,870
Population (percent)	37.9	48.5	0	100	10,802,420
Population (count)	27.9	478.5	0	62,924	10,802,420
Andean region					
Intensity of lights	4.7	21.1	0	100	222,100,200
Population (percent)	44.7	49.7	0	100	55,628,090
Population (count)	24.6	527.9	0	92,873	55,628,090

Table 2 presents pixel-based summary statistics from 2012 to 2021. We extracted light data and population data, covering more than 222 million and 55.5 million observations, respectively. On average, only about 5 percent of the

[16] We use the maximum value from urban pixels to avoid dropping urban pixels and reduce potential bias in our outcomes.

Andean region is entirely lit at night.[17] In comparison, about 45 percent of the territory seems to be populated. This context signals relative heterogeneity across the region.

Keola et al. (2015) argued how agricultural activity emits marginal lights, if any; thus, we can find vast land with low or no intensity of lights captured by satellite sensors. This situation may be especially true for Andean countries, highly rich in natural resources and where the agricultural sector has traditionally played an important economic and social role (Andrian and Manzano 2023).[18] An example of the disparity between the spatial distribution of light and population can be observed in Ecuador and Venezuela. Both countries have more lit areas than the Andean average (Ecuador with almost 11 percent and Venezuela with about 8 percent). Still, while nearly 38 percent of Venezuela's territory is inhabited, Ecuador has approximately 63 percent of its territory populated.

4. Results

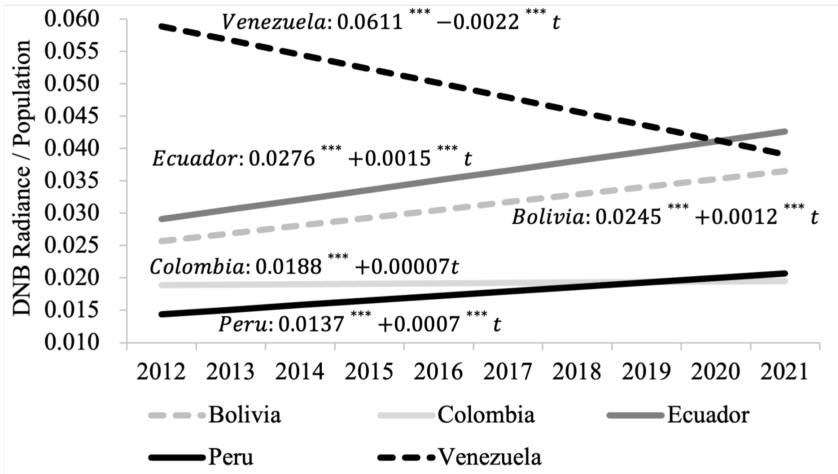
Figure 3 shows how the intensity of light per capita evolved between 2012 and 2021 at the country level.[19] In general, the trends throughout the period are driven mainly by changes in the intensity of lights, except for Venezuela, where two main effects prevail, one due to light data and the other to population data.

[17] The paper assumes a minimum unit value to calculate the Theil index accounting for areas traditionally with very low intensity of light or no light at all captured by the sensor of satellites.

[18] According to national sources, on average, between 2012 and 2021, the agricultural sector represented 12.6 percent of GDP for Bolivia, 9.2 percent for Ecuador, 6.2 percent for Colombia, and 5.7 percent for Peru. Furthermore, the International Labour Organization (ILO) estimated agricultural employment represents 29.7 percent, 27.5 percent, 16.7 percent, and 27.8 percent of total employment in Bolivia, Ecuador, Colombia, and Peru, respectively. For details, see Andrian and Manzano (2023).

[19] We aggregate light data adding up the radiance outputs.

Figure 3: Intensity of Light Per Capita (Linear Trend) by Andean Country



Source: Own calculations. Note: Significant at *10, ***1 percent, from estimates based on Ordinary Least Squares regressions, where t represents years.

Bolivia, Ecuador, and Peru have been experiencing a significant upward trend. Ecuador shows the highest slope and reaches the highest intensity of light per inhabitant among the Andean countries. In particular, Ecuador averages an increase in the intensity of light per capita of 0.0015 per year, experiencing almost 50 percent more light per capita in 2019 than in 2012; then, the pandemic led to a sudden decrease of the indicator by 5.2 percent in 2020, followed by a recovery of 8.8 percent in 2021. Bolivia shows a slightly lower slope than Ecuador, averaging a 0.0012 yearly increase. This country also had an increase of light per capita of about 50 percent from 2012 to 2019, which is more than 6 percent on average per year; however, the pandemic turned into a contraction of 2.2 percent and 1.8 percent in 2020 and 2021, respectively. The intensity of light per capita in Peru is growing at about 5.8 percent per year (60 percent of growth between 2012 and 2021). It is the only Andean country experiencing an increase during the pandemic.

In the case of Colombia, the light per capita only increased nearly 6 percent between 2012 and 2021. In Venezuela, the indicator decreases parallel with the Venezuelan socioeconomic crisis, declining 30 percent between 2014 and 2021. However, since 2015, Venezuela has also experienced a massive international migration outflow still ongoing, which may even be attenuating the fall of the per capita indicator.[20]

A first glance at the Andean region as a whole should help identify dissimilarities at the country level. Moreover, the opposite trend found in Venezuela using light data and population data for recent years strengthens the idea of aggregate heterogeneities. For this, we use a two-level hierarchical structure, with the Andean region as the base level and the *Level* 1 of each country representing the underlying unit. Table 3 shows the one-stage Theil index decomposition accounting for all the countries in the region and testing the exclusion of each country from the sample.

Table 3: One-Stage Theil Index Decomposition: Andean Region-Country

			Excluding									
	All		Bolivia		Colombia		Ecuador		Peru		Venezuela	
	2012	2021	2012	2021	2012	2021	2012	2021	2012	2021	2012	2021
Between-country	0.156	0.071	0.166	0.077	0.164	0.048	0.177	0.069	0.125	0.071	0.033	0.056
	(39.2)	*(23.5)*	*(39.5)*	*(23.3)*	*(38.0)*	*(15.0)*	*(42.8)*	*(23.3)*	*(32.4)*	*(21.3)*	*(17.4)*	*(31.8)*
Within-country	0.241	0.231	0.255	0.253	0.267	0.273	0.237	0.227	0.261	0.264	0.158	0.120
	(60.8)	*(76.5)*	*(60.5)*	*(76.7)*	*(62.0)*	*(85.0)*	*(57.2)*	*(76.7)*	*(67.6)*	*(78.7)*	*(82.6)*	*(68.2)*
Overall	0.397	0.302	0.421	0.331	0.431	0.321	0.414	0.295	0.385	0.335	0.191	0.176

Note: Contribution to the inequality in () in percentage.

The overall inequality for the Andean region using all the sample declined from 0.397 in 2012 to 0.302 in 2021. The between-country and within-country components reveal that the decrease in the overall inequality is due to the decline in the between-country component (from 0.156 to 0.071, respectively); in contrast, the within-country component was relatively stable. Furthermore, the relative importance of the between-country component decreased from about 39 percent in 2012 to 23.5 percent in 2021, while the within-country component gained weight on the inequality; thus, the overall wealth disparity in the region in 2021 is defined mainly by the inequality within each of the country and less by the differences among them.

An exclusion exercise over the sample finds similar patterns and somewhat similar inequality components, except when excluding Venezuela. For example,

[20]More than 7.2 million Venezuelans have fled the country as of March 2023. For details, see the Inter-Agency Coordination Platform for Refugees and Migrants from Venezuela (2023).

if Venezuela is considered as part of the sample and we exclude one by one the other countries, the overall inequality ranged from a minimum (maximum) of 0.385 (0.431) in 2012 to 0.295 (0.335) in 2021. However, suppose we exclude Venezuela and leave the remaining countries within the sample. In that case, the overall wealth inequality for the region dropped significantly, in absolute terms, to 0.191 in 2012 and 0.176 in 2021. Unlike the other scenarios, here, the between-country component gained instead of losing share (almost doubling in percentage contribution, from 17.4 percent to 31.8 percent, respectively).

These findings have at least two immediate implications. First, the within-country component accounted for over two-thirds of total wealth inequality in 2021. Thus, a separate analysis by country is critical to better understanding inequality across the Andean region. Second, excluding Venezuela from the sample significantly changes the figures, gaining relevance to develop further studies on inequality focusing on Venezuela.

Table 4 presents the decomposition results within each country. We adopt a four-level hierarchical structure for Bolivia, Ecuador, Peru, and Venezuela, enabling us to apply a three-stage nested Theil decomposition method. On the other hand, Colombia has a three-level hierarchical structure, so we follow a two-stage nested Theil decomposition method for this country.

Table 4: Multiple-Stage Nested Theil Index Decomposition by Andean Country

	Bolivia		Colombia		Ecuador		Peru		Venezuela	
	2012	2021	2012	2021	2012	2021	2012	2021	2012	2021
Between-0	0.009	0.003	0.095	0.050	0.145	0.124	0.005	0.014	0.228	0.308
	(2.2)	*(1.3)*	*(21.7)*	*(17.6)*	*(26.5)*	*(23.5)*	*(0.9)*	*(3.1)*	*(27.5)*	*(33.7)*
Between-1	0.049	0.021	0.063	0.047	0.130	0.127	0.087	0.055	0.112	0.161
	(12.5)	*(9.3)*	*(14.5)*	*(16.7)*	*(23.7)*	*(24.0)*	*(14.0)*	*(12.7)*	*(13.5)*	*(17.6)*
Between-2*	0.200	0.108	0.279	0.185	0.091	0.099	0.133	0.092	0.207	0.270
	(50.7)	*(48.0)*	*(63.8)*	*(65.7)*	*(16.6)*	*(18.7)*	*(21.6)*	*(21.2)*	*(24.9)*	*(29.5)*
Within-2	0.136	0.093			0.182	0.179	0.392	0.272	0.282	0.175
	(34.6)	*(41.3)*			*(33.1)*	*(33.8)*	*(63.5)*	*(63.0)*	*(34.0)*	*(19.2)*
Overall	0.394	0.224	0.437	0.282	0.549	0.530	0.617	0.433	0.829	0.913

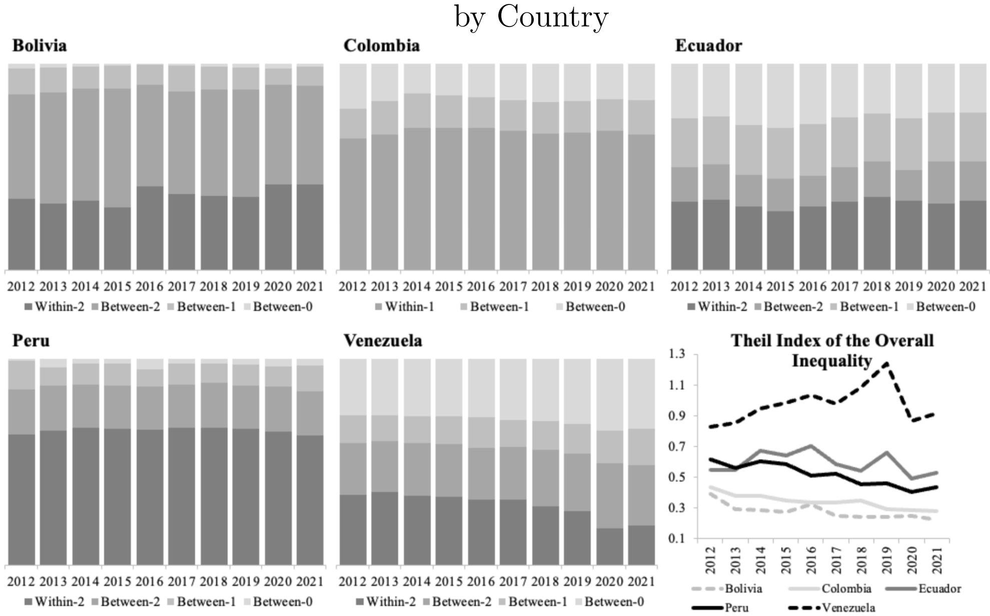
Note: Contribution to the inequality in ( ) in percentage. *For Colombia, it corresponds to the Within-1 component from a two-stage nested Theil decomposition method based on *Level* 0-*Level* 1-*Level* 2.

Bolivia exhibits the lowest overall Theil index, while Venezuela has the highest. Over the period from 2012 to 2021, Bolivia, Colombia, and Peru experienced a substantial decrease in wealth inequality. This reduction was observed across most components, except for Peru's between-0 component, which increased from 0.005 in 2012 to 0.014 in 2021.

In absolute terms, most of the overall reduction in inequality in Bolivia can be attributed to a decline in inequality between provinces. This indicates that the intensity of light has become more similar among provinces in 2021 compared to ten years ago. Colombia and Peru primarily witnessed a decrease in inequality within departments and provinces, respectively. Ecuador has little change in overall inequality; this is also true for its components. In contrast, Venezuela stands out as the only Andean country where overall inequality has increased, primarily driven by changes in inequality between all geographic subgroups. However, inequality within municipalities has been actually decreasing in Venezuela.

Figure 4 illustrates the variations in the contributions of different components from 2012 to 2021. Wealth disparities associated with the lowest-level administrative divisions have significantly contributed to overall inequality in each Andean country.

Figure 4: Relative Importance of the Spatial Dimension on Overall Inequality by Country



Source: Own calculations.

Approximately 90 percent of total inequality in Bolivia can be attributed to within and between components related to provinces in 2021. Furthermore, the decrease in inequality in Bolivia has amplified the relative importance of inequalities within provinces, accounting for 41.3 percent.

In 2021, the within and between province components of Peru constitute about 84.2 percent of total inequality, representing 63 percent and 21.2 percent, respectively. The decrease in inequality in Peru has had little impact on the contribution of these components.

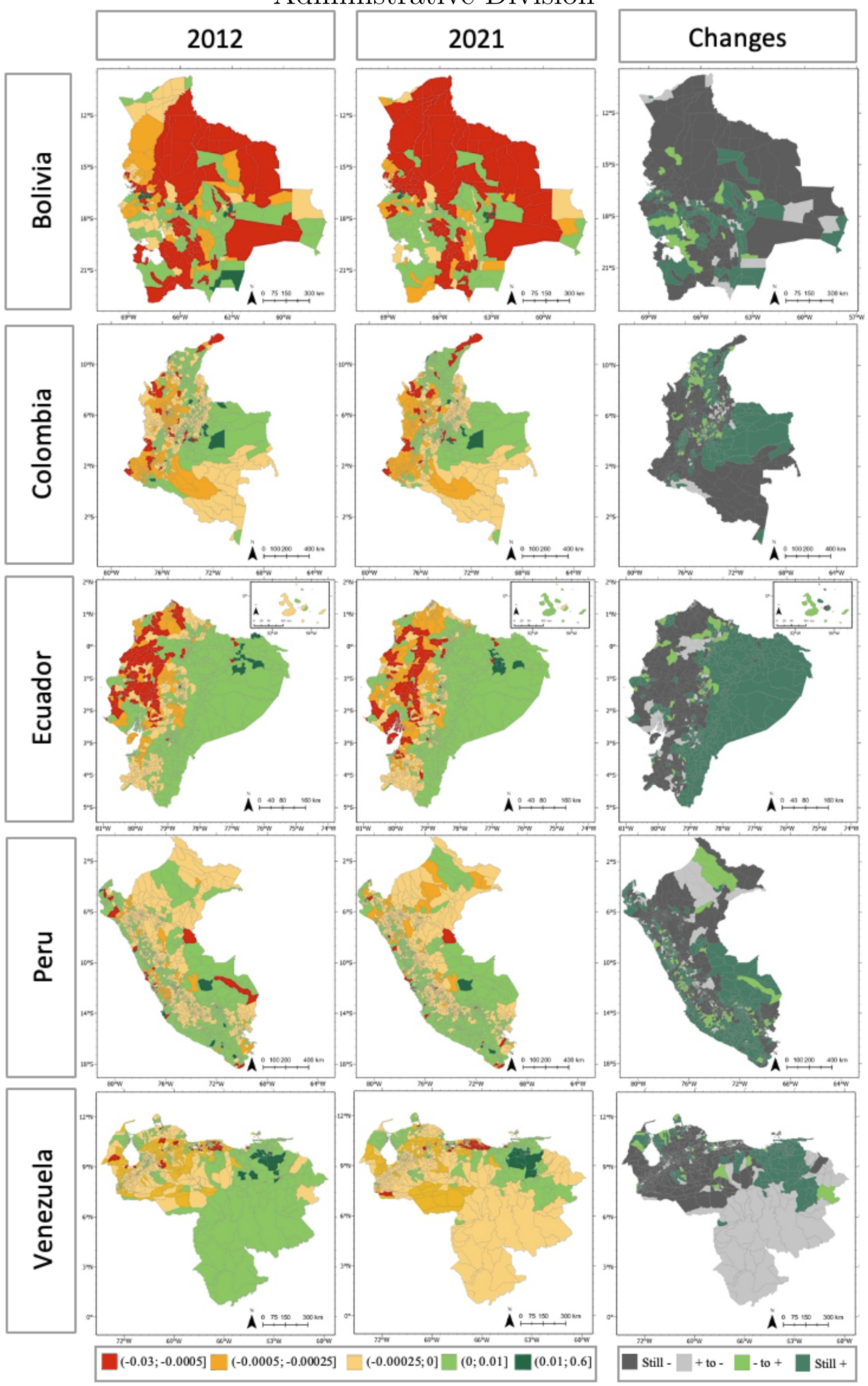
Inequality has decreased across all spatial components in Colombia, although the disparities within departments are slightly gaining relative prominence, representing 65.7 percent in 2021.

In Ecuador and Venezuela, the inequality components exhibit a more balanced contribution to overall inequality. In particular, these countries require special attention among Andean countries. The results indicate that Ecuador has not undergone a significant reduction in inequality over a decade, whereas the findings confirm an increase in overall inequality in Venezuela. In Ecuador, the disparity within cantons has been the most significant contributor to total inequality, accounting for approximately one-third of the overall inequality on average. Conversely, in Venezuela, the differences among regions, *Level* 0, and between municipalities, *Level* 2, traditionally represent the major drivers of overall inequality (which may signal a different aggregate degree of territorial economic development than the rest of Andean countries).

Finally, to examine the presence of spatial heterogeneities, Figure 5 exhibits the raw contributions to the Theil index in 2012, 2021, and the change between these two years, categorized by country at the lowest-level administrative division.

In this paper, the index captures the degree to which the distribution of light data among different groups differs from the distribution of population data among those same groups. In this sense, groups with higher proportions of the intensity of light compared to their population shares contribute positively to the Theil index; in contrast, those with lower shares of the intensity of light relative to their population shares contribute negatively.

Figure 5: Contributions to the Theil Index by Andean Country: Lowest-Level Administrative Division



Source: Own calculations.

In each year's column, red and dark green areas represent spatial locations where the relative proportions are strongly negative and strongly positive, respectively. In contrast, yellowish and light green areas are contributions closer to zero. In the column of changes, green areas must draw our main attention.

In the past decade, approximately one-third of Bolivia and Colombia, and around 40 percent of Peru, have continued to show positive contributions to the Theil index, indicating persistent disparities where light data surpasses population data. These areas represent "structural" challenges in terms of wealth inequality. Bolivia and Peru experienced a similar increase/decrease in areas denoting wealth inequality (around 8 percent and 10 percent, respectively). The situation differs in Colombia, where 10 percent of its territory faced newly emerged areas characterized by wealth inequality or recent inequality spots (light green in the last column), and only 6 percent resulted in newly emerged areas leaving wealth inequality (i.e., a net increase of 4 percent of its territory facing wealth inequality). Despite these variations, all three countries have experienced a significant reduction in overall inequality.[21] This suggests that there has been a general decrease in wealth inequality across areas where inequality has traditionally prevailed.

Ecuador's overall inequality has shown minimal change. Notably, 43 percent of its territory still experienced wealth inequality in 2021 compared to 2012. There was also a net increase of 3 percent in the territory with wealth inequality, with 9 percent of newly emerged parishes demonstrating wealth inequality compared to 6 percent of parishes where inequality had "ceased."

Here, again, Venezuela differs significantly from the other countries. In 2021, wealth inequality appeared highly concentrated in approximately 30 percent of its territory. This concentration can be attributed to persistent wealth disparities in 26 percent of the parishes, as well as the emergence of new parishes (4 percent) where inequality has manifested. The stark spatial concentration of wealth inequality suggests significant variations in economic development across different regions of the country. Furthermore, Venezuela is

[21] For details, see Table 4.

the only Andean country where the Theil index has increased, indicating a net worsening of wealth inequality.

5. Conclusion

In recent years, insights into the extent and spatial nature of inequality across countries have increasingly relied on novel approaches to gather comprehensive data and analyze patterns on a local and global scale. One such approach involves applying remote sensing techniques. This paper uses satellite-recorded nighttime lights and gridded population datasets from 2012 to 2021 to shed light on how spatial dimensions contribute as primary sources of inequality and how these contributions vary across each country of the Andean region. In this sense, we follow multiple-stage nested Theil decomposition method using night light emissions as a proxy of economic wealth.

The study confirms a reduction in overall inequality for the Andean region between 2012 and 2021 (primarily driven by a decline in between-country inequality) and an increase in the relative importance of within-country inequality. This result emphasizes the unique challenges and particularities in the region. Moreover, the paper also verifies the urgency of addressing wealth inequality in Venezuela, highlighting the need to carry out new complementary studies in this field.

The main results also reveal spatial heterogeneities within each country. Bolivia, Colombia, and Peru experienced a substantial decline in wealth inequality over the past decade. Bolivia's reduction in inequality can be attributed to the decline in disparities between provinces, while Colombia and Peru witnessed decreases within departments and provinces, respectively. They also experienced a significant increase in the relative contribution of their within-inequality component.

On the other hand, Ecuador has shown a minimal change in overall inequality, and Venezuela stands out as the only country in the Andean region where inequality has increased, primarily driven by changes in the disparity between all geographic subgroups. Ecuador and Venezuela exhibit more balanced contributions of their components to their inequality outcomes, although Ecuador's cantons and Venezuela's regions play crucial roles.

Reducing inequality should follow different mechanisms operating spatially and temporally. The main findings underscore the persistent challenges in wealth inequality and highlight the potential for local interventions to foster more equitable societies in the Andean region.

5. References

Akita, T. (2003). Decomposing regional income inequality in China and Indonesia using two-stage nested Theil decomposition method. *The Annals of Regional Science*, *37*, 55–77.

Alesina, A., Michalopoulos, S., & Papaioannou, E. (2016). Ethnic inequality. *Journal of Political Economy*, *124*(2), 428–488.

Alstadsæter, A., Johannesen, N., & Zucman, G. (2019). Tax evasion and inequality. *American Economic Review*, *109*(6), 2073–2103.

Andersen, L. E., Guzmán, G., & Garbasevshi, O. (2023, January). *Electricity Consumption, Nightlights, and Local Development in Bolivia*. https://sdsnbolivia.org/en/electricity-consumption-nightlights-and-local-development-in-bolivia/

Andrade-Núñez, M. J., & Aide, T. M. (2020). Using nighttime lights to assess infrastructure expansion within and around protected areas in South America. *Environmental Research Communications*, *2*(2), 021002.

Andreano, M. S., Benedetti, R., Piersimoni, F., & Savio, G. (2021). Mapping poverty of Latin American and Caribbean countries from heaven through night-light satellite images. *Social Indicators Research*, *156*(2-3), 533–562.

Andrian, L. G., & Manzano, O. (2023). Nuevos horizontes de transformación productiva en la Región Andina. *Monografía del BID*, *1022*.

Ayala, L., Pérez, A., & Prieto-Alaiz, M. (2022). The Impact of Different Data Sources on the Level and Structure of Income Inequality. *SERIEs*, *13*(3), 583–611.

Bird, K. (2013). The intergenerational transmission of poverty: An overview. *Chronic poverty: Concepts, causes and policy*, 60–84.

Bourguignon, F. (1979). Decomposable income inequality measures. *Econometrica*, *47*(4), 901–920.

Bruederle, A., & Hodler, R. (2018). Nighttime lights as a proxy for human development at the local level. *PloS one*, *13*(9).

Burkhauser, R. V., Feng, S., Jenkins, S. P., & Larrimore, J. (2012). Recent trends in top income shares in the United States: Reconciling estimates from March CPS and IRS tax return data. *Review of Economics and Statistics*, *94*(2), 371–388.

Cabrera-Barona, P. F., Bayón, M., Durán, G., Bonilla, A., & Mejía, V. (2020). Generating and mapping Amazonian urban regions using a geospatial approach. *ISPRS International Journal of Geo-Information*, *9*(7), 453.

Carr, M. D., & Wiemers, E. E. (2018). New evidence on earnings volatility in survey and administrative data. *AEA Papers and Proceedings*, *108*, 287–291.

Castilleja, L. (2020). La clase media andina frente al shock del Covid-19. *Documento para Discusión IDB-DP-00774*.

Chen, X. (2016). Addressing measurement error bias in GDP with nighttime lights and an application to infant mortality with Chinese county data. *Sociological Methodology*, *46*(1), 319–344.

Conceição, P., & Ferreira, P. (2000). *The young person's guide to the Theil index: Suggesting intuitive interpretations and exploring analytical applications* (UTIP Working Paper No. 14). University of Texas at Austin.

Courtemanche, C., Denteh, A., & Tchernis, R. (2019). Estimating the associations between SNAP and food insecurity, obesity, and food purchases with imperfect administrative measures of participation. *Southern Economic Journal*, *86*(1), 202–228.

Dahl, M., DeLeire, T., & Schwabish, J. A. (2011). Estimates of year-to-year volatility in earnings and in household incomes from administrative, survey, and matched data. *Journal of Human Resources*, *46*(4), 750–774.

Dai, Z., Hu, Y., & Zhao, G. (2017). The suitability of different nighttime light data for GDP estimation at different spatial scales and regional levels. *Sustainability*, *9*(2), 305.

De la Cruz, R., Manzano, O., & Loterszpil, M. (2020). Cómo acelerar el crecimiento económico y fortalecer la clase media: América Latina. *Monografía del BID*, *782*.

Deaton, A. (2005). Measuring poverty in a growing world (or measuring growth in a poor world). *Review of Economics and Statistics*, *87*(1), 1–19.

Deaton, A. (2016). Measuring and understanding behavior, welfare, and poverty. *American Economic Review*, *106*(6), 1221–1243.

Earth Observation Group. (2022, June). *Payne Institute for Public Policy - Colorado School of Mines* [Accessed on June 7, 2022]. https://payneinstitute.mines.edu/eog/nighttime-lights/

Economic Commission for Latin America and the Caribbean, ECLAC, (2018). *Ruralidad, hambre y pobreza en América Latina y el Caribe* (tech. rep. No. LC/TS.2018/119). ECLAC. Santiago.

Economic Commission for Latin America and the Caribbean's Statistical Database. (2022, January). Eclacstat [Accessed on January 12, 2023]. United Nations. https://statistics.cepal.org/portal/cepalstat/dashboard.html?lang=en

Elbers, C., Lanjouw, P., Mistiaen, J. A., & Özler, B. (2008). Reinterpreting between-group inequality. *The Journal of Economic Inequality*, *6*, 231–245.

Elvidge, C. D., Baugh, K., Zhizhin, M., Hsu, F.-C., & Ghosh, T. (2017). VIIRS night-time lights. *International Journal of Remote Sensing*, *38*(21), 5860–5879.

Elvidge, C. D., Baugh, K. E., Zhizhin, M., & Hsu, F.-C. (2013). Why VIIRS data are superior to DMSP for mapping nighttime lights. *Proceedings of the Asia-Pacific Advanced Network*, *35*(62).

Elvidge, C. D., Zhizhin, M., Ghosh, T., Hsu, F.-C., & Taneja, J. (2021). Annual time series of global VIIRS nighttime lights derived from monthly averages: 2012 to 2019. *Remote Sensing*, *13*(5), 922.

Ferreira, T. (2018). *Using satellite data to track socio-economic outcomes: a case study of Namibia* (tech. rep.). Stellenbosch University, Department of Economics.

Floerkemeier, H., Spatafora, N., & Venables, A. (2021). Regional disparities, growth, and inclusiveness. *International Monetary Fund (IMF) Working Paper No. 38*.

Galbraith, J. K. (2019). Sparse, inconsistent and unreliable: Tax records and the world inequality report 2018. *Development and Change*, *50*(2), 329–346.

Galimberti, J. K., Pichler, S., & Pleninger, R. (2023). Measuring inequality using geospatial data. *The World Bank Economic Review*, *37*(4), 549–569.

Gibson, J., & Boe-Gibson, G. (2021). Nighttime lights and county-level economic activity in the United States: 2001 to 2019. *Remote Sensing*, *13*(14), 2741.

Gilliland, J. A., Shah, T. I., Clark, A., Sibbald, S., & Seabrook, J. A. (2019). A geospatial approach to understanding inequalities in accessibility to primary care among vulnerable populations. *PloS One*, *14*(1), e0210113.

Haithcoat, T. L., Avery, E. E., Bowers, K. A., Hammer, R. D., & Shyu, C.-R. (2021). Income inequality and health: Expanding our understanding of state-level effects by using a geospatial big data approach. *Social Science Computer Review*, *39*(4), 543–561.

Henderson, J. V., Storeygard, A., & Weil, D. N. (2012). Measuring economic growth from outer space. *American Economic Review*, *102*(2), 994–1028.

Hodler, R., & Raschky, P. A. (2014). Regional favoritism. *The Quarterly Journal of Economics*, *129*(2), 995–1033.

Inter-Agency Coordination Platform for Refugees and Migrants from Venezuela. (2023). *R4V (website)* [Accessed on March 15, 2023]. https://www.r4v.info/

Jagnani, M., & Khanna, G. (2020). The effects of elite public colleges on primary and secondary schooling markets in India. *Journal of Development Economics*, *146*, 102512.

Keola, S., Andersson, M., & Hall, O. (2015). Monitoring economic development from space: using nighttime light and land cover data to measure economic growth. *World Development*, *66*, 322–334.

Khan, M. S., & Siddique, A. B. (2021). Spatial analysis of regional and income inequality in the United States. *Economies*, *9*(4), 159.

Kharas, H., Di Nucci, C., Hamel, K., & Tong, B. (2020). To move the needle on ending extreme poverty, focus on rural areas.

Lanjouw, P. F., & Tarp, F. (2021). Poverty, vulnerability and Covid-19: Introduction and overview. *Review of development economics*, *25*(4), 1797–1802.

Lessmann, C., & Seidel, A. (2017). Regional inequality, convergence, and its determinants–a view from outer space. *European Economic Review*, *92*, 110–132.

Levin, N., Kyba, C. C., Zhang, Q., de Miguel, A. S., Román, M. O., Li, X., Portnov, B. A., Molthan, A. L., Jechow, A., Miller, S. D., et al. (2020). Remote sensing of night lights: A review and an outlook for the future. *Remote Sensing of Environment*, *237*, 111443.

Li, X., Li, D., Xu, H., & Wu, C. (2017). Intercalibration between DMSP/OLS and VIIRS night-time light images to evaluate city light dynamics of Syria's major human settlement during Syrian Civil War. *International Journal of Remote Sensing*, *38*(21), 5934–5951.

Li, X., Zhou, Y., Zhao, M., & Zhao, X. (2020). A harmonized global nighttime light dataset 1992–2018. *Scientific Data*, *7*(1), 1–9.

Lynn, P., Jäckle, A., Jenkins, S. P., & Sala, E. (2012). The impact of questioning method on measurement error in panel survey measures of benefit receipt: Evidence from a validation study. *Journal of the Royal Statistical Society Series A: Statistics in Society*, *175*(1), 289–308.

Maldonado, L. (2022). Lighting-up the economic activity of oil-producing regions: A remote sensing application. *Remote Sensing Applications: Society and Environment*, *26*, 100722.

Maldonado, L. (2023). Living in darkness: Rural poverty in Venezuela. *Journal of Applied Economics*, *26*(1), 2168464.

Martinez, L. R. (2022). How much should we trust the dictator's GDP growth estimates? *Journal of Political Economy*, *130*(10), 2731–2769.

McCord, G. C., & Rodriguez-Heredia, M. (2022). Nightlights and subnational economic activity: Estimating departmental GDP in Paraguay. *Remote Sensing*, *14*(5), 1150.

Mejía Juárez, V. (2020). Procesos de urbanización y morfología urbana en Ecuador: La evolución de los usos del suelo a la luz de la imagen satelital nocturna de la Tierra 1992-2019.

Meyer, B. D., & Mittag, N. (2021). Combining administrative and survey data to improve income measurement. *Administrative Records for Survey Methodology*, 297–322.

Mirza, M. U., Xu, C., Bavel, B. v., Van Nes, E. H., & Scheffer, M. (2021). Global inequality remotely sensed. *Proceedings of the National Academy of Sciences*, *118*(18).

Morduch, J., & Sicular, T. (2002). Rethinking inequality decomposition, with evidence from rural China. *The Economic Journal*, *112*(476), 93–106.

Moss, T., Bazilian, M., Blimpo, M., Culver, L., Kincer, J., Mahadavan, M., Modi, V., Muhwezi, B., Mutiso, R., Sivaram, V., et al. (2020). The Modern Energy Minimum: The case for a new global electricity consumption threshold. *Energy for Growth Hub*, *30*.

Mveyange, A. (2015). *Night Lights and Regional Income Inequality in Africa* (tech. rep. No. 2015/085). WIDER Working Paper.

Nordhaus, W. D., & Chen, X. (2012). Improved estimates of using luminosity as a proxy for economic statistics: new results and estimates of precision.

Oak Ridge National Laboratory, ORNL. (2023, February). *LandScan Global Population Database. Oak Ridge, TN: Oak Ridge National Laboratory.*

Paredes, D., Iturra, V., & Lufin, M. (2012). *A further step to understand income inequality in Chile: A decomposition using three-stages nested Theil index decomposition method* (tech. rep. No. 25). Universidad Católica del Norte, Chile, Department of Economics.

Parés-Ramos, I. K., Álvarez-Berríos, N. L., & Aide, T. M. (2013). Mapping urbanization dynamics in major cities of Colombia, Ecuador, Perú, and Bolivia using night-time satellite imagery. *Land*, *2*(1), 37–59.

Pinkovskiy, M., & Sala-i-Martin, X. (2016). Lights, camera… income! Illuminating the national accounts-household surveys debate. *The Quarterly Journal of Economics*, *131*(2), 579–631.

Puttanapong, N., Luenam, A., & Jongwattanakul, P. (2022). Spatial analysis of inequality in Thailand: Applications of satellite data and spatial statistics/econometrics. *Sustainability*, *14*(7), 3946.

Rabiei-Dastjerdi, H., & Matthews, S. A. (2021). Who gets what, where, and how much? Composite index of spatial inequality for small areas in Tehran. *Regional Science Policy & Practice*, *13*(1), 191–205.

Rodríguez-Pose, A., & Hardy, D. (2015). Addressing poverty and inequality in the rural economy from a global perspective. *Applied Geography*, *61*, 11–23.

Sachs, J., Lafortune, G., Kroll, C., Fuller, G., & Woelm, F. (2022). *From Crisis to Sustainable Development: the SDGs as Roadmap to 2030 and Beyond* (Sustainable Development Report 2022.). Cambridge University Press. Cambridge.

Seminario, B., & Palomino, L. (2022). *Estimación del PIB a nivel subnacional utilizando datos satelitales de luminosidad: Perú, 1993-2018.* Universidad del Pacífico.

Shorrocks, A., & Wan, G. (2005). Spatial decomposition of inequality. *Journal of Economic Geography*, *5*(1), 59–81.

Shorrocks, A. F. (1980). The class of additively decomposable inequality measures. *Econometrica*, *48*(3), 613–625.

Sinha, A., Balsalobre-Lorente, D., Zafar, M. W., & Saleem, M. M. (2022). Analyzing global inequality in access to energy: Developing policy framework by inequality decomposition. *Journal of Environmental Management*, *304*, 114299.

Smith, B., & Wills, S. (2018). Left in the dark? Oil and rural poverty. *Journal of the Association of Environmental and Resource Economists*, *5*(4), 865–904.

Stampini, M., Robles, M., Sáenz, M., Ibarrarán, P., & Medellín, N. (2015). *Pobreza, vulnerabilidad y la clase media en América Latina* (tech. rep.). IDB Working Paper Series.

Theil, H. (1967). *Economics and information theory*. North-Holland Pub. Co.; Rand McNally.

Wang, X., Rafa, M., Moyer, J. D., Li, J., Scheer, J., & Sutton, P. (2019). Estimation and mapping of sub-national GDP in Uganda Using NPP-VIIRS imagery. *Remote Sensing*, *11*(2), 163.

Weidmann, N. B., & Schutte, S. (2017). Using night light emissions for the prediction of local wealth. *Journal of Peace Research*, *54*(2), 125–140.

Weidmann, N. B., & Theunissen, G. (2021). Estimating local inequality from nighttime lights. *Remote Sensing*, *13*(22), 4624.

Wu, D., Yuan, L., Li, R., & Li, J. (2018). Decomposing inequality in research funding by university-institute sub-group: A three-stage nested Theil index. *Journal of Informetrics*, *12*(4), 1312–1326.

Yin, X., Li, P., Feng, Z., Yang, Y., You, Z., & Xiao, C. (2021). Which gridded population data product is better? Evidences from mainland Southeast Asia (MSEA). *ISPRS International Journal of Geo-Information*, *10*(10), 681.

Zhang, L., Li, X., & Chen, F. (2020). Spatiotemporal analysis of Venezuela's nighttime light during the socioeconomic crisis. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *13*, 2396–2408.

Zhao, M., Zhou, Y., Li, X., Zhou, C., Cheng, W., Li, M., & Huang, K. (2019). Building a Series of Consistent Night-Time Light Data (1992–2018) in Southeast Asia by Integrating DMSP-OLS and NPP-VIIRS. *IEEE Transactions on Geoscience and Remote Sensing*, *58*(3), 1843–1856.