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A Methodology to Estimate High-Resolution Gridded Datasets on Energy Consumption Drivers in Ecuador's Residential Sector during the 2010–2020 Period

Diego Moya [1,2,3,4,*], César Arroba [3], Christian Castro [3], Cristian Pérez [3], Sara Giarola [2,5,6], Prasad Kaparaju [7], Ángel Pérez-Navarro [8] and Adam Hawkes [2]

1 Technology Outlook and Strategy, Technology Strategy and Planning Department, Saudi Aramco, Dhahran 34481, Saudi Arabia
2 Department of Chemical Engineering, Imperial College London, South Kensington, London SW7 2BX, UK
3 Carrera de Ingeniería Mecánica, Facultad de Ingeniería Civil y Mecánica, Universidad Técnica de Ambato, Av. Los Chasquis y Río Payamino, Ambato 180207, Ecuador
4 Institute for Applied Sustainability Research, IIASUR, Quito 170806, Ecuador
5 School of Management, Polytechnic of Milan, 20156 Milan, Italy
6 RFF-CMCC EIEE, 20144 Milan, Italy
7 School of Engineering & Built Environment, Griffith University, Brisbane, QLD 4111, Australia
8 Instituto de Ingeniería Energética, Universitat Politècnica de València, 46022 Valencia, Spain
* Correspondence: d.moya17@imperial.ac.uk or hello@diegomoya.me

Abstract: There are no methodologies in the literature for estimating the temporal and spatial distribution of consumption drivers for the residential sector of a region or country. Factors such as energy requirement, population density, outdoor temperature, and socioeconomic aspects are considered the major drivers of consumption and have been found to directly influence residential energy consumption. In this study, a methodology is proposed to evaluate the impact of the above drivers in domestic energy consumption in Ecuador between 2010 and 2020 using publicly available data. This methodology aims to provide a spatiotemporal approach to estimate high-resolution gridded datasets for a 10-year period, 2010–2020, assessing seven energy drivers: (1) gridded population density, (2) gridded space heating requirements, (3) gridded space cooling requirements, (4) gridded water heating requirements, (5) gridded Gross Domestic Product (GDP), (6) gridded per capita GDP, and (7) the Human Development Index (HDI). Drivers 1 to 6 were analyzed at one square kilometer (1 km^2), whereas HDI was analyzed at the city level. These results can be used to evaluate energy-planning strategies in a range of sustainable scenarios. This methodology can be used to evaluate a range of consumption drivers to evaluate long-term energy policies to reach the net-zero target by midcentury. The proposed methodology can be reproduced in other countries and regions. Future research could explore the spatiotemporal correlation of the consumption drivers provided in this study.

Keywords: residential energy consumption; end-use energy; spatial analysis; spatiotemporal approach; geographical information system; gridded energy data

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1. Introduction

Energy consumption in households is driven by a range of parameters, also called energy consumption drivers, which vary from region to region depending on local features. Demographic characteristics (i.e., population density), socioeconomic conditions (i.e., income), weather parameters (i.e., ambient temperature), and stage of human progress have been shown to have a profound impact on energy consumption in the domestic housing sector of any region or country [1]. In general, outdoor temperature determines the heating or cooling requirements of a house and, thus, its annual energy consumption [2]. Thus, the energy requirements inside a building are determined by outdoor temperature.

To achieve a desirable indoor temperature, factors such as the socioeconomic conditions of a family and the level of procurement and proprietorship of energy technologies are determinants [3]. However, these drivers differ in both time and space within a region. Therefore, an in-depth spatiotemporal assessment of energy drivers for residential areas in a region would assist policymakers in developing energy policies with adequate details regarding both space and time requirements.

Geographical information systems (GIS)-based studies typically address residential energy consumption drivers separately [3–5]. Balezentis [6] estimated three nationwide drivers: household size, dwelling area, and energy intensity. Similarly, Sachs et al. [1] covered two additional drivers in the residential sector: outdoor temperature and end-use energy demand. Jimenez and Yepez-Garcia [7] reported household income in Latin America, and Sorichetta et al. [8] provided a dataset of high-resolution gridded populations for Latin America and the Caribbean in 2010, 2015, and 2020. Although high-resolution spatiotemporal techniques for estimating energy consumption drivers in households are becoming popular, there is still need for methodologies to integrate large amounts of data in a single approach. Overall, the estimation of energy consumption drivers considering spatiotemporal dimensions has yet to be developed.

This study presents a methodology for estimating spatiotemporal high-resolution gridded maps of energy consumption drivers using publicly available data obtained between 2010 and 2020. The seven energy consumption drivers included in this study are (1) gridded population density, (2) gridded space heating (SH) requirement, (3) gridded space cooling (SC) requirements, (4) gridded water heating (WH) requirements, (5) gridded Gross Domestic Product (GDP), (6) gridded per capita GDP, and (7) Human Development Index (HDI). Energy drivers 1 to 6 were analyzed at a resolution of one square kilometer (1 km^2), whereas HDI was analyzed at the city level. These drivers have been identified in the literature as the key factors influencing energy consumption in the residential sector [1]. The methodology presented here can be applied to any region, and the results can be used to inform policymakers in developing energy plans. The methodology is extensively presented in Section 2, while results and conclusion are presented in Sections 3 and 4, respectively.

2. Methodology

Figure 1 summarizes the methodology for estimating energy consumption drivers in a residential area. Ecuador was used as a case study. Overall, six databases were used to acquire these consumption drivers: (i) the NASA MERRA2 database was used for gridded temperature [9]; (ii) the Centre for International Earth Science Information Network of Columbia University (CIESIN) [10] and the National Institute of Statistics and Censuses, from its Spanish translation (INEC) [11], were used for gridded populations; (iii) the Electricity Regularization and Control Agency, from its Spanish translation (ARCONEL), was used for residential electricity consumption [12]; (iv) GDP, from the Central Bank of Ecuador (BCE) [13]; (v) the life expectancy index; and (vi) the education level index, provided by the organizational archives of INEC. After data collection, the CIESIN population was calibrated using INEC data.

After spatiotemporal calibration, a combination of parameters, such as electricity consumption, outdoor temperature, and population, were used to develop data at a prominent spatial resolution of 1 km^2 and a temporal resolution of hourly/monthly. To achieve this and consider weather conditions, the concept of heating degree days (HDD) and cooling degree days (CDD) was initially used to estimate the energy required, as suggested by previous researchers [1], and it is presented in Equations (1)–(6) in Figure 1. Each cell contains data for weighted energy end-use factors, such as the spatial and temporal cooling and heating of a house (Equations (7)–(12)). The resulting standardized index determines the end-use energy requirements for each house, as shown in Equations (14)–(17) (Figure 1). To compute the energy requirements for residential segments, demographic and socioeconomic factors such as GDP (Equations (21) and (33)) and HDI were used at the city level (Equation (22)). Statistical data from government organizations, such as BCE and INEC, were used. The combination of the above parameters generated calibrated datasets to determine the factors affecting the energy consumption in residential areas.

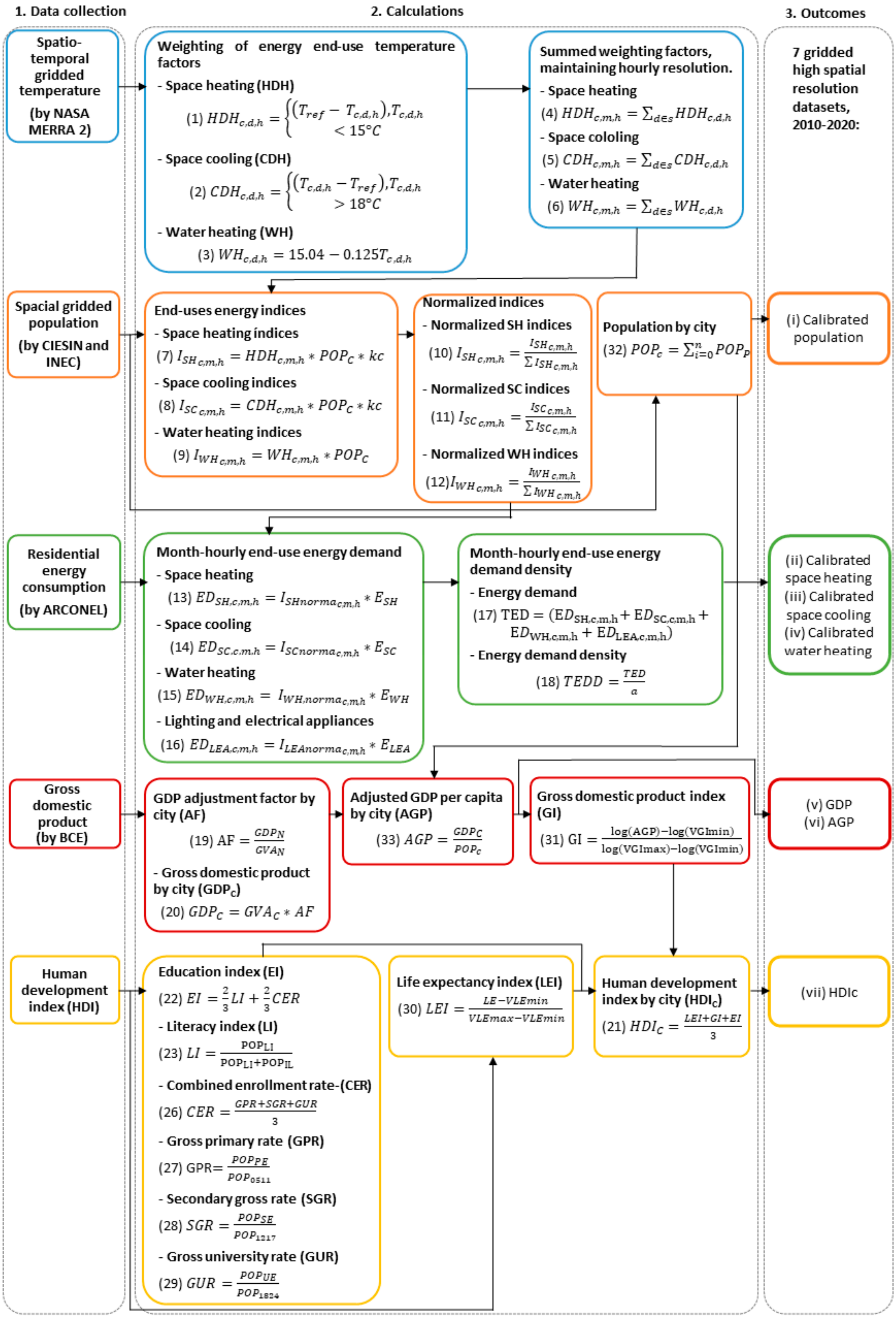

Figure 1. National spatiotemporal data-driven method to analyze the drivers of energy consumption and their requirements for the Ecuadorean residential sector.

2.1. Ambient Temperature Factors

Outdoor temperature data at the highest-resolution terms of space and time relationships were obtained from the literature. NASA MERRA-2 [9] provides data in a nedCDF format at an hourly temporal resolution with a previous calibration of variables, such as the geographical location of the country, time, and temperature at different heights of the ground. The highest eligible spatial resolution presented by NASA MERRA-2 is 0.625 × 0.5 degrees, which means that each pixel covers an approximate distance of 65 km × 75 km. As Ecuador has different climatic regions, it is key to improve the resolution such that each cell covers 1 km × 1 km. This set of outdoor temperature data was used to calculate the initial indicators of energy demand: HDH and CDH. Equation (1) was used to calculate HDH in places with a temperature lower than 15 °C, and Equation (2) was used to calculate CDH in places where space cooling was necessary at a temperature greater than 18 °C. For water heating (WH), it was assumed that the temperature does not have such an impact, as observed for HDH and CDH. Therefore, in this case, Equation (3) was used to calculate WH.

$$HDH_{c,d,h} = \begin{cases} \left(T_{ref} - T_{c,d,h}\right), T_{c,d,h} < 15\ ^\circ\mathrm{C} \\ Else\ 0 \end{cases} \tag{1}$$

$$CDH_{c,d,h} = \begin{cases} \left(T_{c,d,h} - T_{ref}\right), T_{c,d,h} > 18\ ^\circ\mathrm{C} \\ Else\ 0 \end{cases} \tag{2}$$

$$WH_{c,d,h} = 15.04 - 0.125T_{c,d,h} \tag{3}$$

where the subindexes c, d, and h are the cell, day, and hour, respectively. Once these factors were obtained, the sum of HDH, CDH, and WH for each hour was calculated for a month.

$$HDH_{c,m,h} = \sum_{d\in s} HDH_{c,d,h} \tag{4}$$

$$CDH_{c,m,h} = \sum_{d\in s} CDH_{c,d,h} \tag{5}$$

$$WH_{c,m,h} = \sum_{d\in s} WH_{c,d,h} \tag{6}$$

where the subindexes c, m, and h are the cell, month, and hour, respectively.

2.2. Population

Population data are a key driver for determining the energy requirements in residential areas. A dataset on the estimated number of people per cell corresponding to the Ecuadorian population is available in the literature [10]. The spatial database of the population was provided by population count and population density. The dataset is available in Geotiff and ASCII XYZ formats with a spatial resolution of 30 arcs (approximately 1 km) and an annual temporal resolution from 2000 to 2020. The demographic projection was based on the Geographic Coordinate System, WSG84. These units represent the number of people per pixel. The population from [10] was verified against data obtained from the INEC. The final energy use indices were calculated after obtaining population count and density data. These indices assign the degree of heating or cooling demand to the population in each cell, which is a metric of energy demand based on the gridded ambient temperature and population. For the space heating index, Equation (7) was used, whereas Equation (8) was used for space cooling. These equations were multiplied by the factor $kc = f * POP_{den_c}$. This factor directly depends on the population density of each cell to differentiate the energy demand in rural and urban areas. This index does not affect the water-heating index (Equation (9)).

$$I_{SHc,m,h} = HDH_{c,m,h} * POP_C * kc \tag{7}$$

$$I_{SCc,m,h} = CDH_{c,m,h} * POP_C * kc \tag{8}$$

$$I_{WHc,m,h} = WH_{c,m,h} * POP_C \tag{9}$$

Index normalization was performed by dividing the energy consumption of all cells.

$$I_{SHc,m,h} = \frac{I_{SHc,m,h}}{\sum I_{SHc,m,h}} \tag{10}$$

$$I_{SCc,m,h} = \frac{I_{SCc,m,h}}{\sum I_{SCc,m,h}} \tag{11}$$

$$I_{WHc,m,h} = \frac{I_{WHc,m,h}}{\sum I_{WHc,m,h}} \tag{12}$$

2.3. Energy Demand

The data presented by ARCONEL [7] were used to estimate spatial and temporal energy demands [12]. The SISDAT (ARCONEL data system) provides reports of statistical information on the electricity sector by collecting data that includes the entire energy sector of a country. Instead of using energy consumption data at the national level as in [1], we propose using consumption data at the highest spatial resolution available in a region or country. The data provided by SISDAT allow classification by consumer sector (in our case, the residential sector). These data have a temporal resolution at the monthly level and a high spatial resolution at the city and provincial levels. The end-use energy demands were calculated for each hour of each month for a year, considering the value of the percentage of energy that will be applied for each use. Equations (13)–(16) were used to calculate the SH, SC, WH, and lighting and electrical appliance demand (LEA), respectively. It is assumed that the same normalization index for water heating is used for the estimation of lighting and electrical appliance demands.

$$ED_{SH,c,m,h} = I_{SHnorma_{c,m,h}} * E_{SH} \tag{13}$$

$$ED_{SC,c,m,h} = I_{SCnorma_{c,m,h}} * E_{SC} \tag{14}$$

$$ED_{WH,c,m,h} = I_{WHnorma_{c,m,h}} * E_{WH} \tag{15}$$

$$ED_{LEA,c,m,h} = I_{LEAnorma_{c,m,h}} * E_{LEA} \tag{16}$$

The total energy consumption is given by the sum of the energy demands in Equation (17), whereas the energy demand density was obtained by dividing by the area of each cell in Equation (18):

$$TED = (ED_{SH,c,m,h} + ED_{SC,c,m,h} + ED_{WH,c,m,h} + ED_{LEA,c,m,h}) \tag{17}$$

$$TEDD = \frac{TED}{a} \tag{18}$$

2.4. Gross Domestic Product

The Central Bank of Ecuador does not calculate the GDP at the city or parish level. However, it provides Gross Value Added (GVA) in thousands of dollars per city [13]. The GVA data compendium is available for download in Excel format with spatial resolution at the national, provincial, and city levels and annual temporal resolution from 2010 to 2019. The estimation methodology used for city accounts can be found in the bulletin of the monthly economic statistical information from the Central Bank of Ecuador. However, owing to the lack of city GDP data in the literature, it is calculated by applying an adjustment factor (AF) using Equation (19). This AF must be multiplied by the national GVA (GVA_N) to obtain the national GDP (GDP_N). Similarly, this factor was used to convert the city GVA (GVA_C) into an estimate of city GDP using Equation (20). Finally, we obtain the adjusted GDP, called the city GDP (GDP_C).

$$AF = \frac{GDP_N}{GVA_N} \tag{19}$$

$$GDP_C = GVA_C * AF \tag{20}$$

2.5. Human Development Index

The HDI is a synoptic measurement of human development that measures the average achievements of a country in three basic dimensions: the life expectancy index (LEI), education index (EI), and Gross Domestic Product index (GI), calculated by applying Equation (21). The calculation of the HDI was based on the methodology explained in [14], issued by the Ecuador Foundation.

$$HDI_C = \frac{LEI + GI + EI}{3} \tag{21}$$

First, the EI was calculated using Equation (22), which comprises two thirds of the literacy index (LI) and two thirds of the overall or combined enrolment rate (CER).

$$EI = \frac{2}{3}LI + \frac{2}{3}CER \tag{22}$$

As a complement to the data necessary for the calculation, the dataset of the population attending establishments of primary schooling (POP_{PE}), secondary schooling (POP_{SE}), and literacy (POP_L) was compiled from the literature [11]. Lastly, data on the population attending higher education establishments were collected (POP_{UE}), which were registered by the city of origin. These data were tabulated and prepared by the National Information Management Directorate based on the administrative records of the National Higher Education Information System, among other sources.

Once the data were collected and calibrated, the respective calculations of the literacy index (LI) were carried out using Equation (23), which is the quotient between the literate population (POP_{LI}) over the sum of the literate population (POP_{LI}) and illiterate population (POP_{IL}), which are the same as those calculated by Equations (24) and (25), respectively. Where (POP_{LI10}) is the literate population indicated in the 2010 population census. POP_{LI10-n} is the literate population from 2010 to the year that must be calculated.

$$LI = \frac{POP_{LI}}{POP_{LI} + POP_{IL}} \tag{23}$$

$$POP_{LI} = POP_{LI10} - POP_{LI10-n} \tag{24}$$

$$POP_{IL} = POP_{LI10} + POP_{LI10-n} \tag{25}$$

To calculate the average gross primary rate (GPR), the gross secondary rate (SGR) and gross higher education rate (GUR) were used to calculate the average gross primary rate. It is essential to collect the compendium of data of the population aged 5 to 11 (POP_{0511}), 12 to 17 (POP_{1217}), and 18 to 24 (POP_{1824}). It is available for download in Excel format from the National Information System based on the census of the INEC in 2010 [11]. This compendium has spatial resolutions at the national, provincial, city, and parish levels.

The overall or combined enrolment rate (CER) was determined by applying Equation (26), which is the average of the gross primary rate (GPR), gross secondary rate (SGR), and gross higher education rate (GUR). These rates were calculated using Equations (27)–(29):

$$CER = \frac{GPR + SGR + GUR}{3} \tag{26}$$

$$GPR = \frac{POP_{PE}}{POP_{0511}} \tag{27}$$

$$SGR = \frac{POP_{SE}}{POP_{1217}} \tag{28}$$

$$GUR = \frac{POP_{UE}}{POP_{1824}} \tag{29}$$

At the same time, the life expectancy index (LEI) was calculated by using Equation (30), where (VLE_{max}) is the maximum world reference value and is equal to 85 years, and (VLE_{min}) is the minimum world reference value equal to 25 years, which was established in [15]. For this calculation, a set of real values of life expectancy at birth (LE) from the data in the statistical compendium of INEC was necessary. These data were tabulated at a spatial resolution at the provincial level and an annual temporal resolution from 2010 to 2020.

$$LEI = \frac{LE - VLE_{min}}{VLE_{max} - VLE_{min}} \tag{30}$$

To estimate the GDP index, Equation (31) was applied, where (VGI_{max}) is the maximum world reference value and is equal to 40,000, and (VGI_{min}) is the minimum world reference value equal to 100, which is established by the INEC [11]. The equation also uses the (AGP), which is the adjusted GDP, and it is calculated using Equation (33). It was necessary to use the dataset of the estimated number of people from the census of Ecuador, which is available in the database of the National Information System (SNI). The data set of referential population projections, prepared by the Technical Secretariat "Planifica Ecuador" (STPE), is available for download with a spatial resolution at the national, provincial, city, and parish levels and an annual temporal resolution from 2010 to 2020. The demographic projection was based on the INEC methodology. To calibrate the POP at the city level, all parishes of their respective cities were added, as shown in Equation (32). Table 1 summarizes the datasets used in this methodology.

$$GI = \frac{log(AGP) - log(VGImin)}{log(VGImax) - log(VGImin)} \tag{31}$$

$$POP_c = \sum_{i=0}^{n} POP_P \tag{32}$$

$$AGP = \frac{GDP_C}{POP_c} \tag{33}$$

Table 1. Summary of the methodology and datasets used to estimate the seven energy consumption drivers in Ecuador.

More specific subject area	Energy drivers in the residential sector
Method name	Spatiotemporal method to estimate energy consumption drivers in the residential sector
Resource availability	Six databases are required to reproduce this methodology: 1. Gridded temperature from NASA MERRA2 [9]; 2. Gridded population from CIESIN (Centre for International Earth Science Information Network of Columbia University) [10]; 3. Gridded population from the INEC (National Institute of Statistics and Censuses, from its Spanish translation) [11]; 4. National electricity consumption in the residential sector by ARCONEL (Electricity Regularization and Control Agency, from its Spanish translation) [12]; 5. Gross Domestic Product (GDP) by BCE (Central Bank of Ecuador) [13]; 6. National life expectancy index and National education level index based on the administrative records of the INEC.

3. Results

Figure 2 illustrates the expected results after applying this methodology in Quito, the capital city of Ecuador. Here, four consumption drivers in Quito's residential sector are illustrated. Figure 2a shows the heating degree days for 2010, 2015, and 2020. Variations in the degree of heating demand can be observed as a function of outdoor temperature across Pichincha Province. In Figure 2b, we can see the population density distribution. As expected, the population is concentrated in Quito, which has the highest population density. Figure 2c shows the results of combining outdoor temperature data with population and energy consumption by applying the methodology presented in this article. Finally, Figure 2d shows the GDPpc distribution across the Pichincha Province. The methodology presented herein allows researchers to estimate the residential consumption drivers for enhanced energy planning and policy strategies.

Table 2 provides a description of the dataset after applying the methodology of this study for the period between 2010 and 2020. First, access to data was provided. This dataset is publicly available. Second, the type and format of the dataset were presented. Finally, a description of the dataset and the addresses of the sources are provided. The datasets shared on the Mendeley platform [16] provided nine geospatial datasets at high resolution with respect to (i) population count, (ii) population density, (iii) SH, (iv) SC, (v) WH, (vi) total end-use energy demand (TE), (vii) Gross Domestic Product (GDP), (viii) GDP per capita (GDPpc), and (ix) the Human Development Index (HDI). Figure 1summarizes the specific methods used with the calculated datasets. Overall, the gridded population dataset primarily uses data from CIESIN, which is calibrated using official data provided by the INEC. GIS-based GDP uses data provided by Ecuador's BCE. GDPpc is estimated using GDP and the previously calculated population counts. The HDI is a combination of data provided by the INEC, BCE, and other official institutions, such as the Ministry of Education and the Secretary of Higher Education. The calculation of the four gridded energy demand datasets for the residential sector (SH, SC, WH, and TE) combines datasets from NASA temperature (HDD and CDD) with population and energy balances by the Agency for the Regulation and Control of Energy and Non-Renewable Natural Resources. Details about the process of calibration and validation of the datasets can be found in [17,18].

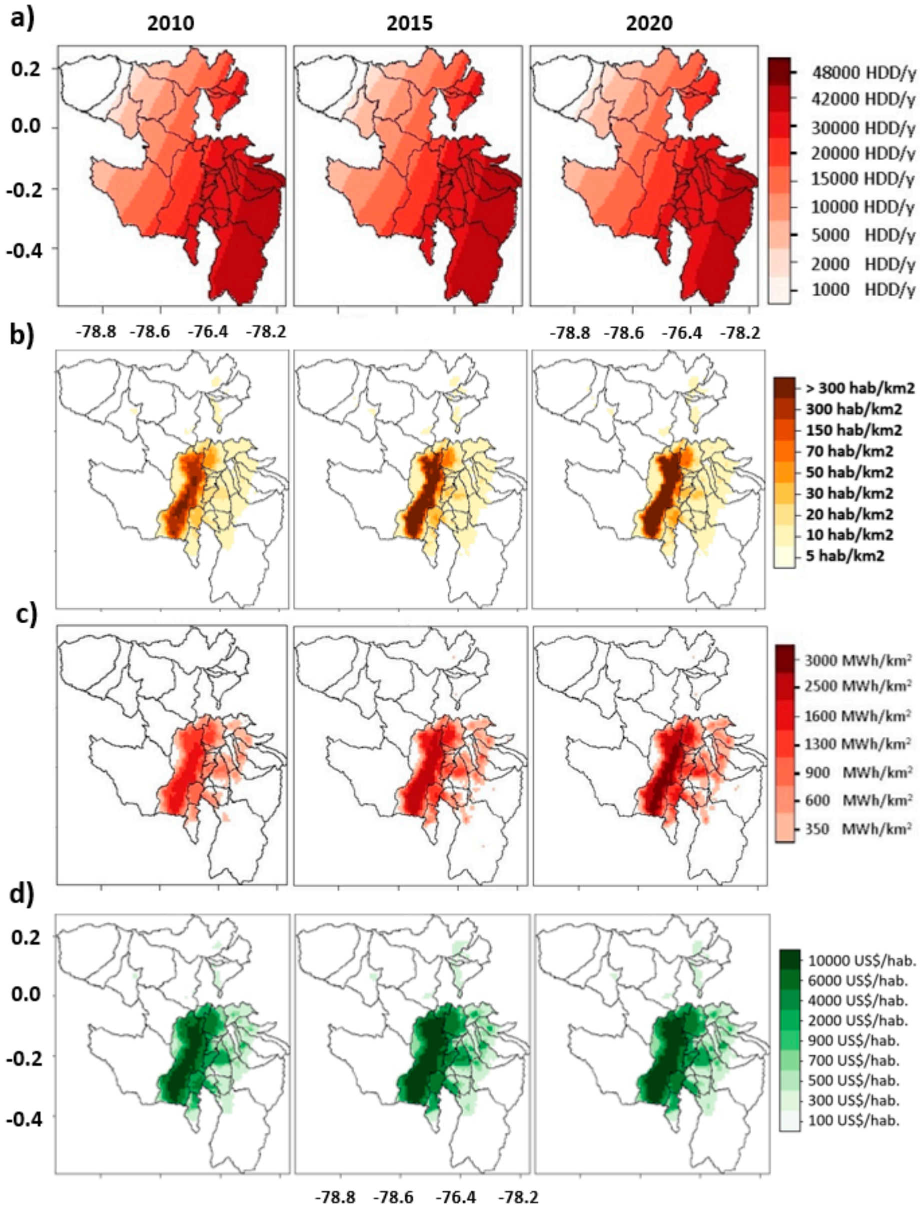

Figure 2. Comparison of energy consumption drivers in Quito City within Pichincha Province: (**a**) Annual heating degree days (HDD/y); (**b**) Population density; (**c**) Total energy demand in each squared kilometer; and (**d**) Gross domestic product per capita.

Table 2. Specifications of the dataset covering seven energy consumption drivers in Ecuador.

Data accessibility	Moya, Diego; Castro, Cristian; Arroba, César; Pérez, Cristian; Copara, Dennis; Borja, Rodrigo (2022), "Geospatial datasets of energy consumption drivers in the Ecuador's residential sector", Mendeley Data, V1, https://data.mendeley.com/datasets/bmfh63cc74, (accessed on 1 February 2023). doi: 10.17632/bmfh63cc74.1, in [16].
Subject	Energy
Specific subject area	Gridded energy consumption drivers of the residential sector
Type of data	Raster data (geospatial dataset)
Data format	Gridded data in .tif format. High-resolution.

Table 2. *Cont.*

How the data were acquired	Custom-built scripts written in R Statistic software and packages. QGIS was also used where needed.
Description of data collection	Data were collected from national and international institutions. Five national institutions were identified as key data providers: (1) the National Institute of Statistics and Censuses, INEC; (2) the Central Bank of Ecuador, BCE; (3) Ministry of Education, MINEDU; (4) Secretary of Higher Education, SENESCYT; and (5) the Agency for the Regulation and Control of Energy and Non-Renewable Natural Resources, ARCONEL. Two International institutions provide relevant data: the Centre for International Earth Science Information Network, CIESIN, and the NASA-MERRA2 program.
Data source location	INEC, Juan Larrea N15-36 y José Riofrío Código Postal: 170402, Quito, Ecuador BCE, Av. 10 de Agosto N11-409 y Briceño, Quito, Ecuador MINEDU, Av. Amazonas N34-451 y Av. Atahualpa, Quito, Ecuador SENESCYT, Av. 24 de Mayo y Che Guevara, Quito, Ecuador ARCONEL, Av. Naciones Unidas 7-71 y, Quito 170506, Ecuador CIESIN, 61 Rte 9W, Palisades, NY 10964, USA NASA-MERRA2, NASA Headquarters, 300 E. Street SW, Suite 5R30 Washington, DC 20546, USA
Related research article	Moya, D., Copara, D., Borja, A., Pérez, C., Kaparaju, P., Pérez-Navarro, Á., Giarola, S., Hawkes, A. (2022). Geospatial and temporal estimation of climatic, technical, and socioeconomic drivers of energy consumption in the residential sector in Ecuador Energy Conversion & Management [18].

The geospatial data were provided in a range of different layers for seven consumption drivers in the residential sector of Ecuador from 2010 to 2020. Figure 3 shows the country's population density. Population data were originally collected from CIESIN and then calibrated using INEC data. Figure 4 shows the Gross Domestic Product (GDP) of Ecuador calculated using data provided by the BCE. Figure 5 presents GDP per capita (GDPpc), which is the relationship between the data provided in Figures 3 and 4. Figure 6 shows the Human Development Index (HDI). Figure 7 shows the total end-use energy demand, accounting for space heating, space cooling, and water heating. All datasets are provided at a spatial resolution of 1 km^2, except for the HDI dataset, which comes at the city level. Population, GDP, GDPpc, and HDI have annual temporal resolutions, whereas end-use energy demands are provided at hourly, monthly, and annual temporal resolutions. Table 3 reports the dataset description of the names of each file.

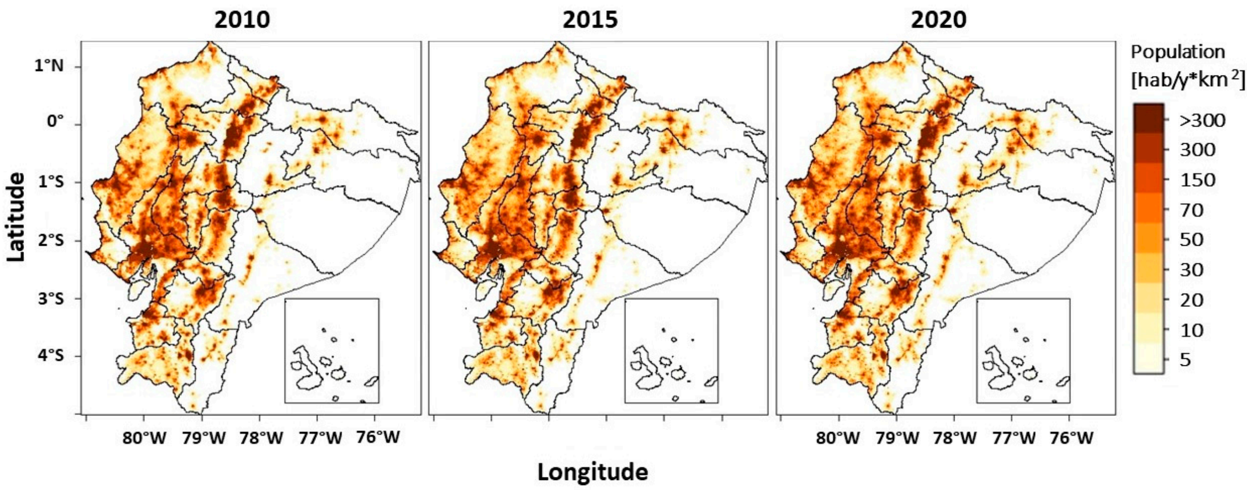

Figure 3. Annual geospatial population density of Ecuador in 2010, 2015, and 2020.

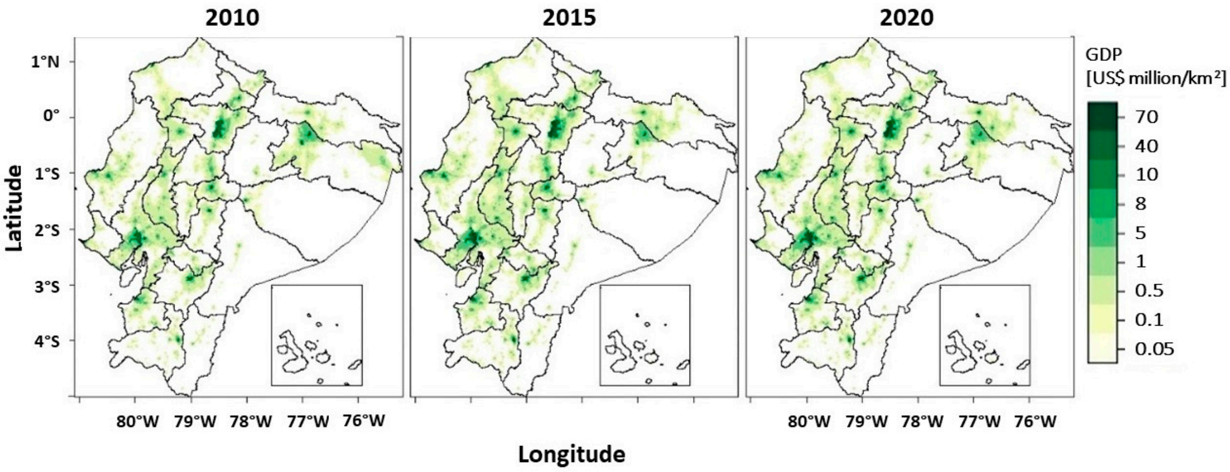

Figure 4. Annual geospatial GDP of Ecuador in 2010, 2015, and 2020.

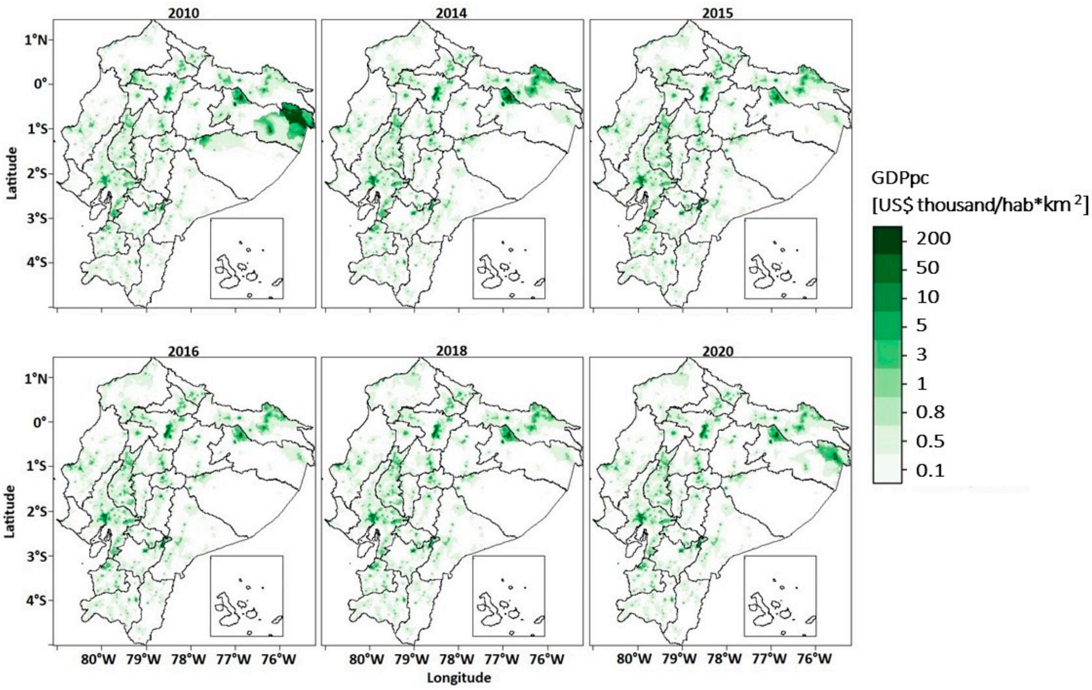

Figure 5. Annual geospatial GDPpc of Ecuador from 2010 to 2020.

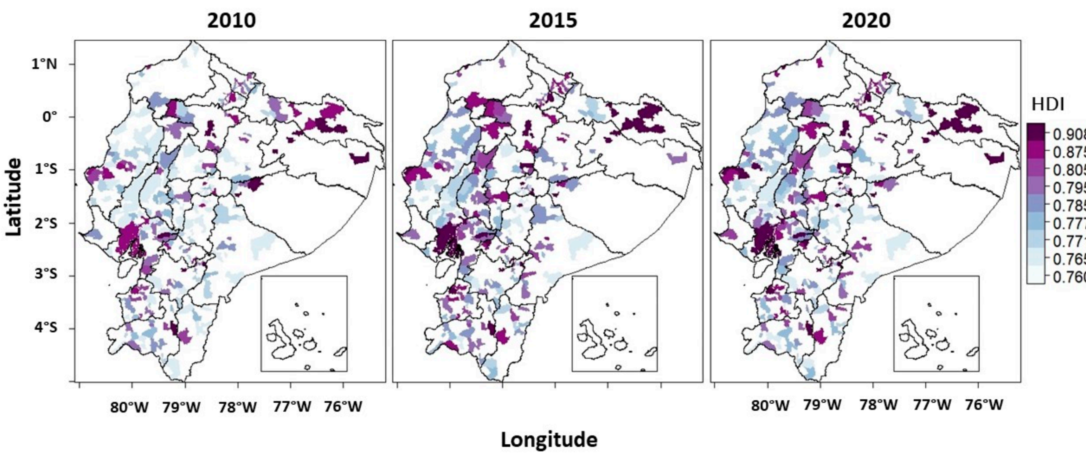

Figure 6. Annual geospatial HDI of Ecuador from 2010 to 2020.

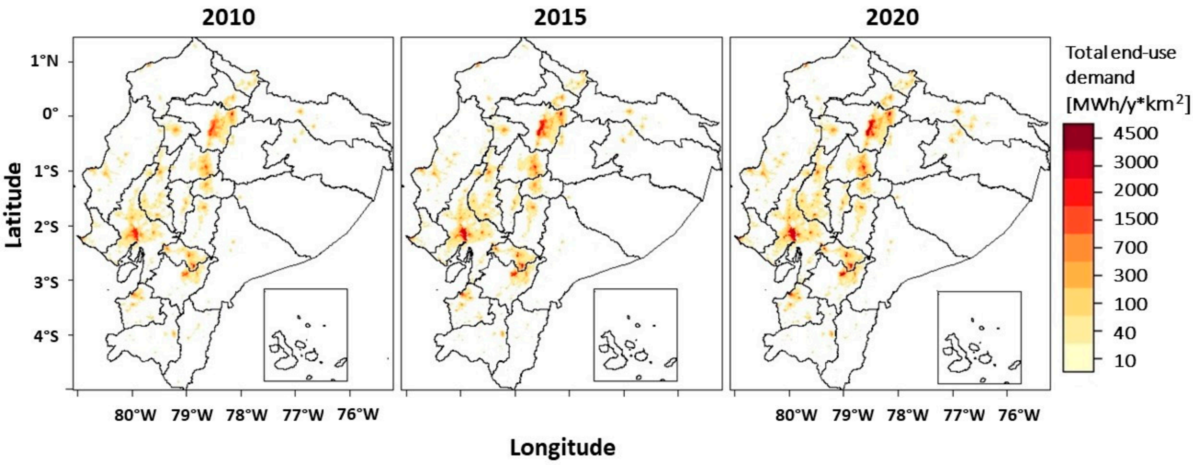

Figure 7. Annual geospatial total end-use energy demand of Ecuador's residential sector from 2010 to 2020. These include space heating, cooling, and water heating.

Table 3. Dataset explanation and example of the names of each consumption driver file.

Folder	Driver	File Name: Explanation Example	Description of Example
01	Population density	country_driver_year_resolution.tif ecu_pd_2010_1km.tif	Ecuador = ecu Population density = pd Year = 2010 1 km^2 Resolution = 1 km
02	Population count	country_driver_year_resolution_total.tif ecu_ppp_2010_1km_Aggregated.tif	Ecuador = ecu Population count = ppp Year = 2010 1 km^2 Total population = aggregated
03	Space heating	country_year_month_hour_driver.tif ecu_2010_01_01_CH.tif	Ecuador = ecu Year = 2010 January = 01 Hour = 01 CH = space heating demand
04	Space cooling	country_year_month_hour_driver.tif ecu_2010_01_01_DVH.tif	Ecuador = ecu Year = 2010 January = 01 Hour = 01 DVH = space cooling demand
05	Water heating	country_year_month_hour_driver.tif ecu_2010_01_01_DCA.tif	Ecuador = ecu Year = 2010 January = 01 Hour = 01 DCA = water heating demand
06	Total end-use energy demand	country_year_month_hour_driver.tif ecu_2010_01_01_TDE.tif	Ecuador = ecu Year = 2010 January = 01 Hour = 01 TDE = total energy demand
07	GDP	country_driver_year_resolution.tif ecu_gdp_2010_1km.tif	Ecuador = ecu GDP = gdp Year = 2010 1 km^2 Resolution = 1 km

Table 3. *Cont.*

Folder	Driver	File Name: Explanation Example	Description of Example
08	GDPpc	country_driver_year_resolution.tif ecu_gdp_pc_2010_1km.tif	Ecuador = ecu GDPpc = gdp_pc Year = 2010 1 km^2 Resolution = 1 km
09	HDI Provided at 1 km^2 at city level	country_driver_year_resolution.tif ecu_hdi_2010_1km.tif	Ecuador = ecu HDI = hdi Year = 2010 1 km^2 Resolution = 1 km

This article presents detailed methodology to estimate nine gridded datasets of energy consumption drivers in Ecuador's residential sector. The datasets can be found in [16], and the related research article can be found in [18]. This article expands on the methodology and dataset description, which makes it reproducible in further studies. To date, there is not a single methodology estimating energy consumption drivers considering the spatiotemporal dimension. Most of the studies present separate methodologies to address the drivers. However, this research also presents limitations for future applications of the framework. Researchers must consider that official data formats and resolutions can vary from country to country. Therefore, special consideration must be given. Another challenge is the validation of the methodology. As presented in [18], gridded data can be validated against aggregated datasets. This might introduce errors, especially when there is no available methodology of the aggregated dataset to compare results.

4. Conclusions

This article presents the steps, formulas, and data sources used in the methodology to identify seven datasets of energy consumption drivers in Ecuador's residential sector. This research provides the most effective way to consider spatiotemporal variability of energy consumption drivers for further modeling greenhouse gas abatement in residential buildings, while still maintaining physical and economic credibility. The data were collected from national and international sources. Then, the data were calibrated when required (e.g., population). A range of geospatial calculations were conducted using the R Software geospatial packages. Results were obtained for seven consumption drivers. The methodology presented herein was expanded from a previously validated approach. The validation process for the datasets presented in this study comprised two stages. First, once the datasets were calculated, the population counts, GDP, and energy demand datasets were selected for validation. Second, the calculated datasets were compared with the aggregated values of the 24 provinces of Ecuador. This means that the values reported by government institutions were aggregated at the provincial level and compared with the aggregated values from the calculated datasets. In the case of the population dataset, the validation process revealed that the population datasets presented by CIESIN differed by 3.48% with respect to the INEC reports.

The methodology and datasets reported herein provide highly spatiotemporally resolved drivers of energy consumption in Ecuador's residential sector. These are the highest achievable spatiotemporal resolution data of gridded population, GDP, GDPpc, HDI, residential space heating demand, space cooling demand, and water heating demand to date in the country and worldwide provided in a single study. Policymakers, developers, businesses, civil society, and researchers can benefit from these datasets and the methodology used to build them. These datasets are useful for evaluating energy policies, energy infrastructure development, and energy technology diffusion at the local, municipal, provincial, regional, and national levels of the country. The datasets reported here can be used for further insights, research, and development. Postprocessing can be applied to segment a range of energy consumption classes along with their spatial attributes for long-term energy planning. This will help in the development of zonal-based solutions instead of single national solutions. Gridded residential energy demand, along with GDPpc and HDI, are key datasets for assessing the technical, economic, and social aspects of the deployment of new and efficient technologies in the residential sector. Policymakers, developers, businesses, civil society, and researchers can use these datasets to evaluate the technical, economic, and environmental impact of the diffusion of new technologies. These datasets are key to including the heterogeneity and diversity of residential energy consumers in energy modeling by the research community. Heterogeneity refers to consumers' geographical characteristics. Diversity refers to the range of socioeconomic characteristics consumers possess.

The methodology and datasets provided in this article can serve to inform evidence-based decision making. There are some practical implications of this research, specifically in the field of energy policy design and implementation. Policymakers, firms, and civil society can use this research to evaluate future expansion and planning of residential energy sectors. Urban and energy policy can be focused on specific needs identified in the datasets. Policymakers will be able to see how energy demand grows at the same time as socioeconomics and development keep their own profiles. Other energy policies such as subsidies can be focused on populations that belong to lower socioeconomic realities. In this way, public resources can be used efficiently.

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Nomenclature

HDH	Heating degree hours
CDH	Cooling degree hours
SH	Space heating
SC	Space cooling
WH	Water heating
$_c$	Cell
$_d$	Day

h	Hour
m	Month
$T_{c,d,h}$	Temperature in a cell for a specific day and hour
T_{ref}	Reference temperature
WH	Waiting factor for water heating
kc	Scaling factor
POP_{den_c}	Population density per cell
Km^2	Square kilometre
I_{SH}	Index for space heating
I_{SC}	Index for space cooling
I_{WH}	Index for water heating
IAE	Lighting and electric appliances
E	Energy consumed
ED	Energy density
TED	Total energy demand
TEDD	Total energy demand density
AF	Gross Domestic Product adjustment factor by city
GDP_N	Gross Domestic Product national
GVA_N	Gross value added national
GDP_C	Gross Domestic Product by city
GVA_C	Gross value added by city
AGP	Adjusted GDP per capita
POP_C	Population by city
POP_P	Population by parish
GI	Gross Domestic Product index
VGImax	World benchmark maximum GI value
VGImin	World benchmark minimum GI value
HDI_C	Human development index by city
EI	Education index
LI	Literacy index
CER	Combined enrolment rate
AR	Alphabetization rate
VARmax	World benchmark maximum AR value
VARmin	World benchmark minimum AR value
GPR	Gross primary rate
SGR	Secondary gross rate
GUR	Gross university rate
POP_{PE}	Population attending primary level establishments
POP_{0511}	Total population between 5 and 11 years
POP_{SE}	Population attending secondary level establishments
POP_{1217}	Total population between 12 and 17 years
POP_{UE}	Population attending higher level establishments
POP_{1824}	Total population between 18 and 24 years
$POP_{15\text{ and more}}$	Total population of 15 and more
POP_L	Population attending literacy establishments
LEI	Life expectancy index
LE	Real value in years of life expectancy at birth
VLEmax	World benchmark maximum LE value
VLEmin	World benchmark minimum LE value
IR	Illiteracy rate
POP_{LI}	Literate population
POP_{IL}	Illiterate population
POP_{LI10}	Literate population registered in the 2010 population census
POP_{LI10-n}	Literate population from 2010 to n number of years

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