

Maldonado, Leonardo J.

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# Living in darkness: rural poverty in Venezuela

Leonardo Maldonado 

Department of Applied Economics, University of Minnesota, Twin Cities, MN, USA

## ABSTRACT

This paper uses nighttime lights imagery and gridded population datasets to estimate 2000–2020 rural poverty rates for Venezuela at the state and municipality levels. Then, I examine if there has been a significant change in rural poverty during the economic collapse ongoing since 2013–2014. The main finding reveals that most of the Venezuelan territory experienced a considerable increase in rural poverty rates between 2014 and 2020. Furthermore, I confirm how new rural poor areas appear across the country in clusters, surrounding municipalities with moderate to high poverty rates. This suggests that in recent years, more Venezuelans have sunk in darkness.

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Crisis; nighttime lights; rural poverty; Venezuela

## 1. Introduction

Today, most of the world's extreme poor live in rural areas. Rural poverty represents 80 percent of total extreme poverty, while about 45 percent of rural residents are at least moderately poor (Castañeda et al., 2018; Olinto et al., 2013). Most of them have no access to electricity, being electricity deprivation a category of “multidimensional poverty.”<sup>1</sup> Despite significant efforts to increase global access to electricity,<sup>2</sup> there are still more than 750 million people suffering lack access to electricity, not equally distributed between rural and urban areas (Ritchie & Roser, 2019). The International Energy Agency and others estimate that half of people without electricity live in fragile and conflict-affected settings and about 83 percent are in rural areas (2022). The scenario is not different for Central and South America, where more than 25 million people lagged on electricity access. This data is significantly valuable on aggregated terms. However, deepening any analysis about poverty at the local level requires obtaining data overcoming availability issues from infrequent and expensive household surveys.

This paper applies a remote sensing approach to address the unavailability of local rural poverty data for Venezuela. I use satellite-recorded night light emissions and gridded population data to estimate rural poverty rates at the state and municipality levels. I follow a technical procedure to extract, calibrate, and harmonize nighttime light data from two instruments to align them to population data on a cell area of 1 × 1

**CONTACT** Leonardo Maldonado  [lmaldonadoucvc@gmail.com](mailto:lmaldonadoucvc@gmail.com)  Department of Applied Economics, University of Minnesota, St. Paul Campus, Twin Cities, MN 55108, USA

<sup>1</sup>For details, see World Bank (2018)'s report on poverty and shared prosperity. Multidimensional poverty is a measure that considers income and access to basic infrastructure, education, health, and security.

<sup>2</sup>In 2020, 91 percent of the world population had access, which is significantly greater than the 70 percent in 1990 and the 83 percent in 2010 (2022).

kilometers, covering 2000–2020. The results identify Amazonas, Apure, Barinas, Delta Amacuro, and Guarico as the five states with the highest rural poverty rate in 2020, while the Capital District, Carabobo, Miranda, Nueva Esparta, and Vargas have the lowest rates. I also examine if there has been a significant change in rural poverty throughout the recent economic collapse experienced in Venezuela. The paper verifies that most of the Venezuelan territory had a considerable increase in rural poverty rates since 2013–2014.

The general assumption in this literature is that night light emissions implicitly capture information about economic activity. Elvidge et al. (1997), Sutton and Costanza (2002), Doll et al. (2006), Ghosh et al. (2010), Henderson et al. (2012), confirm the relationship between economic activity and lights, the last one proposing a statistical framework to measure actual economic growth. More recently, Bruederle and Hodler (2018) use nighttime lights to estimate human development at a local level, Ferreira et al. (2018) tracks regional socio-economic outcomes for Namibia, and Arderne et al. (2020) identify electrification targets using open data and nighttime lights imagery.

In this context, oil-dependent countries as Venezuela (oil exports accounted for around 75 percent of its total export revenue on average during the last decade and more than 60 percent by 2020), where government efforts of diversification, industrialization, and poverty alleviation proceed from a stable oil market, are less documented. These economies are usually more subject to external shocks (for example, sudden changes in international commodity prices), which might endanger their finances, impacting public policies and the household behavior to migrate or settle down in a specific area. Furthermore, countries with an important oil industry have specificities that may influence how the institutional framework, policy planning, and political economy evolve (Manzano et al., 2008) and do not necessarily invest more in local electrical infrastructure (Min, 2010).

This paper relies on the idea that nighttime lights and spatially distributed population data allow measuring rural poverty, considering any inhabitant living in unlit cells as rural poor (Smith & Wills, 2018). This assumption leads to two immediate limitations. First, access to electricity is the only dimension to consider in poverty identification. Second, this paper neither identifies urban poverty nor cannot rule out its presence. For example, Petare is a neighborhood located in the Sucre municipality in the steep hills of northwestern Miranda state, Venezuela. According to 2011 census results, the population in Petare is 372,470. It is still considered one of the largest urban slums in Latin America with significant access to informal electricity service; therefore, its poverty rate is not accounted for by this approach. Nevertheless, both limitations still allow us to understand any eventual estimate as a lower bound for rural and overall poverty in Venezuela.

Smith and Wills (2018) argue that using darkness to estimate poverty is simpler than identifying poverty in the light and that electrification could play a significant role in explaining rural poverty. Electrification is inferior in rural areas, mainly because they are located far from national grids or urban centers, involving high infrastructure costs to extend electrical grids. Therefore, having access to electricity could signaling policy efforts to alleviate poverty. It should also give a significant marginal return to rural residents, reducing the time allocated to fuelwood collection and increasing labor supply, schooling, household per capita income, and expenditure (Khandker et al., 2014). Furthermore, Smith and Wills (2018) confirm that people tend to switch from kerosene

to electric lighting soon after leaving extreme poverty, making access to electricity a good benchmark for rural poverty.

Venezuela is experiencing an economic collapse described in Kurmanaev (2019) as “...the worst outside of war in Decades”, which impacts poverty indicators. The 2021 National Survey of Living Conditions (ENCOVI) found that about 65 percent of Venezuelan households suffered multidimensional poverty in 2021.<sup>3</sup> That figure rises to 95 percent when measured by the poverty line, with almost 77% in extreme conditions. From 2013 to 2021, the gross domestic product (GDP) shrank about 75 percent, and the significant impacts of oil price shocks and domestic mismanagement led to a socio-economic crisis and a political situation with no precedent in Latin America (Cerra, 2016; Halff et al., 2017; Maldonado & Olivo, 2022; Saboin & Olivo, 2020; Vera, 2017). In 2016, the country entered hyperinflation and from then to the end of 2021, the Central Bank of Venezuela (BCV) reports an inflation rate near 30 billion percent. In this context, Venezuela has been experiencing a massive displacement crisis (more than 7 million Venezuelans have fled the country by September 2022 according to the Inter-Agency Coordination Platform for Refugees and Migrants from Venezuela, R4V, 2022).

The Venezuelan electrical system has gone into a dramatic deterioration. Electricity rationing was implemented by zones since 2008, and the regime declared an electrical emergency in 2009, announcing generation capacity development projects. Nonetheless, those development projects were not able to provide enough power supply to even support an already constrained demand in part due to a deprofessionalization of the sector and a narrow political criterion imposed on the planning and execution process (González Oquendo, 2019; Guevara Baro, 2020). Thus, service interruptions have been increasing, with progressively worse blackouts since 2010 (one of the mains leaving in the dark 90% of Venezuelan territory for several days in 2019, having adverse humanitarian consequences and sectorial effects as indicated by Sabatini & Patterson, 2021). In this sense, the country's energy crisis is still ongoing, and rebuilding the electricity sector is mandatory nowadays (Sabatini & Patterson, 2021). For example, the results of the 2019–2020 ENCOVI suggest that 90 percent of households in Venezuela report interruption of electric service, of which 32 percent reported daily failures. This scenario reminds us that it is not only the case that the central government must effectively provide electricity grids, but even with electrical grids installed, there could be long periods of low intensity or lack of lights. This remarks how access to public services, such electricity, might be a vital predictor of poverty in Venezuela.

Alongside the socio-economic crisis occurs a political turmoil characterized by high polarization and citizen protests. The central claims lie in inferior quality and access to fuel, electricity, and water supply, as well as intense scenarios looking to regain social and civil rights and asking for a government change in 2014, 2017, and 2019. In particular, the regime response was repression by security forces and pro-government armed civilians (Denis, 2021; Venezuelan Observatory of Social Conflict, 2020). The current Venezuelan context is ideal for shedding light on how poverty is evolving in Venezuela and generating data to support eventual recovery efforts and poverty alleviation programs. This

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<sup>3</sup>The ENCOVI is a project launched in 2014 and conducted by academic researchers from three top universities of Venezuela: Andrés Bello Catholic University (UCAB), Central University of Venezuela (UCV), and Simón Bolívar University (USB), as a response to the lack of household's microdata collected by the National Institute of Statistics of Venezuela.

paper is an empirical exercise to spatially characterize rural poverty spanning 2000–2020. One main finding confirms how 2013–2014 were critical years from which rural poverty started rising in Venezuela.

The contribution of this paper is threefold. Firstly, Venezuela has no recent estimations of rural poverty at a geographically disaggregated level, and households microdata does not characterize poverty by urban-rural classification. Is rural poverty the same across all states and municipalities? This paper fills this gap by estimating rural poverty at subnational levels, matching satellite measures of nighttime lights with gridded population count as a novel less-costly alternative to obtain detailed independent results from methodologies based on surveys or administrative data. Spatial techniques are beneficial in reducing measurement errors in existing administrative data, especially in territories with informal settlements. A first approximation to understanding Venezuela's local dynamics requires recognizing these specificities.<sup>4</sup> A better understanding of the spatial distribution of rural poverty across the Venezuelan territory would allow policymakers to account for geographical locations while setting national and subnational policies.

Secondly, unlike Smith and Wills (2018), I calibrate and harmonize light datasets to generate time series spanning 2000–2020. I also derive the sigmoid relationship suggested by Zhao et al. (2019) and Li et al. (2020) between the light inputs. The sigmoid-like curve reveals a light intensity threshold that separates unlit areas or cells with low light intensity from brighter cells. Every pixel with population and light values below that “rural poverty threshold” defines a rural poor area.

Thirdly, this paper uses two multitemporal gridded population datasets to estimate rural poverty as an attempt to evaluate robustness and precision. In this sense, it is possible to verify which population distribution yields more precise and consistent estimates over time for Venezuela.

Two main strands of literature could benefit from this work. On the one hand, studies closely related to multidimensional and energy poverty in developing economies. Spagnoletti and O’Callaghan (2013), Khandker et al. (2014), González-Eguino (2015), Lee et al. (2016), Njiru and Letema (2018), Mendoza et al. (2019), Getie (2020) are some examples of studying the role of the access to electricity to poverty alleviation. On the other hand, studies characterizing poverty within regional dynamics and in resource-based countries as in Bazilian et al. (2013), Loayza and Rigolini (2016), and Smith and Wills (2018).

## 2. Study area and data

Venezuela is geographically located in northern South America. It is divided into one Capital District, 15 non-oil producing states (Amazonas, Aragua, Bolívar, Carabobo, Cojedes, Lara, Miranda, Mérida, Nueva Esparta, Portuguesa, Sucre, Táchira, Trujillo, Vargas, and Yaracuy), eight oil-producing states (Anzoátegui, Apure, Barinas, Delta Amacuro, Falcón, Guárico, Monagas, and Zulia), and Federal dependencies consisting in small offshore islands in the Caribbean Sea and the Gulf of Venezuela. In this exercise, the Federal dependencies are excluded due to the small number of observations.

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<sup>4</sup>This is not a new challenge. However, the studies highlighting the relevance of understanding rural poverty in Venezuela are from more than two decades ago (Llambí et al., 1994; Martel, 1995; Márquez, 1994; Riutort, 1999).

The characterization of rural poverty at the municipality level covers the period 2000–2020. To construct this sample and obtain estimates, I extract and process gridded datasets of population counts as well as satellite-recorded nighttime lights.

The population data come from two sources. The Oak Ridge National Laboratory (ORNL, 2021) provides the LandScan Global Population database. It represents an ambient population (average over 24 hours) distribution and is currently available annually from 2000 to 2019. I also use annual top-down unconstrained geospatial population distribution from the repository of WorldPop (2021) spanning the period 2000–2020. ORNL and WorldPop's imagery could be found at 30 arc-second resolution or a cell area of  $1 \times 1$  kilometers. In both cases, population counts are recalculated for the last five years to consider the severe international migration outflow experienced in Venezuela.<sup>5</sup>

Two instruments capture the light data. On the one hand, I have access to annual satellite imagery of the U.S. Air Force Defense Meteorological Satellite Program (DMSP) - Operational Linescan System for the period 1992–2013. DMSP datasets exist for 30 satellite-years.<sup>6</sup> On the other hand, the Earth Observation Group of the Payne Institute for Public Policy (Colorado School of Mines) produces a new -version 2- consistently processed time series of annual global nighttime light imagery from the Visible Infrared Imaging Radiometer Suite (VIIRS) on-board the Suomi National Polar-Orbiting Partnership satellite platform for the period 2012–2020. Looking for pre-filtered light data, I use the DMSP annual composites of stable lights and the VIIRS annual masked average radiance products (Elvidge et al., 2021).<sup>7</sup>

Figure 1 shows the spatial location of Venezuela with its states and the distribution of VIIRS lights across the territory for 2020. Each satellite imagery contains light intensity on a grid, where whiter pixels mean more light intensity and black pixels unlit areas. In the DMSP data, the unit of intensity of light is a six-bit digital number (DN), recorded for every 30 arc-second pixels. The values range from zero (unlit) to 63 (brightest light), and the sensors have no onboard calibration. Unlike DMSP data, the VIIRS raw data has a spatial resolution of 15 arc-seconds, providing more details; it has onboard calibration and a wider radiance range leading to more robust low light detection, thus not suffering from frequent saturation as in DMSP imagery.<sup>8</sup>

It is possible to align the population count pixels with nighttime lights on the same coordinate system, reaching a final sample spanning 2000–2020. Nevertheless, that requires performing extra technical work over the light data. DMSP data has no onboard calibration, so the paper must carry out an inter-annual calibration procedure from 2000 to 2013. There are also differences between DMSP and VIIRS datasets related to sensor

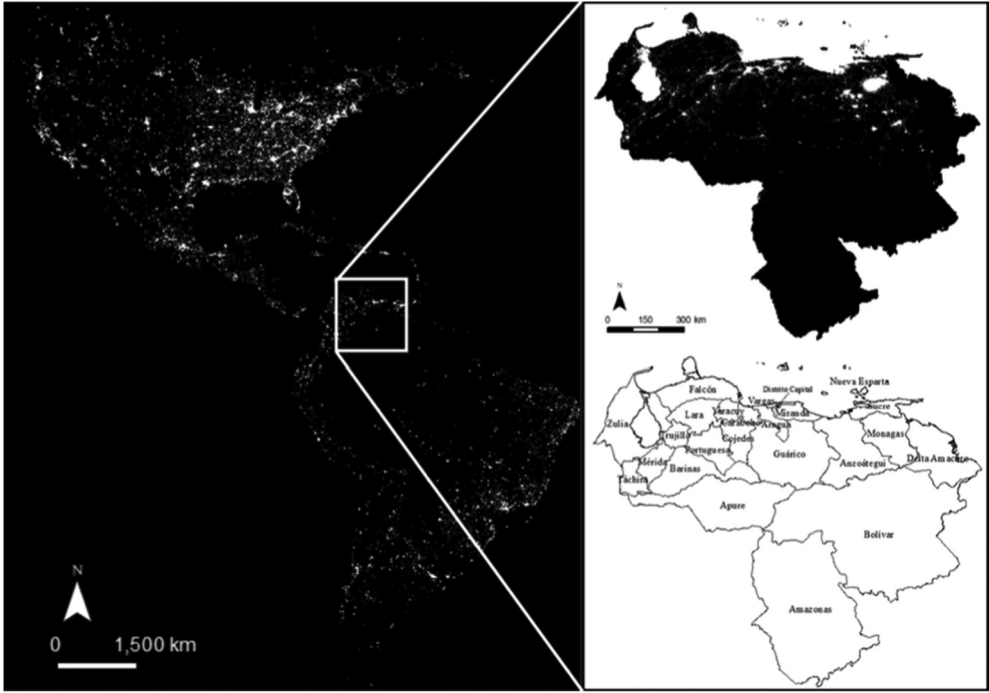
<sup>5</sup>For this, I assume an equally proportionally distributed effect throughout all pixels. The ORNL's files are at <https://landscan.ornl.gov/landscan-datasets>, while the WorldPop's files can be found at <https://www.worldpop.org/project/categories?id=3>.

<sup>6</sup>There are data from satellite F10 and F12 for the year 1994, F12 and F14 for 1997–1999, F14 and F15 for 2000–2003, and F15 and F16 for 2004–2007. In those years, I use the data from the newer satellite.

<sup>7</sup>The files are at the online repository of the Earth Observation Group (2022, January), Payne Institute – Colorado School of Mines: <https://payneinstitute.mines.edu/eog/nighttime-lights/>. For details, see the readme file associate with the respective sources.

<sup>8</sup>The measure of light intensity from DMSP data is top-coded at 63 and suffers saturation (Bluhm & Krause, 2018). However, this paper will characterize rural poverty through unlit areas or low-intensity lights, making irrelevant a top-coding correction approach.





**Figure 1.** VIIRS nighttime lights: Venezuela, 2020. Image and data processing by earth observation group, Payne institute for public policy, Colorado school of mines.

variations in spatial resolution, spectral response, point of spread function, overpass time at night, and wider radiance range of the VIIRS (Elvidge et al., 2013; Li et al., 2017, 2020; Zhao et al., 2019). Therefore, the analysis requires a harmonization procedure. In this case, the harmonization would result in identifying a light intensity threshold separating unlit areas or pixels recording very low light intensity from the rest.

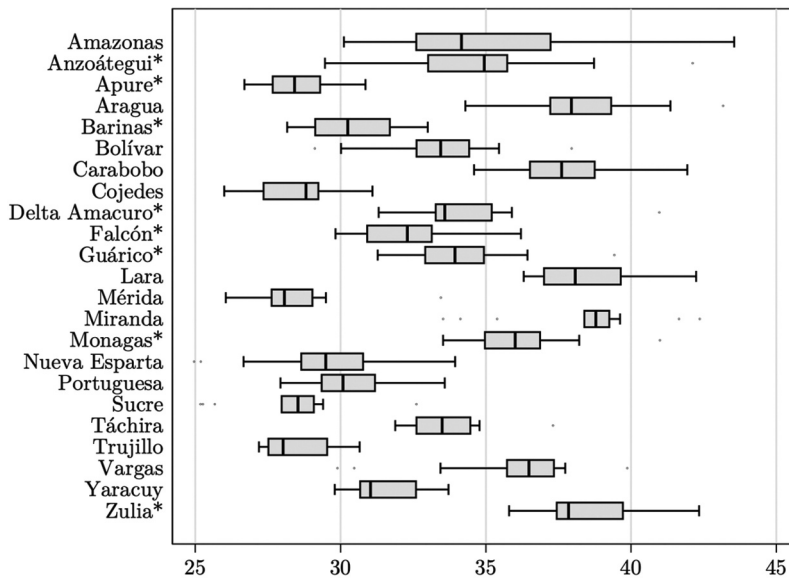
### 2.1. Nighttime lights: inter-annual calibration

Elvidge et al. (2009) propose a general and flexible framework for calibrating DMSP nighttime lights. The idea is to select a region with a relatively stable intensity of lights throughout the entire sample, an area more consistent and invariant across the years in terms of night light emissions. Then, they suggest selecting that region and the satellite-year with its maximum intensity of light as a benchmark or reference to apply a second-order regression model year by year (Equation 1). Finally, the calibration consists of using the yearly estimated coefficients to obtain fitted and rounded  $DN$  values for all the sample areas ( $DN_{adjusted}$ ).

$$DN_{adjusted} = \hat{\alpha}_0 + \hat{\alpha}_1 DN + \hat{\alpha}_2 DN^2 \quad (1)$$

In this case, I calculate the relative mean deviation (RMD) as a measure of the stability of lights. I consider all lit pixels and all the states of Venezuela between 2000 to 2013.





**Figure 2.** Boxplots of relative mean deviation, 2000–2013. The boxplots include outliers. distrito capital is not considered because of its relatively small number of pixels with respect to the other states. Pixel values of zero are excluded to calculate the relative mean deviation index. \*oil-producing states.

Figure 2 shows the results in boxplots. Trujillo has a lower median of RMD than the rest of the states, with most of its pixels denoting less relative deviation in the sample. In 2013, the intensity of lights in Trujillo averaged its highest value (12.3). For these reasons, Trujillo is selected as the reference state and 2013 as the base year to apply Equation 1. The estimated coefficients from the second-order regression model are in Table 1.

## 2.2. Nighttime lights: harmonization

The idea is to estimate 2014–2020 DMSP annual composites using 2013–2020 VIIRS annual composites as an input. Figure 3 shows each step of this procedure.

Firstly, I apply a cubic convolution resampling technique suitable for continuous data, smoothing and scaling the VIIRS spatial resolution to 30 arc-seconds (the same as for DMSP data). Then, I describe the relationship between the values of the calibrated DMSP and the logarithmic transformation of the VIIRS data -adding one to account for unlit pixels- through a sigmoid function with four parameters:  $a$ ,  $b$ ,  $c$ , and  $d$  (Equation 2). Zhao et al. (2019) and Li et al. (2020) propose this method noting that the radiance variation of processed VIIRS data differs across types of areas. They confirm that a sigmoid function captures adequately that relationship under different lit environments among rural, rural-urban transition zones, and urban cores.

$$DN_{simulated} = a + b \left( \frac{1}{1 + e^{-c(\text{Log}(\text{VIIRS}+1)-d)}} \right) \quad (2)$$

**Table 1.** Coefficients for the inter-annual calibration of DMSP using Equation 1 .

Year	$\hat{a}_0$	$\hat{a}_1$	$\hat{a}_2$	$R^2$
2000	0.4902	0.6503	0.0021	0.8922
2001	0.4896	0.6420	0.0023	0.8931
2002	0.6321	0.7028	0.0014	0.8878
2003	0.6654	0.3426	0.0057	0.8828
2004	1.0809	0.5769	0.0031	0.8962
2005	0.7819	0.4270	0.0054	0.9475
2006	0.7598	0.5679	0.0042	0.9268
2007	1.0371	0.6188	0.0034	0.9290
2008	0.4314	0.6501	0.0033	0.9597
2009	0.4215	0.5717	0.0041	0.9554
2010	0.8457	0.8495	0.0012	0.9527
2011	0.5562	0.6492	0.0044	0.9589
2012	0.3154	0.8131	0.0027	0.9741
2013	0.0000	1.0000	0.0000	1.0000

Trujillo is the reference because of its low relative mean deviation with no outliers in 2000–2013. The maximum intensity of light is reached in 2013 (base satellite-year to calibrate). Total observations per year are 9,579.

Table 2 shows the parameters obtained through the regression. Both datasets have 2012 and 2013 as common years, but 2012 VIIRS data is annualized using the months from April to December. Therefore, to avoid seasonality issues, this paper derives the parameters only accounting for the relationship in 2013.

### 3. Methodology

Rural areas relate to less illuminated space than urban areas, which could explain the low or moderate intensity of lights in regions with vast land (Li et al., 2020; Zhao et al., 2019). Agriculture and population dispersion play an important role in rural areas, and agricultural activity emits marginal lights (Keola et al., 2015). In fact, Keola et al. (2015) conclude that agricultural activity is better estimated through land cover datasets rather than using lights independently of the degree of development of a country. In this sense, areas moderately lit may capture most of the information to describe rural features while unlit areas or areas with very low light intensity could relate to rural poverty.

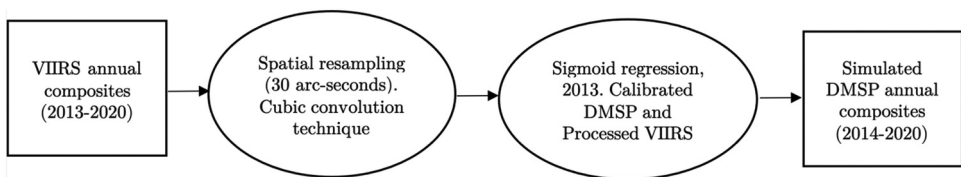
Smith and Wills (2018) suggest that darkness reveals poverty more easily than light. In particular, they characterize rural poverty assuming that any people living in unlit cells are rural poor. This paper considers that not only unlit cells but pixels with low intensity of light describe rural poverty. As Sutton (2003) argued, certain human activities always grow slightly around their light source due to blooming effects; thus, most of the low light intensity values from the calibrated and simulated DMSP are not necessarily urban areas. If that is the case, blooming effects might be shading rural features.

In this context, how low should the light intensity be to identify rural poverty? What is

**Table 2.** Parameters obtained through the sigmoid regression, 2013.

$a$	$b$	$c$	$d$	$R^2$	Observations
7.4384	55.3555	1.1929	1.6425	0.7218	164,826

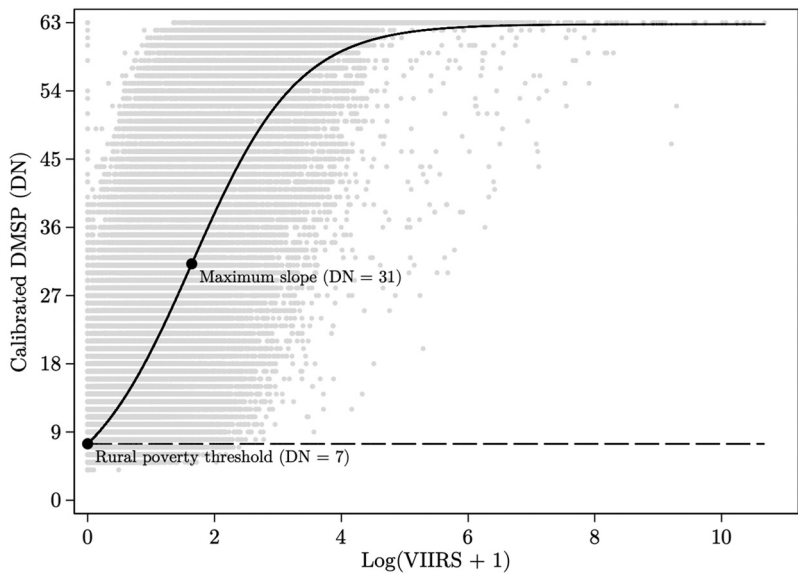
Note: the parameters represent the minimum value from DMSP on the fitting curve ( $a$ ), the difference between maximum and minimum values ( $b$ ), maximum slope ( $c$ ) and processed VIIRS value on the maximum slope ( $d$ ).



**Figure 3.** Simulating DMSP annual composites, 2014–2020.

the light threshold to define rural poverty? This paper answers these questions for Venezuela, not arbitrarily but through the technical identification of the sigmoid function proposed by Zhao et al. (2019) and Li et al. (2020). Both studies focus on using estimated parameters to describe human activity in urban cores. However, this methodology also identifies different lit environments allowing to obtain a rural poverty threshold.

Figure 4 presents the estimated sigmoid curve from the harmonization procedure. The rural threshold is the minimum value on the fitting curve ( $DN = 7$ ). Values of DMSP greater than 7 are already within the urban-rural transition zone. At the beginning, DN values increase more than proportional to  $\text{Log}(\text{VIIRS} + 1)$ , until the point of maximum slope ( $DN = 31$ ). In this zone, rural areas are transitioning to urban areas. After that point, the DMSP values still increase but less than proportional, tending to urban core values ( $DN \rightarrow 63$ ). In this context, the paper assumes that values in the urban-rural transition zone do not represent rural poverty. Therefore, the identification strategy to



**Figure 4.** Relationship between DMSP and VIIRS: sigmoid function, 2013. 2013 is a common year with data of lights from DMSP and VIIRS. The sigmoid function reaches its minimum at  $7.4384 \approx 7$  DN (threshold to group unlit pixels or pixels with low intensity values of lights during the harmonization process).

define rural poverty is:  $DN \leq 7$  with at least one inhabitant on a cell area of  $1 \times 1$  kilometers.

The estimates of rural poverty rates are based on two multitemporal gridded population datasets, ORNL's LandScan and WorldPop, as an attempt to evaluate robustness and precision. Nevertheless, Bustos et al. (2020) already warn us about significant technical dissimilarities in gridded population datasets and the relevance of choosing one over another depending on which is best suited for particular research needs in regional analyses.

To reduce volatility and noises regarding measurement errors or satellite sensitivity not captured during the calibration procedure, I create a measure of agglomeration grouping every grid fulfilling the decision criterion for rural poverty. This allows aggregating the rural poverty rate estimates at the municipality level weighting by the number of pixels.

This paper has two evident limitations. Firstly, the identification of rural poverty is based on access to electricity which is only one category of multi-dimensional poverty. Secondly, this paper neither identifies urban poverty nor cannot rule out its presence. Nevertheless, both limitations allow us to understand any eventual estimate from this approach as a lower bound for rural and overall poverty.

## 4. Results

Table 3 and 4 report some summary statistics for Venezuela and its states, respectively. On average, around 93 percent of the Venezuelan territory has a light intensity below the rural poverty threshold. WorldPop data show more populated territory than ORNL data. According to WorldPop, about 55.6 percent of total pixels have at least one inhabitant compared to 43.2 percent when using ORNL. The population density is similar independently of the source, but the population count reveals a major difference (74,666 with ORNL versus 13,294 with WorldPop); those values correspond to the same municipality: Sucre, Miranda. More pixels with WorldPop data satisfy the decision criterion for rural poverty (42.8 percent of total pixels).

The eight oil-producing states cover about 40 percent of the total territory, but their populated pixels more than double those of non-oil states. The light distribution does not reveal this significant difference. Five out of the 23 states plus the Capital District have less than 70 percent of their area below the rural poverty threshold. Neither of those states produces oil. Furthermore, excluding unlit areas and except for the Capital District, lights seem to be similarly sparse within each state.

The top states revealing significant gaps between the extension of lights and population are Amazonas, Bolivar, Carabobo, Delta Amacuro, Nueva Esparta, and the Capital District. To a lesser extent, Monagas and Zulia. In all those cases, only Carabobo, Nueva Esparta, and the Capital District consistently have more areas with zero or low light intensity than populated areas.

The results of rural poverty as a percentage of the state-level population are in Figure 5. In general, the satellite sensitivity reveals volatility during 2003–2004 and, in most cases, an absolute peak in 2003. During the period 2002–2003, Venezuela experienced significant political turmoil leading to a general strike and the onset of exchange rate controls. There are also broad trends. For example, the years 2013–2014 seem to

**Table 3.** Summary statistics (Pixel-Based): Venezuela, 2000–2020.

Variable	Observations	Mean	Standard deviation	Minimum	Maximum
<i>Total</i>					
Intensity of light $\leq 7$ DN	22,608,096	0.9256	0.2624	0	1
Population, ORNL	21,531,520	0.4324	0.4954	0	1
Rural poverty, ORNL	21,531,520	0.3703	0.4829	0	1
Population count, ORNL	21,531,520	25.7496	482.7273	0	74,666
Population, WorldPop	22,608,096	0.5560	0.4969	0	1
Rural poverty, WorldPop	22,608,096	0.4823	0.4997	0	1
Population count, WorldPop	22,608,096	25.7800	214.1708	0	13,294
<i>Non-oil producing states</i>					
Intensity of light $\leq 7$ DN	13,539,540	0.9416	0.2346	0	1
Population, ORNL	12,894,800	0.2722	0.4451	0	1
Rural poverty, ORNL	12,894,800	0.2216	0.4153	0	1
Population count, ORNL	12,894,800	27.9680	548.5228	0	74,666
Population, WorldPop	13,539,540	0.3687	0.4825	0	1
Rural poverty, WorldPop	13,539,540	0.3110	0.4629	0	1
Population count, WorldPop	13,539,540	28.7864	234.7769	0	13,294
<i>Oil-producing states</i>					
Intensity of light $\leq 7$ DN	9,068,556	0.9018	0.2976	0	1
Population, ORNL	8,636,720	0.6718	0.4696	0	1
Rural poverty, ORNL	8,636,720	0.5924	0.4914	0	1
Population count, ORNL	8,636,720	22.4375	362.9097	0	54,111
Population, WorldPop	9,068,556	0.8357	0.3706	0	1
Rural poverty, WorldPop	9,068,556	0.7381	0.4396	0	1
Population count, WorldPop	9,068,556	21.2915	178.9511	0	8,868

The ORNL population data is available until 2019.

**Table 4.** Summary of nighttime lights and population (Pixel-Based): state-level, 2000–2020.

State	Intensity of light (DN)				Population, ORNL		Population, WorldPop	
	0-7	8-30	31-63	Gini index	At least one inhabitant (total area)	Average density per 1 km <sup>2</sup>	At least one inhabitant (total area)	Average density per 1 km <sup>2</sup>
<i>Non-oil producing states</i>								
Amazonas	99.86%	0.11%	0.02%	0.3794	4.23%	0.5	4.07%	0.5
Bolivar	98.63%	1.19%	0.18%	0.355	19.51%	2.3	29.40%	4.8
Cojedes	90.09%	8.95%	0.97%	0.3249	80.24%	17.7	95.12%	19
Merida	86.57%	12.10%	1.33%	0.3134	66.65%	58.4	100.00%	56.3
Portuguesa	84.87%	13.55%	1.57%	0.3344	78.86%	39.6	98.41%	38.8
Lara	84.31%	12.75%	2.94%	0.3810	68.76%	84.5	99.96%	81.2
Tachira	80.86%	16.19%	2.95%	0.3489	80.71%	94.4	99.99%	95.7
Sucre	78.65%	19.32%	2.03%	0.3234	80.25%	71.8	99.62%	69.3
Yaracuy	74.41%	22.60%	2.99%	0.3183	76.32%	74.6	99.98%	83.8
Trujillo	72.42%	24.86%	2.72%	0.3124	73.20%	74.5	99.99%	74.3
Aragua	66.20%	25.76%	8.04%	0.382	81.70%	165.7	99.50%	207.5
Miranda	57.84%	29.61%	12.56%	0.3685	73.63%	259.2	99.86%	275.1
Vargas	49.02%	39.44%	11.54%	0.3500	43.57%	281.2	100.00%	300.6
Carabobo	33.41%	43.27%	23.32%	0.3749	69.86%	455.6	91.38%	410.1
Nueva Esparta	27.83%	38.48%	33.69%	0.3134	91.68%	364.5	100.00%	393
Capital District	1.31%	18.17%	80.53%	0.1747	93.35%	6,282.1	100.00%	5,189.6
<i>Oil-producing states</i>								
DeltaAmacuro	98.79%	1.04%	0.17%	0.3485	38.44%	2.7	65.73%	3.6
Apure	98.62%	1.28%	0.10%	0.2934	72.23%	3.7	66.63%	4.9
Guarico	95.13%	4.25%	0.61%	0.3529	81.96%	11.5	90.76%	9.1
Barinas	93.17%	6.13%	0.70%	0.3311	74.12%	18.6	95.66%	19.1
Falcon	88.30%	10.33%	1.37%	0.3513	79.33%	27.7	98.37%	28
Zulia	84.92%	11.91%	3.16%	0.3825	54.25%	68.5	98.11%	71.6
Anzoategui	78.96%	17.49%	3.56%	0.3654	72.03%	33.4	74.99%	26.4
Monagas	70.79%	21.22%	7.99%	0.3720	51.41%	34.4	97.21%	26.6

The states are sorted by the proportion of zero/very low intensity of lights, DN 0–7. Pixel values with DN 0–7 are excluded to calculate the Gini index. The ORNL population data is available until 2019.

reveal a common “before and after”. Before that period, there was general stability or even a slight downward trend (i.e., mostly between 2009 and 2013). Although the Venezuelan GDP shrank in 2009 and 2010, in 2010 were parliamentary elections and in 2012 presidential elections. As of 2013–2014, which coincides with the beginning of the current recession, rural poverty generally increased.

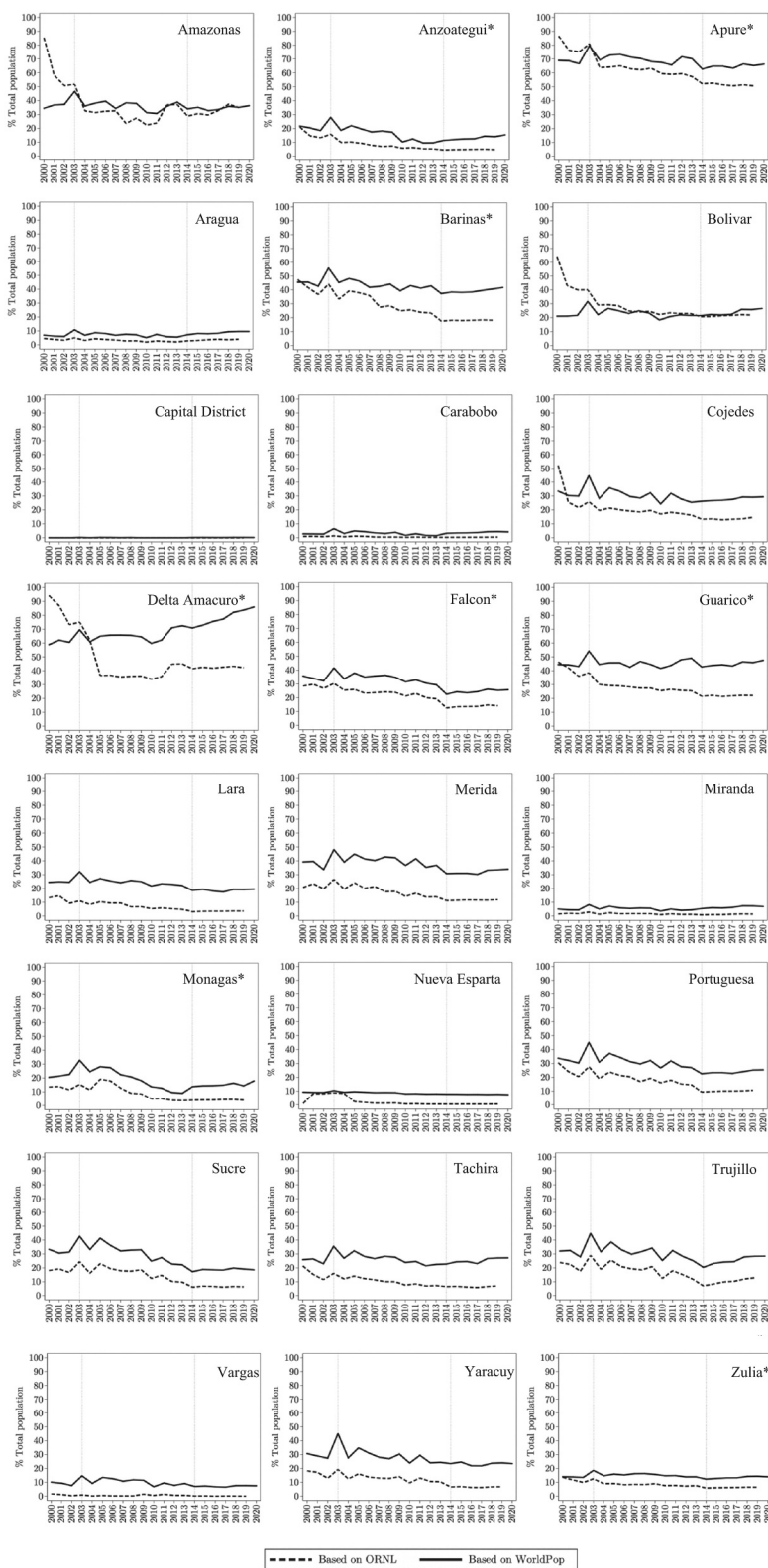
I find evidence that 2013–2014 was a switching period for rural areas in Venezuela using both sources, from which rural poverty has been spatially “expanding”. I calculate the number of populated pixels with values below the rural poverty threshold to calculate the relative change to 2014 (base year). [Figure 6](#) shows how the maximum values of the relative change reduced over time until 2014. All those relative differences are positives after 2014, confirming that unlit pixels with population started gaining extension in the presence of the ongoing economic collapse in Venezuela.

Rural poverty rate estimates with WorldPop are more consistent over time, and they are usually above the results from ORNL. Both ORNL and WorldPop have consistently shown higher accuracy in approximating the known population (Bustos et al., 2020). However, Bustos et al. (2020) specifically suggest using WorldPop over ORNL for determining populated areas and population estimates along with thresholds in low-density areas (i.e., rural regions). Furthermore, [Figure 7](#) represents the relative dispersion of each municipality result around its mean by population dataset throughout 2000–2020 (i.e., the coefficient of variation or the ratio of the standard deviation to the mean). In this case, results with ORNL show higher values compared to WorldPop, indicating more precise estimates from the latter. Therefore, even if both sources led to similar broad trends, this paper relies mostly on the estimates with WorldPop.

[Table 5](#) reports summary statistics and estimates of rural poverty rates for 2014 and 2020 based on WorldPop at the state and municipality level. The top five states with the highest rural poverty rate in 2020 are Amazonas (90 percent), Delta Amacuro (84.8 percent), Apure (71.2 percent), Barinas (60.6 percent), and Guarico (57.6 percent), while the bottom five are Nueva Esparta (11.9 percent), Miranda (10 percent), Vargas (7.6 percent), Carabobo (7.0 percent), and the Capital District (0.1 percent).

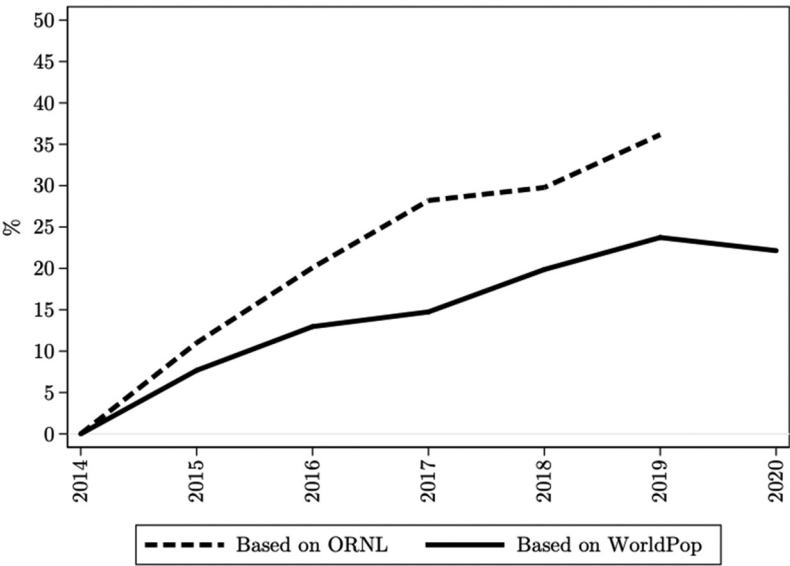
[Figure 8](#) shows how the rural poverty is spatially distributed in Venezuela for 2014 (panel a), as well as the change of rural poverty rates from 2014 to 2020 (panel b). In 2014, the higher rural poverty rates locate in the south and central Merida, central Tachira, and the Guayana region (Amazonas, Bolivar, and Delta Amacuro). Apure, Barinas, Falcon, and Zulia also show moderate to high rates in most of their territory. The Capital region (Miranda, Vargas, and the Capital District), the Eastern region (Anzoategui, Monagas, and Sucre), Aragua, Carabobo, Lara, Yaracuy, and the central north of Portuguesa have moderate to low rates. The Colombia-Venezuela border to the west of Tachira shows light intensity above the threshold, making difficult the identification of rural poverty; however, the paper cannot rule out the presence of urban poverty.

Rural poverty is increasing during the collapse, and new rural poor areas are appearing between 2014 to 2020 in clusters, mostly surrounding municipalities with moderate to high poverty rates. However, rural poverty is not following similar paths across all states and municipalities. For example, except for Nueva Esparta, the southwest of Sucre, Yaracuy, and some municipalities in Bolivar, Cojedes, Lara, Merida, Tachira, and

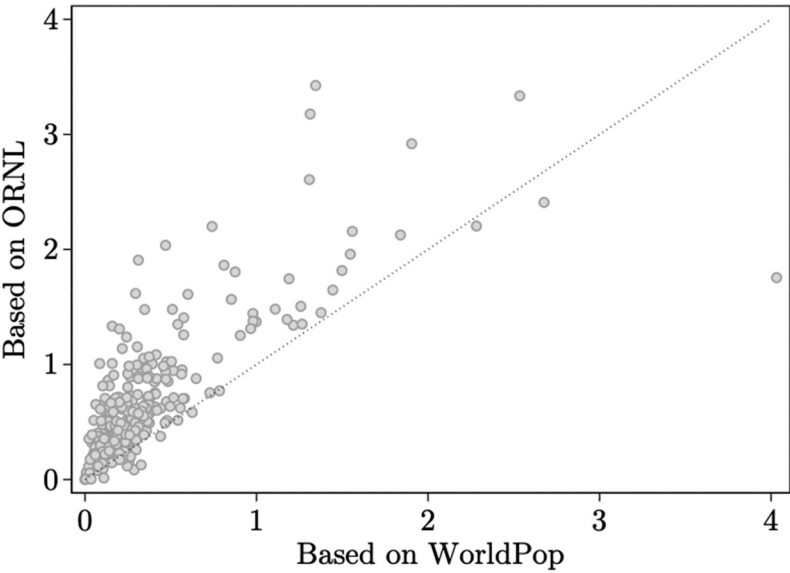


**Figure 5.** Rural poverty rate: State-Level. \*oil-producing state.





**Figure 6.** Rural poverty agglomeration Switch (Base Year 2014). The values represent the maximum relative change of each year to 2014 over the full sample at the state level.



**Figure 7.** Coefficient of variation: municipality-level, 2000–2020. The bisector is used as a reference.

Zulia, the rest of the country’s territory experienced an intensification of rural poverty.<sup>9</sup> These heterogeneities may be caused by the electricity rationing frequently imposed since

<sup>9</sup>For details, see [Table 5](#).

**Table 5.** Rural poverty rate based on WorldPop: municipality-level (sorted by 2020 estimates).

State and Municipality	Mean	Standard deviation	Minimum	Maximum	2014	2020
<i>Amazonas</i>	85.40%	8.50%	61.80%	91.90%	76.10%	90.00%
Alto Orinoco	100.00%	0.00%	99.80%	100.00%	100.00%	100.00%
Atabapo	96.70%	3.80%	88.90%	100.00%	90.00%	100.00%
Manapiare	84.10%	24.10%	28.60%	100.00%	28.60%	100.00%
Maroa	90.30%	16.60%	35.60%	100.00%	87.80%	100.00%
Rio Negro	95.70%	10.50%	55.60%	100.00%	100.00%	100.00%
Autana	99.60%	0.80%	97.70%	100.00%	98.00%	99.50%
Atures	31.30%	3.90%	26.40%	43.40%	28.20%	30.20%
<i>Delta Amacuro*</i>	76.30%	6.60%	62.60%	85.90%	78.70%	84.80%
Antonio Diaz	99.70%	0.30%	99.00%	100.00%	99.00%	100.00%
Pedernales	72.90%	18.00%	33.70%	96.70%	87.60%	96.70%
Casacoima	71.80%	5.00%	62.50%	79.30%	68.90%	79.30%
Tucupita	60.90%	3.10%	55.10%	67.70%	59.30%	63.30%
<i>Apure*</i>	73.40%	5.50%	64.50%	84%	67.50%	71.20%
Pedro Camejo	85.90%	6.00%	75.90%	98.80%	81.70%	85.50%
Achaguas	83.40%	3.70%	77.60%	91.00%	77.60%	82.70%
Muñoz	81.20%	5.60%	73.00%	91.90%	73.00%	76.80%
Romulo Gallegos	71.70%	3.20%	63.70%	75.60%	69.90%	74.90%
Paez	61.70%	3.50%	54.80%	68.70%	63.00%	65.50%
San Fernando	65.20%	5.40%	58.80%	80.20%	58.80%	61.20%
Biruaca	65.10%	11.00%	47.70%	81.70%	48.30%	52.10%
<i>Barinas*</i>	62.70%	6.40%	52.70%	76%	55.80%	60.60%
Andres Eloy Blanco	89.90%	3.60%	84.00%	96.20%	84.00%	89.80%
Cruz Paredes	80.70%	5.70%	64.30%	89.70%	79.30%	85.70%
Bolivar	73.10%	3.90%	67.10%	79.70%	69.90%	78.30%
Sosa	84.60%	7.20%	75.00%	98.20%	75.00%	76.00%
Pedraza	75.50%	5.30%	67.80%	85.90%	68.00%	74.70%
Arismendi	68.10%	5.30%	56.00%	80.90%	64.00%	70.50%
Ezequiel Zamora	66.00%	2.90%	60.80%	72.30%	63.90%	67.90%
Antonio Jose de Sucre	53.30%	3.70%	47.20%	64.60%	53.40%	54.50%
Rojas	74.30%	17.20%	49.30%	97.00%	49.30%	53.20%
Obispos	45.80%	10.40%	32.40%	73.10%	32.40%	37.30%
Alberto Arvelo Torrealba	25.20%	8.20%	15.20%	50.10%	17.00%	21.70%
Barinas	16.20%	3.30%	12.90%	27.60%	13.00%	17.20%
<i>Guarico*</i>	54.50%	4.80%	46.60%	65%	51.70%	57.60%
Santa Maria de Ipire	65.40%	15.70%	34.70%	86.90%	70.00%	86.90%
San Geronimo de Guayabal	80.70%	3.90%	74.40%	91.80%	74.40%	80.60%
San Jose de Guaribe	69.90%	4.30%	65.20%	79.80%	65.30%	71.20%
Ribas	71.60%	4.90%	63.60%	80.50%	63.60%	70.80%
Ortiz	69.90%	5.50%	61.20%	86.70%	63.40%	70.50%
El Socorro	68.60%	4.80%	60.00%	80.80%	66.60%	69.30%
Chaguaramas	63.20%	4.90%	57.50%	76.20%	58.40%	67.90%
Monagas	56.70%	4.60%	50.40%	65.70%	53.40%	60.90%
Las Mercedes	48.80%	5.70%	36.20%	61.50%	49.10%	55.20%
Miranda	46.90%	3.30%	43.10%	57.10%	46.70%	49.80%
Mellado	50.50%	4.10%	44.80%	61.10%	48.10%	48.80%
Zaraza	43.00%	2.50%	37.60%	48.20%	40.40%	46.10%
Infante	41.50%	2.70%	37.20%	48.00%	39.50%	44.60%
Camaguan	21.60%	1.70%	19.10%	26.80%	20.70%	22.30%
Roscio	19.60%	3.10%	14.40%	28.90%	16.50%	18.70%
<i>Bolivar</i>	55.90%	5.10%	46.80%	66%	53.90%	57.20%
Sucre	96.00%	1.90%	91.90%	98.70%	95.40%	97.50%
Sifontes	94.20%	2.20%	90.30%	97.50%	94.00%	95.60%
Cedeño	90.80%	2.20%	86.90%	94.60%	89.50%	93.40%
Gran Sabana	51.50%	12.90%	26.40%	70.60%	61.20%	70.60%
Padre Pedro Chien	78.70%	9.60%	62.40%	91.50%	62.40%	70.50%
Angostura	57.70%	5.40%	45.10%	67.20%	60.20%	67.20%
Piar	46.30%	5.80%	37.70%	61.50%	40.80%	43.40%
El Callao	37.30%	5.30%	28.60%	49.20%	32.60%	33.00%
Roscio	31.60%	3.60%	24.50%	43.00%	30.80%	30.80%
Heres	23.60%	3.50%	17.80%	32.70%	22.80%	21.50%

(Continued)

**Table 5.** (Continued).

State and Municipality	Mean	Standard deviation	Minimum	Maximum	2014	2020
Caroni	7.30%	3.70%	3.20%	18.50%	3.80%	6.00%
Merida	57.40%	8.80%	44.30%	73%	45.90%	51.50%
Aricagua	99.50%	0.80%	97.70%	100.00%	99.20%	99.30%
Guaraque	98.50%	2.10%	94.70%	100.00%	94.90%	96.50%
Justo Briceño	97.90%	2.60%	91.70%	100.00%	91.70%	96.50%
Arzobispo Chacon	97.10%	4.20%	90.50%	100.00%	91.70%	92.80%
Andres Bello	72.80%	8.90%	61.00%	92.60%	63.00%	71.30%
Padre Noguera	58.60%	9.10%	46.70%	87.10%	46.70%	68.30%
Caracciolo Parra Olmedo	72.90%	8.50%	60.70%	86.20%	62.70%	65.40%
Julio Cesar Salas	60.60%	10.80%	40.90%	82.80%	40.90%	57.20%
Santos Marquina	77.10%	16.90%	52.20%	97.10%	55.80%	57.20%
Sucre	61.70%	6.50%	51.10%	73.90%	54.30%	56.40%
Antonio Pinto Salinas	60.40%	11.70%	45.80%	80.10%	47.50%	54.60%
Obispo Ramos de Lora	57.80%	12.40%	38.20%	77.40%	39.00%	49.90%
Cardenal Quintero	73.30%	18.40%	47.10%	97.40%	47.50%	47.90%
Zea	40.60%	9.10%	25.00%	58.60%	25.00%	47.00%
Tulio Febres Cordero	46.00%	4.90%	36.90%	55.90%	37.00%	44.00%
Rangel	50.90%	13.50%	32.80%	80.20%	37.40%	35.20%
Miranda	31.30%	7.00%	19.50%	45.90%	21.40%	27.50%
Pueblo Llano	44.70%	21.30%	15.90%	87.80%	15.90%	25.30%
Alberto Adriani	22.30%	4.90%	15.10%	33.40%	19.80%	24.20%
Campo Elias	22.50%	3.10%	18.20%	31.80%	21.20%	21.80%
Libertador	21.80%	2.20%	18.10%	26.30%	20.30%	20.40%
Rivas Davila	31.10%	15.80%	9.20%	56.20%	10.70%	14.20%
Tovar	19.90%	7.50%	10.70%	34.20%	10.80%	10.70%
Falcon*	57.20%	8.30%	43.40%	71%	45.00%	50.20%
Democracia	86.50%	4.90%	77.10%	95.90%	77.10%	83.90%
Jacura	92.40%	8.70%	76.30%	100.00%	76.30%	83.30%
Union	85.50%	5.80%	73.80%	97.40%	73.80%	82.30%
Petit	85.30%	9.10%	66.50%	98.90%	66.50%	81.40%
Piritu	89.50%	8.30%	75.30%	100.00%	76.40%	80.80%
Bolivar	81.80%	9.10%	65.40%	95.40%	65.70%	75.30%
Palma Sola	91.60%	12.00%	67.50%	100.00%	85.80%	72.20%
Buchivacoa	81.60%	13.70%	56.90%	95.60%	56.90%	66.90%
Urumaco	73.80%	10.00%	55.20%	89.80%	55.20%	66.00%
Acosta	67.10%	6.80%	55.90%	84.30%	55.90%	61.90%
Mauroa	68.90%	9.90%	49.70%	79.60%	49.70%	60.70%
Sucre	69.90%	16.50%	46.60%	97.40%	46.60%	56.50%
Federacion	65.00%	13.10%	44.90%	83.00%	46.30%	49.90%
Dabajuro	50.30%	4.20%	43.40%	62.80%	44.60%	48.10%
San Francisco	55.90%	9.90%	41.10%	72.60%	43.80%	45.30%
Monseñor Iturriza	37.80%	5.30%	25.90%	50.50%	34.40%	41.00%
Cacique Manaure	41.90%	6.40%	32.90%	54.50%	32.90%	37.80%
Tocopero	46.10%	12.10%	31.00%	74.90%	32.50%	37.70%
Falcon	40.40%	12.00%	23.90%	65.20%	23.90%	32.60%
Zamora	34.30%	7.90%	22.80%	48.50%	24.90%	25.30%
Silva	25.10%	2.70%	20.90%	30.70%	20.90%	22.20%
Colina	30.70%	10.40%	16.00%	49.20%	16.00%	19.50%
Miranda	16.20%	3.10%	11.00%	22.90%	11.00%	14.10%
Carirubana	8.90%	3.30%	4.70%	16.50%	4.80%	5.40%
Los Tanques	3.10%	1.10%	1.00%	5.00%	4.00%	5.00%
Cojedes	47.60%	6.30%	38.20%	62%	41.30%	44.80%
Pao de San Juan Bautista	92.90%	6.70%	80.00%	100.00%	80.00%	88.20%
Girardot	82.00%	4.00%	74.00%	88.60%	81.00%	86.40%
Anzoategui	78.70%	13.40%	59.00%	100.00%	60.40%	67.70%
Romulo Gallegos	49.60%	5.00%	43.80%	61.80%	45.90%	45.60%
Ricaurte	47.00%	7.30%	39.10%	70.50%	39.10%	41.80%
Tinaco	33.20%	5.60%	26.40%	47.30%	26.90%	27.60%
Ezequiel Zamora	19.30%	4.70%	12.50%	35.30%	17.90%	20.20%
Falcon	13.50%	5.10%	1.80%	27.30%	12.60%	15.70%
Lima Blanco	12.60%	4.60%	6.90%	25.80%	7.60%	9.50%

(Continued)

**Table 5.** (Continued).

State and Municipality	Mean	Standard deviation	Minimum	Maximum	2014	2020
<i>Tachira</i>	42.00%	8.10%	30.10%	57.40%	34.50%	41.80%
Francisco de Miranda	99.80%	0.50%	98.10%	100.00%	98.10%	100.00%
Uribante	91.20%	2.70%	86.00%	97.50%	86.00%	89.60%
Panamericano	76.40%	7.80%	64.10%	91.00%	69.70%	72.10%
Samuel Dario Maldonado	73.60%	12.50%	52.00%	93.80%	64.70%	70.90%
Fernandez Feo	69.10%	6.20%	59.70%	79.90%	61.20%	69.20%
Rafael Urdaneta	74.80%	20.20%	38.00%	100.00%	38.00%	67.20%
Libertador	72.10%	9.90%	55.30%	83.90%	55.30%	66.30%
Sucre	74.10%	13.70%	57.30%	100.00%	59.10%	64.30%
Jose Maria Vargas	61.20%	18.30%	33.10%	96.20%	33.10%	56.20%
Garcia de Hevia	55.40%	3.50%	48.30%	62.20%	52.60%	53.80%
Seboruco	48.00%	11.30%	29.90%	73.20%	39.70%	51.60%
Cordoba	48.00%	4.30%	41.00%	59.20%	42.20%	49.20%
Simon Rodriguez	63.70%	21.60%	34.70%	97.50%	34.70%	48.20%
Antonio Romulo Costa	52.80%	14.90%	33.90%	85.40%	41.90%	39.20%
Libertad	13.50%	17.10%	0.00%	45.10%	20%	38.90%
Ayacucho	34.60%	5.80%	24.20%	47.20%	32.20%	37.60%
San Judas Tadeo	39.80%	10.90%	25.80%	64.60%	30.20%	33.80%
Jauregui	39.30%	6.50%	28.10%	50.90%	31.40%	33.50%
Torbes	33.30%	6.70%	22.60%	46.70%	25.00%	29.60%
Michelena	19.30%	8.80%	5.10%	38.60%	11.20%	28.50%
Lobatera	13.60%	7.40%	3.80%	28.60%	15.80%	26.50%
Andres Bello	12.90%	3.20%	7.60%	18.70%	8.00%	16.80%
Bolivar	11.70%	7.00%	0.90%	31.60%	12.30%	14.40%
Junin	10.20%	3.80%	5.50%	20.80%	8.40%	13.50%
Cardenas	14.30%	2.10%	10.40%	18.50%	13.70%	11.90%
San Cristobal	9.20%	2.20%	6.20%	13.60%	8.20%	11.70%
Independencia	2.50%	3.60%	0.00%	10.00%	3.40%	9.80%
Pedro Maria Ureña	4.80%	2.30%	1.10%	10.40%	3.90%	7.90%
Guasimos	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
<i>Portuguesa</i>	44.80%	8.50%	33.10%	62.70%	35.30%	39.40%
Papelon	87.50%	7.30%	75.60%	96.20%	75.60%	82.60%
Monseñor Jose Vicente de Unda	77.40%	8.70%	64.00%	92.60%	65.10%	69.60%
Guanarito	64.70%	4.00%	59.50%	73.20%	62.50%	65.50%
Santa Rosalia	81.10%	15.10%	56.70%	96.10%	56.70%	62.10%
San Genaro de Boconoito	58.00%	13.40%	42.80%	92.20%	43.20%	47.10%
Ospino	54.80%	10.50%	40.60%	72.10%	40.60%	44.40%
Sucre	50.60%	12.60%	32.00%	72.50%	32.40%	43.10%
Turen	52.80%	10.70%	37.70%	76.40%	37.70%	41.70%
Agua Blanca	27.40%	12.90%	9.10%	65.80%	19.30%	26.90%
Guanare	23.10%	5.40%	17.20%	38.30%	17.50%	18.90%
San Rafael de Onoto	13.40%	5.00%	6.80%	27.30%	17.20%	17.70%
Araure	10.70%	3.80%	5.30%	22.80%	10.80%	13.10%
Esteller	15.40%	4.60%	9.40%	28.90%	9.40%	11.60%
Paez	10.40%	4.30%	6.30%	23.60%	6.90%	7.80%
<i>Trujillo</i>	39.70%	8.20%	26.40%	57.10%	28.90%	38.00%
Juan Vicente Campo Elias	98.40%	3.50%	85.00%	100.00%	95.50%	100.00%
Jose Felipe Marquez Cañizalez	90.90%	8.10%	78.30%	100.00%	80.60%	83.20%
Bocono	61.30%	7.20%	46.80%	72.00%	46.80%	62.60%
Monte Carmelo	70.00%	12.30%	47.80%	91.70%	47.80%	61.60%
Andres Bello	64.00%	15.60%	40.20%	96.80%	40.20%	58.40%
Motatan	44.60%	7.90%	28.30%	60.00%	35.90%	51.20%
Carache	55.60%	10.10%	41.40%	75.50%	41.40%	45.40%
Pampan	37.40%	6.90%	24.60%	57.30%	24.60%	38.10%
Miranda	37.50%	10.40%	23.20%	65.70%	24.80%	37.20%
Candelaria	45.60%	15.10%	24.80%	80.90%	24.80%	36.90%
Sucre	32.90%	9.60%	10.90%	51.50%	17.60%	32.90%
Urdaneta	36.10%	12.40%	17.00%	63.00%	17.00%	28.60%
La Ceiba	37.40%	20.80%	13.50%	92.90%	13.50%	25.00%
Trujillo	21.70%	4.30%	15.30%	32.20%	15.30%	22.50%
Rafael Rangel	16.80%	5.80%	9.20%	26.20%	19.50%	21.90%

(Continued)

**Table 5.** (Continued).

State and Municipality	Mean	Standard deviation	Minimum	Maximum	2014	2020
Bolivar	16.90%	4.20%	9.80%	26.60%	11.50%	18.40%
Pampanito	7.90%	3.30%	2.30%	14.10%	9.20%	14.10%
Escuque	9.50%	2.20%	6.90%	13.00%	8.40%	12.90%
Valera	6.60%	3.10%	3.30%	15.10%	4.00%	6.10%
San Rafael de Carvajal	1.90%	1.50%	0.00%	6.60%	0.50%	2.40%
<i>Lara</i>	<i>41.70%</i>	<i>5.90%</i>	<i>33.40%</i>	<i>54.80%</i>	<i>35.00%</i>	<i>37.00%</i>
Urdaneta	76.20%	8.20%	64.40%	86.20%	65.70%	66.80%
Crespo	63.60%	4.20%	56.90%	74.60%	61.70%	60.70%
Andres Eloy Blanco	58.50%	5.00%	50.40%	71.60%	52.00%	58.10%
Torres	57.40%	7.70%	44.90%	70.30%	46.80%	48.80%
Moron	51.40%	8.00%	38.80%	65.40%	40.00%	44.40%
Simon Planas	37.30%	8.70%	28.00%	62.20%	28.40%	32.40%
Jimenez	20.50%	8.40%	10.10%	41.90%	11.90%	12.70%
Iribarren	9.80%	2.10%	7.00%	16.60%	8.00%	8.40%
Palavecino	0.70%	1.00%	0.00%	4.50%	0.50%	0.80%
<i>Zulia*</i>	<i>36.20%</i>	<i>4.70%</i>	<i>29.00%</i>	<i>46.40%</i>	<i>30.80%</i>	<i>33.60%</i>
Catatumbo	88.30%	2.00%	82.90%	91.90%	86.70%	89.80%
Jesus Maria Semprun	78.80%	3.30%	70.70%	83.90%	78.30%	79.40%
Francisco Javier Pulgar	76.70%	10.70%	59.70%	91.80%	61.50%	68.70%
Almirante Padilla	57.70%	6.50%	45.10%	76.30%	54.70%	63.00%
Colon	66.00%	6.70%	55.60%	78.70%	57.20%	59.90%
Machiques de Perija	54.40%	3.20%	48.80%	60.40%	54.40%	55.80%
Sucre	60.80%	10.40%	44.30%	79.40%	44.50%	50.70%
Baralt	43.80%	9.40%	30.20%	66.30%	30.20%	40.20%
Guajira	54.90%	14.30%	35.00%	77.00%	35.00%	39.20%
Rosario de Perija	43.40%	3.30%	38.60%	52.40%	43.30%	39.00%
Valmore Rodriguez	36.50%	5.50%	29.50%	54.90%	29.50%	33.50%
Miranda	22.20%	4.50%	15.00%	31.90%	15.00%	18.40%
Mara	18.40%	2.60%	14.40%	26.00%	14.40%	16.20%
Jesus Enrique Lossada	14.70%	3.00%	11.40%	23.80%	13.40%	15.40%
La Cañada de Urdaneta	13.80%	2.20%	9.70%	19.20%	9.70%	13.70%
Santa Rita	11.90%	3.70%	6.60%	21.80%	7.90%	9.80%
Lagunillas	9.10%	2.00%	6.20%	14.50%	6.20%	7.10%
Cabimas	6.00%	2.20%	3.30%	11.30%	3.30%	3.60%
Simon Bolivar	3.50%	2.30%	1.60%	11.70%	1.70%	2.60%
Maracaibo	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
San Francisco	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
<i>Sucre</i>	<i>44.40%</i>	<i>13.10%</i>	<i>27.00%</i>	<i>66.80%</i>	<i>27.30%</i>	<i>30.40%</i>
Benitez	76.90%	5.40%	67.90%	87.00%	67.90%	71.80%
Libertador	79.60%	18.70%	54.20%	98.30%	54.20%	57.10%
Andres Eloy Blanco	61.50%	14.70%	39.20%	83.10%	39.20%	44.90%
Cruz Salmeron Acosta	57.20%	13.50%	39.10%	82.20%	39.10%	41.60%
Cajigal	54.50%	20.30%	27.50%	93.70%	27.50%	34.40%
Bolivar	47.00%	13.60%	27.60%	77.30%	27.60%	32.40%
Mariño	44.10%	15.80%	24.50%	75.30%	24.50%	28.60%
Montes	41.50%	12.30%	25.90%	60.50%	29.10%	28.00%
Ribero	39.20%	12.80%	22.20%	62.30%	22.20%	26.90%
Valdez	33.40%	8.10%	24.50%	46.00%	24.50%	26.30%
Arismerendi	44.50%	16.50%	19.50%	62.70%	19.50%	23.30%
Mejia	50.10%	25.90%	18.70%	93.70%	18.70%	22.80%
Sucre	14.30%	4.30%	10.20%	25.30%	10.30%	10.20%
Andres Mata	18.90%	10.80%	4.70%	42.00%	4.70%	7.40%
Bermudez	2.90%	3.20%	0.20%	13.30%	0.30%	0.40%
<i>Anzoategui*</i>	<i>30.70%</i>	<i>7.60%</i>	<i>19.40%</i>	<i>46.10%</i>	<i>23.70%</i>	<i>29.10%</i>
Monagas	47.30%	15.50%	26.70%	76.50%	47.00%	74.50%
Cajigal	69.90%	9.00%	55.40%	91.20%	55.40%	65.80%
General Sir Arthur McGregor	59.70%	5.20%	50.10%	72.10%	55.00%	62.90%
Libertad	52.50%	5.80%	41.50%	65.60%	43.80%	53.40%
Miranda	50.00%	12.80%	33.40%	76.70%	38.50%	48.80%
Guanipa	44.60%	12.40%	24.50%	67.00%	31.40%	42.20%
San Juan de Capistrano	69.60%	25.90%	34.90%	98.90%	38.70%	39.10%

(Continued)

**Table 5.** (Continued).

State and Municipality	Mean	Standard deviation	Minimum	Maximum	2014	2020
Aragua	42.00%	5.30%	34.80%	56.10%	34.80%	37.80%
Bruzual	45.40%	8.50%	33.10%	61.30%	33.10%	35.50%
Carvajal	36.40%	7.10%	23.80%	53.30%	32.00%	32.60%
Simon Rodriguez	23.00%	14.40%	0.20%	52.70%	12.70%	26.30%
Santa Ana	29.90%	9.30%	16.80%	49.00%	23.10%	23.10%
Piritu	19.90%	7.80%	9.40%	39.00%	12.10%	18.20%
Fernando de Peñalver	18.30%	6.30%	9.30%	33.50%	11.20%	15.60%
Freites	15.00%	5.30%	3.10%	28.90%	12.80%	14.90%
Independencia	5.00%	1.50%	2.80%	8.50%	5.30%	7.40%
Bolivar	7.60%	2.00%	4.50%	14.80%	5.10%	6.60%
Sotillo	4.00%	1.70%	1.60%	8.70%	2.60%	2.80%
Anaco	4.00%	2.30%	0.70%	9.50%	2.50%	2.50%
Guanta	0.70%	1.00%	0.00%	4.10%	0.90%	0.90%
Lic. Diego Bautista Urban	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
<i>Monagas*</i>	<i>25.70%</i>	<i>9.80%</i>	<i>9.80%</i>	<i>44.70%</i>	<i>18.80%</i>	<i>24.50%</i>
Uracoa	71.70%	8.00%	58.50%	85.80%	58.50%	69.30%
Aguasay	37.80%	18.80%	1.70%	67.80%	37.70%	51.50%
Acosta	47.10%	19.70%	1.10%	73.00%	34.20%	44.80%
Libertador	35.50%	8.50%	24.10%	53.70%	25.60%	35.90%
Caripe	28.50%	9.20%	10.00%	47.00%	23.40%	26.10%
Piar	19.60%	15.10%	0.00%	52.50%	6.70%	20.20%
Bolivar	26.10%	9.50%	11.60%	46.20%	18.30%	19.70%
Maturin	16.40%	4.70%	9.30%	27.50%	13.30%	16.80%
Sotillo	11.00%	2.10%	7.20%	15.50%	9.00%	13.80%
Punceres	22.00%	12.40%	3.90%	48.10%	13.10%	11.10%
Cedeño	14.00%	12.00%	0.10%	42.80%	4.40%	9.00%
Santa Barbara	4.10%	6.40%	0.00%	19.30%	0.00%	0.60%
Ezequiel Zamora	0.30%	0.70%	0.00%	2.50%	0.00%	0.00%
<i>Yaracuy</i>	<i>29.40%</i>	<i>7.20%</i>	<i>20.40%</i>	<i>47.00%</i>	<i>25.40%</i>	<i>24.50%</i>
Veroes	63.30%	11.60%	49.00%	96.10%	51.50%	51.10%
Bolivar	68.20%	12.60%	48.80%	86.70%	56.40%	49.10%
Manuel Monge	69.60%	20.40%	40.00%	97.00%	49.90%	43.30%
San Felipe	44.90%	9.40%	34.40%	76.70%	38.60%	39.20%
La Trinidad	46.30%	14.50%	33.30%	85.60%	41.60%	33.30%
Nirgua	33.10%	3.10%	29.00%	43.00%	33.80%	32.70%
Aristides Bastidas	10.80%	6.20%	3.00%	23.20%	15.80%	23.20%
Peña	19.50%	6.10%	12.20%	37.50%	12.20%	16.60%
Bruzual	14.00%	4.80%	8.60%	32.40%	12.70%	12.10%
Jose Antonio Paez	12.10%	3.70%	8.50%	26.20%	11.20%	10.70%
Urachiche	9.40%	1.80%	6.80%	14.50%	11.20%	10.20%
Cocorote	6.00%	1.80%	3.10%	9.80%	8.40%	8.40%
Independencia	9.40%	2.90%	5.70%	18.90%	7.40%	7.50%
Sucre	4.70%	1.50%	2.80%	10.10%	4.70%	5.60%
<i>Aragua</i>	<i>17.50%</i>	<i>4.10%</i>	<i>11.20%</i>	<i>26.50%</i>	<i>14.50%</i>	<i>18.30%</i>
Urdaneta	67.20%	5.30%	58.20%	76.90%	58.20%	65.10%
Camatagua	45.20%	8.00%	29.20%	64.20%	35.80%	45.10%
San Casimiro	35.90%	5.30%	28.50%	50.50%	31.00%	37.40%
San Sebastian	34.00%	4.80%	22.80%	47.70%	32.80%	33.70%
Tovar	41.20%	14.80%	18.90%	73.70%	22.90%	31.80%
Ocumare de la Costa de Oro	37.10%	11.50%	20.10%	60.80%	28.10%	30.50%
Santos Michelena	14.50%	6.90%	5.80%	26.80%	12.90%	26.40%
Santiago Mariño	14.80%	2.90%	9.20%	19.20%	13.90%	18.60%
Jose Rafael Revenga	3.80%	3.80%	0.20%	11.40%	3.70%	11.20%
Jose Felix Ribas	6.10%	2.90%	2.10%	14.50%	4.50%	7.60%
Mario Briceño Iragorry	2.70%	3.20%	0.00%	8.90%	5.20%	7.40%
Zamora	5.70%	1.30%	3.90%	9.70%	5.90%	6.70%
Girardot	3.90%	0.60%	2.20%	4.70%	4.20%	4.00%
Sucre	2.10%	1.50%	0.00%	6.70%	2.10%	2.30%
Bolivar	0.50%	0.60%	0.00%	1.90%	0.40%	1.80%
Francisco Linares	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Jose Angel Lamas	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%

(Continued)

**Table 5.** (Continued).

State and Municipality	Mean	Standard deviation	Minimum	Maximum	2014	2020
Libertador	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
<i>Nueva Esparta</i>	<i>13.80%</i>	<i>2.10%</i>	<i>11.60%</i>	<i>18.70%</i>	<i>12.20%</i>	<i>11.90%</i>
Tubores	100.00%	0.00%	100.00%	100.00%	100.00%	100.00%
Peninsula de Macanao	17.80%	2.40%	14.20%	25.20%	16.50%	15.70%
Isla de Coche	32.60%	18.90%	13.30%	76.00%	17.10%	14.20%
Diaz	0.30%	0.20%	0.00%	0.70%	0.50%	0.60%
Gomez	0.10%	0.20%	0.00%	0.60%	0.00%	0.40%
Antolin del Campo	0.00%	0.10%	0.00%	0.30%	0.00%	0.00%
Arismendi	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Garcia	0.60%	0.60%	0.00%	2.10%	0.40%	0.00%
Maneiro	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Marcano	0.00%	0.10%	0.00%	0.10%	0.00%	0.00%
Mariño	0.20%	0.20%	0.00%	0.50%	0.00%	0.00%
<i>Miranda</i>	<i>9.90%</i>	<i>2.30%</i>	<i>6.40%</i>	<i>15.00%</i>	<i>8.00%</i>	<i>10.00%</i>
Pedro Gual	45.50%	6.10%	36.10%	57.70%	36.90%	39.70%
Acevedo	40.30%	6.90%	30.60%	58.60%	30.60%	37.20%
Paez	31.30%	5.20%	23.20%	43.50%	23.20%	26.80%
Paz Castillo	11.50%	5.10%	4.20%	22.40%	11.00%	17.30%
Andres Bello	11.90%	4.80%	1.50%	22.60%	6.40%	13.90%
Brion	13.60%	1.90%	9.80%	18.70%	11.10%	13.80%
Buroz	11.90%	4.50%	5.90%	22.10%	7.20%	10.70%
Lander	7.80%	1.10%	5.20%	10.00%	7.30%	8.60%
Zamora	9.60%	2.50%	6.00%	16.30%	8.30%	8.50%
Independencia	8.10%	0.80%	6.80%	9.80%	6.90%	7.70%
Guaicaipuro	3.50%	1.40%	1.40%	6.00%	3.90%	6.00%
Urdaneta	3.60%	1.60%	0.40%	6.80%	3.20%	5.00%
Plaza	2.50%	1.40%	0.70%	5.30%	3.20%	4.70%
Simon Bolivar	4.10%	1.10%	2.20%	6.40%	4.00%	4.30%
Sucre	1.50%	1.10%	0.00%	3.40%	2.90%	3.20%
Cristobal Rojas	1.20%	1.40%	0.00%	3.40%	1.80%	2.70%
Chacao	0.20%	0.30%	0.00%	0.80%	0.70%	0.50%
El Hatillo	0.30%	0.30%	0.00%	1.20%	0.40%	0.30%
Baruta	0.10%	0.30%	0.00%	1.00%	0.00%	0.00%
Carrizal	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Los Salias	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
<i>Vargas</i>	<i>9.30%</i>	<i>2.40%</i>	<i>6.60%</i>	<i>14.70%</i>	<i>7.00%</i>	<i>7.60%</i>
Vargas	9.30%	2.40%	6.60%	14.70%	7.00%	7.60%
<i>Carabobo</i>	<i>5.20%</i>	<i>2.20%</i>	<i>2.00%</i>	<i>9.90%</i>	<i>5.80%</i>	<i>7.00%</i>
Bejuma	23.40%	7.00%	14.60%	37.10%	29.40%	31.80%
Montalban	14.40%	7.20%	1.00%	28.90%	17.30%	19.90%
Carlos Arevalo	10.60%	3.30%	6.10%	18.70%	7.30%	12.20%
Puerto Cabello	7.30%	3.40%	1.90%	16.00%	8.40%	8.00%
Juan Jose Mora	6.90%	1.90%	3.60%	12.60%	7.20%	7.20%
San Joaquin	2.20%	2.20%	0.00%	6.70%	3.90%	6.70%
Miranda	5.60%	1.90%	1.40%	9.20%	4.70%	5.00%
Diego Ibarra	1.00%	1.40%	0.00%	4.10%	1.70%	3.90%
Naguanagua	1.00%	1.30%	0.00%	3.60%	1.90%	3.50%
Guacara	1.70%	1.00%	0.10%	3.40%	2.50%	3.00%
Valencia	2.10%	1.00%	0.70%	4.70%	1.00%	1.70%
Libertador	0.70%	0.70%	0.00%	1.70%	0.70%	1.40%
San Diego	0.40%	0.50%	0.00%	1.20%	0.90%	1.20%
Lago Valencia	0.00%	0.10%	0.00%	0.30%	0.00%	0.00%
Los Guayos	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
<i>Capital District</i>	<i>0.10%</i>	<i>0.10%</i>	<i>0.00%</i>	<i>0.20%</i>	<i>0.20%</i>	<i>0.10%</i>
Libertador	0.10%	0.10%	0.00%	0.20%	0.20%	0.10%

\*Oil-producing state.



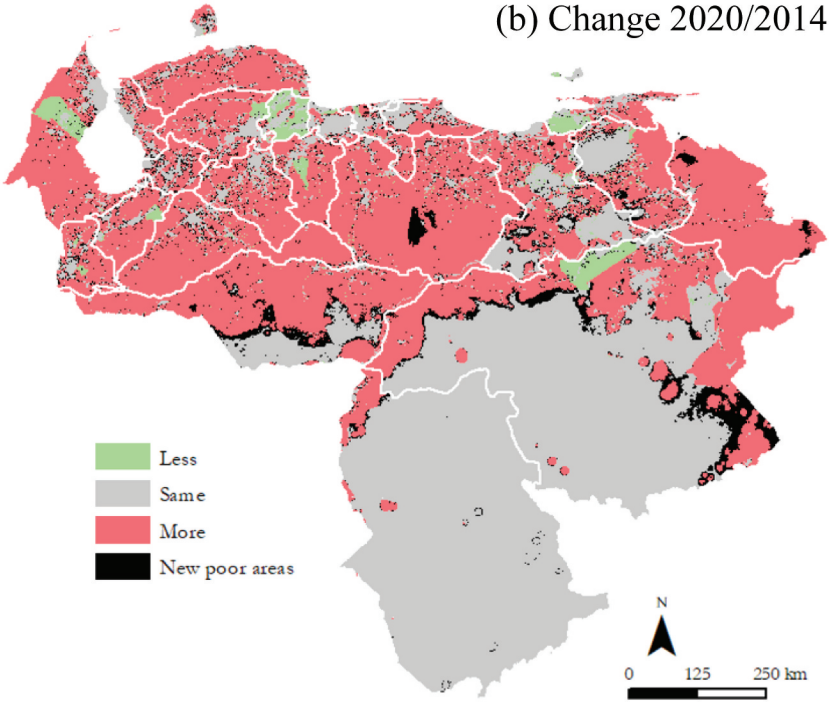
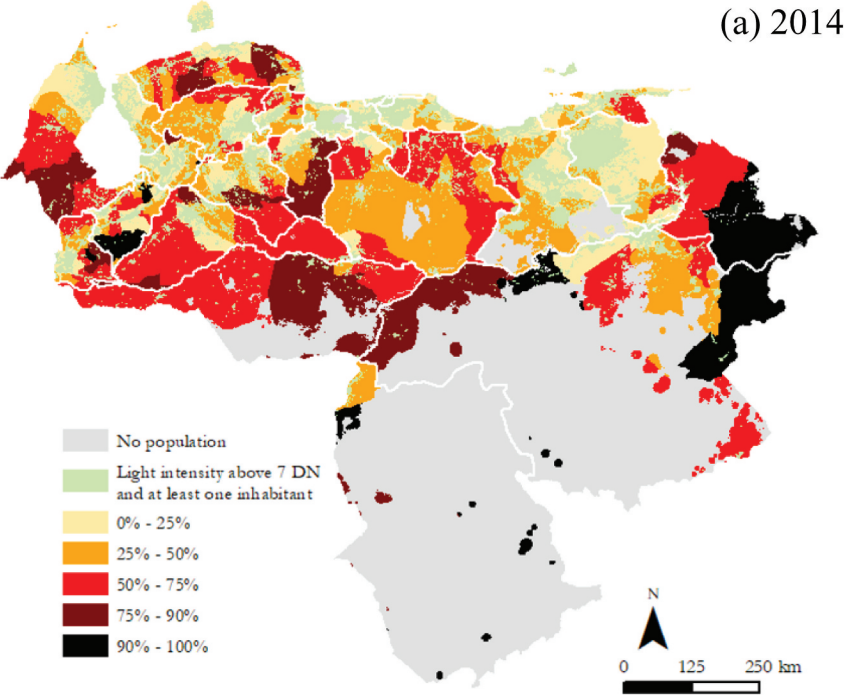


Figure 8. Rural Poverty Rate in Venezuela.

2008, the regime policy decisions prioritizing the power demand of main urban cores, and the mismanagement of the electricity sector.

## 5. Conclusion

The lack of local poverty data is a significant limitation to setting development policies in emerging countries, and this paper tries to close that gap for rural Venezuela. Here I use an alternative approach based on remote sensing techniques to generate subnational rural poverty data for Venezuela, a country facing political turmoil and severe socio-economic crisis. In this case, I use DMSP and VIIRS nighttime light imagery and two spatially distributed population datasets, ORNL and WorldPop, to estimate rural poverty rates at the state and municipality levels from 2000 to 2020.

The harmonization procedure between DMSP and VIIRS products identified a light intensity threshold for low values associated with poor rural areas in Venezuela ( $DN = 7$ ). This threshold allows for obtaining the poverty estimates. The paper also verifies how the WorldPop data led to more precise and consistent results over time, suggesting its use for further geospatial analysis for Venezuela. With this technical approach, the findings identify Amazonas, Apure, and Delta Amacuro as the top three states with the highest rural poverty rate in 2020, and Carabobo, Vargas, and the Capital District as the bottom three.

This paper confirms subnational heterogeneities in the results but with broad common trends. The satellite sensitivity reveals volatility during 2003–2004 and, in most cases, an absolute peak in 2003 (a year of significant political instability). There was a switching period in 2013–2014 (beginning the current Venezuelan recession), from which rural poverty intensified and new rural poor areas appeared across the country, surrounding municipalities with moderate to high poverty rates. Except for Nueva Esparta, the southwest of Sucre, Yaracuy, and some municipalities in Bolivar, Cojedes, Lara, Merida, Tachira, and Zulia, the rest of the country experienced an intensification of rural poverty. These results suggest poverty clustering and that more Venezuelans have sunk into darkness in recent years.

Since 2008 the Venezuelan regime is frequently imposing electricity rationing regionally to prioritize the energy demand of main urban cores (such as the Capital District), which may contribute to these subnational heterogeneities. On the other hand, mismanagement of the electricity sector prevails while a narrow political criterion still drives the planning and execution of official generation capacity projects. Unfortunately, this context highlights the lack of effective territorial intelligence and the need for a development agenda that is politically unbiased and based on reliable, independent subnational data.

The power crisis is underway and even escalated with the 2019 national blackout, which had humanitarian costs across the healthcare, water supply and public transport systems, and significant disrupting effects on the commercial and retail sectors and oil production (Sabatini & Patterson, 2021). This context yielded more electricity rationing in Western states (Apure, Barinas, Merida, Tachira, Trujillo, and Zulia), contemplating official energy interruption of four hours in each state, likely impacting the latest poverty results.<sup>10</sup> Now, inhabitants of those states reported sustained economic degradation and

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<sup>10</sup>The National Electricity Corporation of Venezuela explained that these “load management plans” are caused by low levels in the Uribante reservoir.

actual energy cuts of about 6–12 hours or even days (Prensa Aula Abierta, 2020; Venezuelan Observatory of Public Services, 2021).

The Venezuelan context warns about the current need to reform its electricity sector. A significant step toward it is to build up local data to support eventual recovery efforts and poverty alleviation programs and allow impact evaluations. That is the main contribution of this paper, which findings also encourage future research zooming in on regional inequalities and identifying national binding constraints in infrastructure development to promote economic growth.

The opinions expressed herein are those of the author and do not necessarily represent the views of the University of Minnesota.

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## Disclosure statement

No potential conflict of interest was reported by the author(s).

## Notes on contributor

**Leonardo Maldonado** is a Ph.D. candidate in Applied Economics at the University of Minnesota (UMN) and an Economics Consultant for the Country Department Andean Group at the Inter-American Development Bank (IDB). He is interested in Development Policy, Natural Resource Economics, and Remote Sensing. Formerly, Leonardo worked as Research Assistant at the UMN and Economics Consultant for the Country Department Central America, Haiti, Mexico, Panama, and the Dominican Republic at the IDB, INCAE Business School in Costa Rica, and IESA's International Center for Energy and Environment in Venezuela. He taught Econometrics, Mathematics, Macroeconomics, Microeconomics, and Principles of Economics courses. He has authored, co-authored, and reviewed multiple studies mainly focused on Latin American countries. Leonardo holds a B.A. in Economics from the Central University of Venezuela, a Master's degree in Applied Economics from the Andres Bello Catholic University (Summa Cum Laude), a MicroMaster's certificate in Data, Economics, and Development Policy from the Massachusetts Institute of Technology, and a professional certificate in Geographic Information Systems (GIS) Essentials from the University of Alaska Fairbanks.

## ORCID

Leonardo Maldonado  <http://orcid.org/0000-0002-9400-3346>

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