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Assessing cities growth-degrowth pulsing by emergy and fractals: A methodological proposal

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ABSTRACT

As a powerful tool for assessing cities development, the emergy synthesis considers the energy quality concept, which allows it to quantify all the effort provided by nature in providing resources, however, it usually demands a huge amount of data and still lacks a complete and updated database for long-term studies. Cities seem to develop according to fractals, building up parts that resemble the whole, which is also relevant in emergy theory and observable through night-time lights from cities that are used to investigate how energy use distributes as cities change. This work proposes an alternative method for estimating the fractal dimension and non-renewable empower density (NRED) of cities from satellite night-time images and assess the relationship between them. Nine cities in Brazil, selected through a cluster analysis, were considered as a case study. Results show a strong positive correlation (0.94 for Pearson index) between fractals and NRED, which can be of help in estimating each other for further studies. The method proposed is time and cost effective when compared to previously used methods based on red/blue/green (RBG) satellite images, representing a potential alternative for assessing urban expansion in spatiotemporal models and assessing cities limits to growth.

1. Introduction

There is an increasing global interest in understanding and assessing cities shape and limits to growth, and their effects on environmental sustainability and urban sprawl (Sutton et al., 2007; Zhang & Li, 2018). According to the United Nations Environment Program (UN, 2019a), cities generate over 80% of the GDP of many countries in Asia and the Pacific and are engines of economic growth that have lifted millions out of poverty. Cities provide high-quality outcomes in terms of economic development, knowledge transfer, innovation, and social interaction. Cities provide access to recreational areas and public services (e.g. water and sanitation, health care, electricity, and emergency services), and usually feature the central administrative, financial, legislative, and judiciary offices. On the other hand, although occupying 2% of the Earth's surface, cities consume 60–80% of the global energy (Sodiq et al., 2019). In particular, cities demand a high density of energy and goods from their surrounding neighborhood (Odum, 1996; Odum & Odum, 2006; Giannetti et al., 2020), and also import from other regions and countries, which results in the emergence of spatial networks of hierarchical energy transformations (Braham et al., 2019).

In general, in a given region, smaller centers of built-up areas support larger cities with materials and energy, and larger cities act as hubs for manufacturing and distributing goods. This hierarchy results in a convergence of energy, from primary energy transformations to concentration of energy in final goods and services (Giannetti et al., 2020; Odum, 2007). This energy-based network is visualized through night-time lights, with cities as bright nodes connected through major roads (Odum, 2007). Due to the high energy demand and environmental impacts of cities (Fistola, 2011; Jacobi, 2013; Sevegnani et al., 2018), night-time lights observations are being used to understand how urban aggregates growth, are organized, distributed and connected (Ghosh et al., 2009, 2010, 2013; Henderson et al., 2012; Mellander et al., 2015; Hu & Yao, 2019; Coscieme et al., 2014a, 2014b; Sutton et al., 2007), which are important aspects for informing public policies (Evans, 2019).

Since 2007, more than half of the world's population has been living in urban areas, with a 70% increase expected by 2050 (UN, 2019a). The

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11th goal of the United Nation's 2030 Agenda for Sustainable Development (SDG, 2019) emphasizes the need for sustainable cities and communities by making cities and human settlements inclusive, safe, resilient and sustainable. To make a city more sustainable, the UN (2019a) highlights the importance of investments in renewable energy, efficiency in water and electricity use, planning for more green areas, and fast, reliable and affordable public transportation and waste and recycling systems (see also Newman (2020) for a case on climate change). Although recognizing the importance of investing in social, economic, environmental and urban governance in cities (Evans, 2019; UN, 2019b), a focus on how cities contribute to approach (and exceed) the Earth's biophysical limits, in particular regarding energy on a larger scale, should be considered in supporting public policies (Agostinho et al., 2019; Sodiq et al., 2019; Wackernagel et al., 2017).

The concentration of economic enterprises and people in cities ultimately depends on the availability of "cheap" fossil fuels, a condition that will much likely not be maintained in the future, with fossil fuels becoming less available and more expensive (Mohr et al., 2015; Ward et al., 2012). According to Odum and Odum's (2006) pulsing-paradigm cycle, the decreasing resource base of the world's fossil fuel economy will force society into a different stage where pursuing economic growth will have to reconcile with the general systems principles of energy, matter and information (see also Bardi (2015) and Brown and Ulgiati (2011)).

Considering that large urban aggregates growth resembles the development of self-organized structures (Schweitzer & Steinbrink, 1998), the complexity of cities can be studied by considering, among other characteristics, their fractal[1] structure (or scaling exponent), as a means to understand how cities are spatially organized. This is supported by Chen (2014), and other studies on the fractal dimension of cities (e.g. Batty & Longley, 1994; Benguigui et al., 2000; Frankhauser, 1998; Marques, 2005; Xu & Min, 2013). Fractals can be investigated through different approaches, mainly involving measurements of area, population, and GDP over time. However, none of these approaches considers the biophysical limits of a city, as a consumer system of highly concentrated energy. This hampers the ability of fractals to be used in studies involving future scenarios of city development.

In order to investigate cities' limits to growth beyond physical spatial restrictions from fractals, the use of emergy accounting (with an 'm'; Odum, 1996) which considers renewable (R) and non-renewable (N) natural resources and resources provided by the economy (F) is proposed. Emergy accounting is a tool based on the thermodynamics and systems theory which provides a number of sustainability indicators (Giannetti et al., 2010; Brown & Ulgiati, 2011). In particular, emergy is able to take into account the sustainability of the entire set of energy flows in urban metabolism (Agostinho et al., 2018), including those flows without a market value, by summing up the equivalent solar energy needed to produce each different form of energy through a series of environmental and anthropic processes. According to Odum (1996), the empower density (i.e. emergy per time per unit surface) can be used to spatially represent the energy transformation hierarchy, indicating how emergy is distributed in a territory (e.g. Braham et al., 2019). Chen and Zhou (2008) indicate that energy and energy transformations determine the spatial order and structure of cities self-organized networks, however, the use of energy rather than emergy would provide incomplete insights on the full range of resources demanded by urban metabolism, as energy does not consider the whole life cycle of energy and material forms. All these characteristics make emergy values a potential reference for investigating how city's growth affects the geography of resources in a territory, allowing to investigate the fractal structure of urban growth from a sustainability perspective.

However, time-series emergy values of cities are scarcely available, calling for the use of proxy measures and other methodological alternatives. In this vein, Coscieme et al. (2014a) used night-time lights satellite observations to estimate and visualize emergy values of urban areas with intensive energy use and rural/wilderness areas. In this "thermodynamic geography", emergy is used to characterize a territory "as a continuum of physical and morphological elements, infrastructures and urban settlements, rather than a combination of separated systems" (Pulselli, 2010). Following this approach, Neri et al. (2018) used night-time lights images to estimate the non-renewable component of empower density for a list of 57 countries from 1995 to 2012. Some authors (e.g. Agostinho et al., 2010; Lee & Brown, 2019; Mellino et al., 2014) have proposed and used methods to calculate the renewable component of empower density using georeferenced data of spatial distribution of solar radiation, geological heat flow, wind-kinetic energy and precipitation. Combined, these methods can be used to estimate empower density of cities in time series, including the non-renewable and renewable components.

Considering the current restrictions for cities' growth due to reduced availability of biophysical resources, understanding cities development patterns under the pulsing-curve becomes of paramount importance to propose more precise public policies. This city metabolism can be assessed under the emergy perspective, however, large databases containing emergy flows for urban systems are rarely found in literature, mainly on small scales. That said, this paper aims to propose an approach that considers the use of night-time satellite images to estimate non-renewable empower density (NRED) and the fractal dimension of cities. These estimates are used to investigate how the physical dimension of urban growth relates with urban metabolism in terms of emergy. A case study for nine cities of the State of São Paulo, Brazil, selected through a cluster analysis, is presented in order to assess dynamics of urban expansion and metabolism in cities with different characteristics.

2. Methods

2.1. The pulsing-paradigm curve

Odum's pulsing-paradigm for general systems self-organization (Odum, 1996) involves stages of slow production, growth and succession followed by a pulse in consumption, a descent and a recession (Fig. 1). "Pulsing" refers to the slow building up, or stocking, of products converging into centers of production, followed by a dispersal of products towards multiple centers of fast consumption and a sharp descent in the overall amount of products. Four main stages of the pulsing cycle can

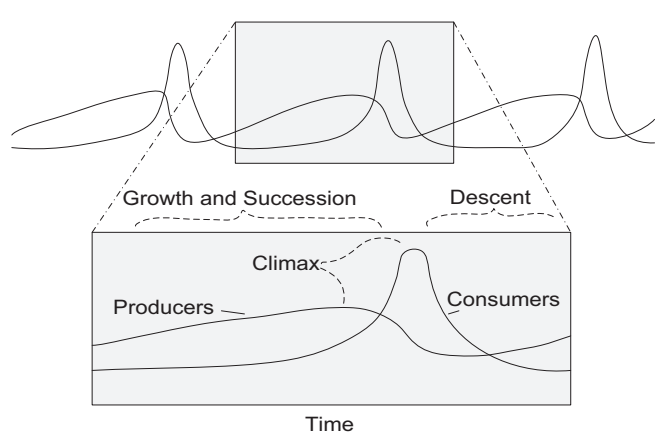

Fig. 1. The pulsing-paradigm curve and its growth, climax and descent stages. Source: Odum (1996).

[1] The word "fractal" was coined by Mandelbrot in his fundamental essay from the Latin fractus, meaning broken, to describe objects that were too irregular to fit into a traditional geometrical setting. Many fractals have some degree of self-similarity, i.e. they are build up of parts that resemble the whole in some way (Falconer, 2003).

be identified: (1) *Growth on abundant available resources*, with a sharp increase in the system's population, structures and assets, based on low-efficiency and high competition; (2) *Climax and transition*, when the system reaches the maximum size allowed by the available resources, becomes more efficient, develops collaborative competition patterns, and stocks information; (3) *Descent*, with adaptations to resource scarcity, a decrease in population and assets, an increase in recycling patterns, and an efficient transmission of the information accumulated; (4) *Low-energy restoration*, characterized by no-growth, consumption lower than production, and increasing storage of resources to be used to feed the next cycle (Odum & Odum, 2006).

Modern societal development is based on fossil energy use and implies considering the Earth as a limitless source of resources with an infinite capacity for absorbing/diluting wastes generated by human activities. This wrong idea is inconsistent with the pulsing-paradigm of self-organization. Using peak oil production data, Bardi (2019) emphasizes the importance of fossil fuel production for assets accumulation. In this vein, we consider non-renewable emergy (energy derived from fossil fuels) as the main driver of pulsing-paradigm stages of growth and degrowth. Fossil energy has been driving growth during the last century, but its non-renewable nature implies that this energy source will no longer be available to support growth, calling for alternative energy sources and/or a redefinition of our systems organization and dynamics away from business-as-usual.

2.2. Calculation procedures

Since different scientific approaches and data are used in this work, the methodological procedures are schematically represented by Fig. 2. Two main stages and their procedures can be identified in the figure, each one explained individually and in detail in the subsequent sections.

2.2.1. City boundary map

In order to select a number of cities to be considered as a case study, a cluster analysis on the 645 cities of the State of São Paulo, Brazil was performed. To identify the areas under study, a 2015 shapefile of city boundaries available from the Brazilian Institute of Geography and Statistics (IBGE, 2019) was used, assessed in QGIS® 3.4.2. The State of São Paulo was chosen due to its economic importance and contribution to Brazil's gross domestic product. The State of São Paulo is characterized by a high concentration of energy, money, universities, research centers, industries, population, and with high agrobusiness importance for Brazil. Furthermore, São Paulo experienced substantial changes in urban dynamics during the last decades, thus representing an interesting case for the study of fractal structure of urban development. A hierarchical cluster analysis considering the Euclidean distance was performed (i.e. the square root of the sum of the square differences among the measures considered) and selecting the Ward method as a parameter, which is one of the most appropriate methods for quantitative data. Please refer to Murtagh (1983) for further details on the chosen cluster variables.

We considered GDP per capita, percentage of total inhabitants living in urban areas and inhabitants per square meter as similarity variables, which resulted in three clusters: G1 with 237 cities, G2 with 256 cities, and G3 with 152 cities (Fig. 3). These variables were chosen due to their importance in representing the main characteristics of cities. A tendency can be observed of G1 in having higher GDP per capita than other clusters, followed by G3 and G2. Regarding the percentage of urban population, G3 includes cities with high concentration (from 90 to 100%) of people living in urban areas, closely followed by G1, while G2 includes cities with lower concentration of people in urban areas (from 30 to 85%). Population density (in log scale) shows a similar behavior, with G3 presenting higher population density than G1 and G2. According to Fig. 3, G3 can be understood as a group of the 'more

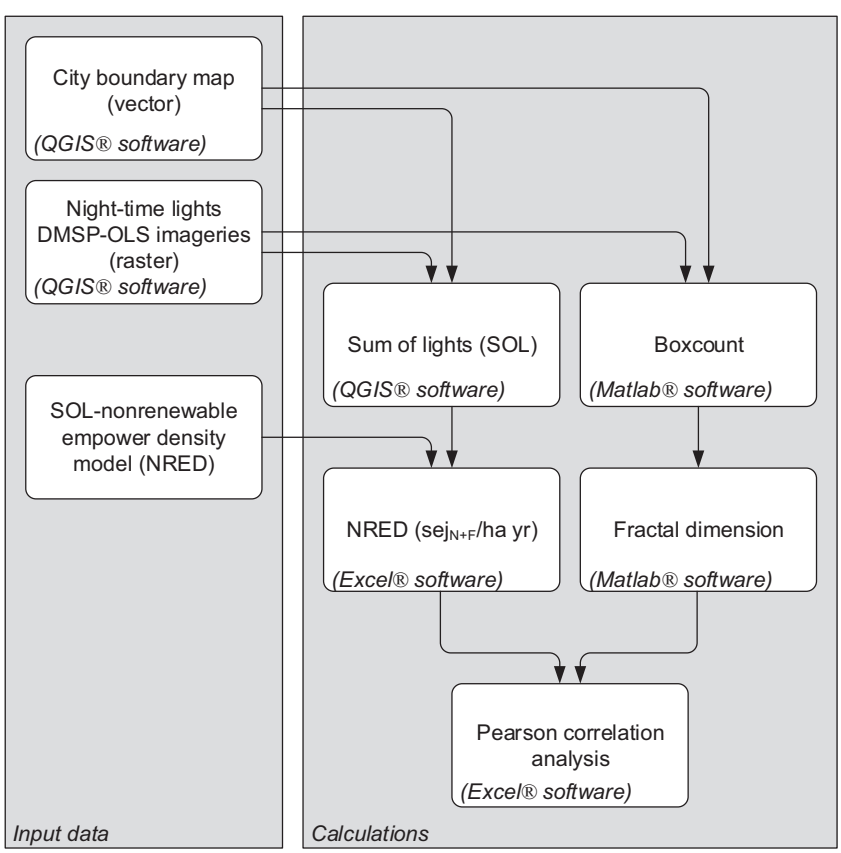

Fig. 2. Schematic representation of the methodological procedures used in this work. Legend: GIS = geographical information system; DMSP-OLS = Defense meteorological satellite program - operational linescan system; SOL = sum of lights; sej = solar emjoule.

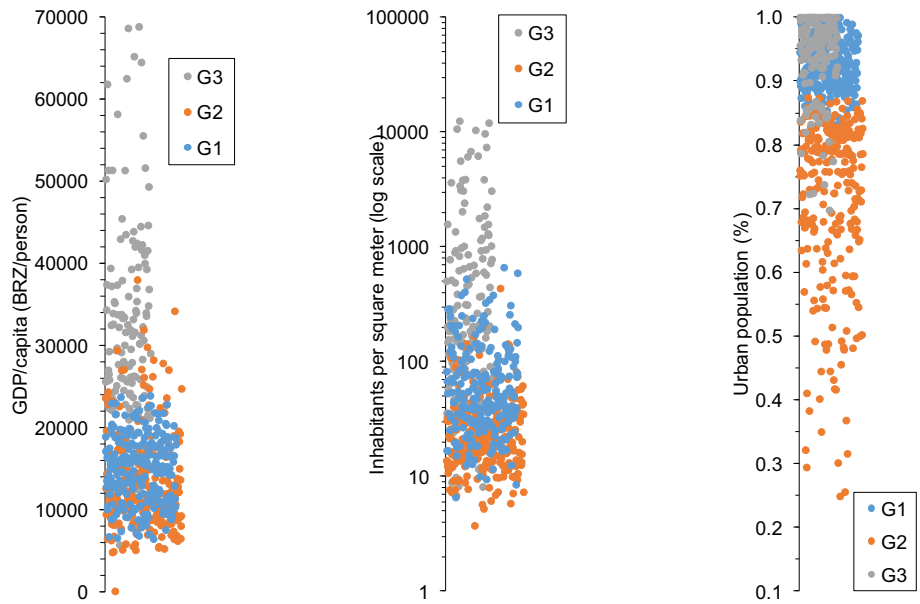

Fig. 3. Cluster results for the 645 sampled cities grouped according to three similarity variables. G, cluster.

urbanized' cities that produce mainly industrialized goods and provide high quality services such as financial services, know-how development, and scientific research, among others. This results in high GPD generation but at the same time a strong resource dependency (energy, water, food, etc.) from other regions. The opposite can be said for G2, characterized by 'less urbanized' cities where the economy seems to be based on agricultural production and extraction of natural resources such as minerals, wood, etc. At the same time, cities in G2 tend to have higher biocapacity due to large areas of natural vegetation and cropland. Finally, G1 includes 'moderately urbanized' cities, an intermediate cluster between G3 and G2.

Following Ge and Lin (2009), after running a cluster analysis, cities with an area smaller than 410 km^2 were excluded, as DMSP-OLS satellite images are not sufficiently accurate at that scale. This returned a total sample of 212 (G1 with 84 cities, G2 with 72 cities and G3 with 56 cities), from which three cities from each cluster with the highest, lowest

Table 1
Cities of the State of São Paulo considered in this study.

Cluster	Human development index (HDI) within the cluster		
	Highest	Median	Lowest
G1	Assis	Mirandópolis	Itápolis
G2	Presidente Bernardes	Bananal	Ribeirão Branco
G3	Jundiaí	Pompéia	Jaboticabal

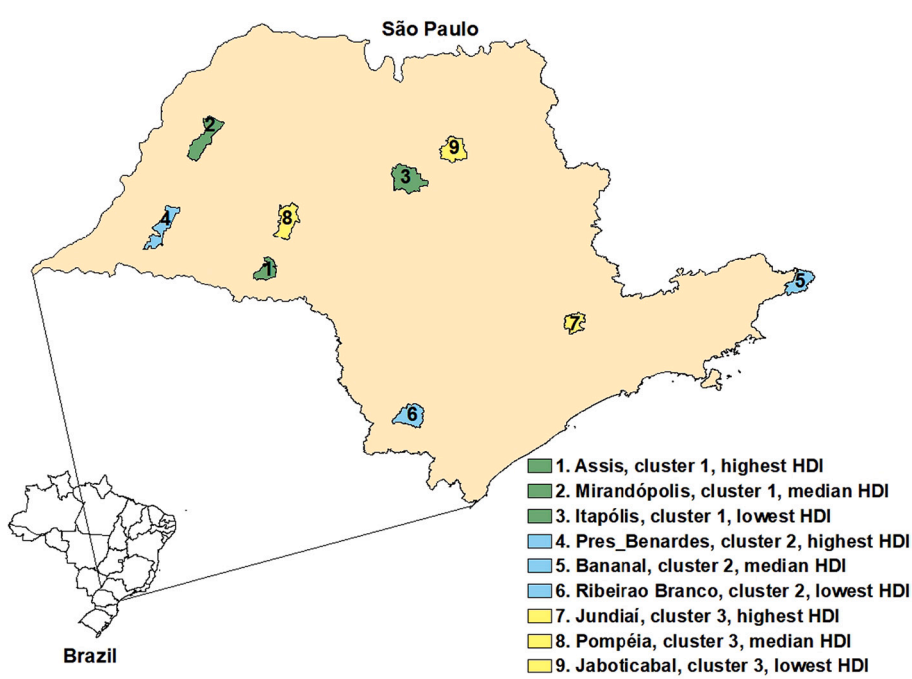

Fig. 4. The nine cities of the State of São Paulo considered in this case study. Cities in green belong to cluster 1; cities in blue to cluster 2; cities in yellow to cluster 3. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

and median value of human development index within the cluster were selected, returning a total of 9 cities (Fig. 4 and Table 1). The HDI was particularly considered when selecting representative cities from the sample due to its ability to show the mutual relationship between people and the cities they live in. This case study can be replicated for a larger sample of cities across the world.

2.2.2. Nighttime lights DMSP-OLS imageries

The Earth Observation Group (EOG) of the National Centers for Environmental Information at NOAA (https://ngdc.noaa.gov/eog/index.html) provides annual cloud-free composite satellite images of night-time lights worldwide; images from 1992 onwards are available. Night-time lights are mapped at a resolution of 900 m^2 (30 × 30 m pixels) on a digital-number scale with values ranging from 0 (totally dark areas, e.g. in rural and wilderness settings) to 63 (maximum brightness detectable by the sensor, e.g. in densely populated urban areas). These images are used in a large number of studies on urban areas and energy use, as well as on a range of other aspects (Bennett & Smith, 2017; Elvidge et al., 2001, 2009; Jasinski, 2019; Li et al., 2018; Sutton et al., 2012; Tuttle et al., 2013 and Xiao et al., 2018). From this dataset night-time lights data for the State of São Paulo for the years 1992, 1994, 1998, 2002, 2004, 2008 and 2012 were extracted, since 1992 is the first year with available DMSP-OLS images and 2012 is the latest one. Data were processed in QGIS® 3.4.2.

2.2.3. Sum of lights (SOL)

The sum of lights (SOL) are obtained by the sum of the pixel values within an area, as an indicator of the total amount of night-lights emitted from the cities under study. Before extracting the SOLs, the original images derived from multiple satellites for the same year were calibrated following Elvidge et al. (2009) and Liu et al. (2012). For calibrating the images, the F18/2012 image for the State of São Paulo was considered as a reference, as it shows the highest values of SOL observed across the time-series. All "instable" pixels (i.e. lights observed only by one of multiple satellites in a year from a specific pixel) were removed, and the average value from different satellite observations of stable pixels was considered. According to Li et al. (2017), calibration is a necessary step to achieve a globally consistent series of night-time light values over the years, in order to track urban sprawl in rapidly-developing regions. Values for each pixel are in accordance with the original image, ranging from 0 to 63. The values of pixels are summed up to calculate the SOL of each city for each studied year. Data were processed in QGIS® 3.4.2.

2.2.4. SOL – non-renewable empower density (NRED) model

The relationship between SOL and NRED (including both non-renewable resources from nature 'N' and those imported from the larger economy 'F') was investigated by Coscieme et al. (2014a, 2014b). More recently, Neri et al. (2018) developed a model that relates SOL with NRED, allowing for the reconstruction of continuous time series of NRED at the national scale. This model is, however, not applicable at city scale (Neri et al., 2018). In order to explore the relationship between SOL and NRED at the local scale, and considering the lack of emergy data at city scale, emergy values calculated for the States of Brazil by Demetrio (2011) were used instead. The SOL for the States of Brazil were extracted following the method used for extracting SOL for cities, as previously described, and the correlation between SOL and NRED was explored. A significant positive correlation characterizes SOL and NRED for the States of Brazil (sub-national scale), which is aligned to the positive correlation between these variables obtained by Coscieme et al. (2014a) and Neri et al. (2018) when assessing national scales. Appendix A shows the numbers and procedures that resulted in the adjusted local scale linear model $sej_{N+F}/ha = (2.36\ E17 * SOL/ha) + 2.15\ E15$.

2.2.5. Non-renewable empower density (NRED)

The emergy investment 'U' in a city is the sum of renewable 'R' and non-renewable 'N' emergy from nature with the emergy imported from the larger economy 'F'; U = R + N + F. Although characterized as resources imported from the larger economy, the 'F' resources are mostly dependent on fossil energy throughout their production chain, which makes them non-renewable resources. Considering a business-as-usual cities development model, 'F' has been shown in the emergy literature as the main driver sustaining cities, which renders it a good proxy to assess cities development patterns and support discussions on cities' pulsing paradigm. By using the SOL calculated for the cities under study, the SOL-NRED model can be used to derive the NRED ('N' + 'F', in sej/ha year) of each city for the years 1992, 1994, 1998, 2002, 2004, 2008 and 2012.

2.2.6. Box-counting

Box-counting is a data gathering method which allows for investigating complex patterns by breaking images – among other information sources – into smaller and smaller pieces (usually in two dimensions). The image is analysed to understand whether or not some of its features change with scale (Falconer, 2003). Several applications of box-counting are found in the scientific literature (e.g. Chatterjee et al., 2019; Lovejoy et al., 1987; Wang et al., 2019). Box-counting consists of accommodating the image under study within a reticulate with squares of size "s", then the number of squares that intersect with the image are added up and represented by "N". This process is repeated for multiple iterations with reticulate of decreasing "s", in order to provide statistically significant results. The reclassified night-time satellite images for the nine cities for each year (giving a total of 63 images) were uploaded in MATLAB® R2020a and the following boxcount programing lines were used: >boxcount(imagem), >>[N, s] = boxcount(imagem). A correlation matrix of "s" and "N" is obtained for each image, then used to calculate the fractal dimension of each city for each year.

2.2.7. Cities' fractal dimension

Fractals are complex geometrical structures characterized by self-similarity that cannot be measured by a simple topological dimension. The fractal dimension of a shape is a value that indicates how this shape occupies the space in which it exists. The fractal dimension can assume fractional values, representing the degree of complexity of the shape. According to Addison (1997), the box-counting is a good method for measuring the fractal dimension, commonly used, as it is relatively easy to apply when compared to other methods (e.g. Batty & Longley, 1994; Man et al., 2019). The "N-s" matrix obtained from the boxcounting allows investigating the relationship between the size of the squares in the reticulate ("s") with the number of squares that intercept the image ("N"). From this, a linear logarithmic curve of the relationship between "1/s" and "N" can be derived, whose slope represents the fractal dimension of the city under study. This procedure is repeated in this study for the different cities and years considered, calculating 63 fractals dimensions. The following MATLAB® R2020a routine is used to obtain the fractal dimension: >>>p=polyfit(log(s),log(N),1).

3. Results and discussion

3.1. Temporal analysis of NRED and fractal dimension of cities

Fig. 5 presents NRED from 1992 to 2012, estimated every two-four years for the nine cities considered in this study. Under a general view, some non-expected concave or convex trends for NRED can be observed, most prominently for Assis and Jaboticabal in 1998, and for Presidente Bernardes in 2008. Since all NRED values were estimated through SOL, at first, significant changes would not occur for short time periods between two-four consecutive years, since urban expansion usually occurs in larger time windows. Data and procedures were carefully revised and, so far, the existing non-expected behavior due to quality of satellite images used and/or due to the reduced area for the evaluated cities could be explained (keeping in mind that images should have at least 512 pixels for an accurate box-counting procedure).

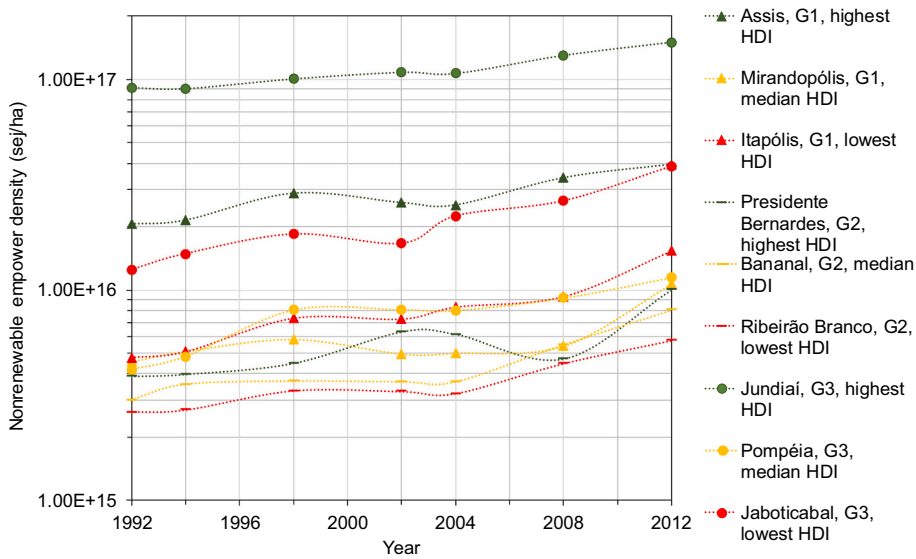

Fig. 5. Non-renewable empower density time series (on a logarithmic scale) of the nine cities of the State of São Paulo considered in this study. HDI: human development index. G: cluster.

Anyhow, the currently best data and satellite images were used and once better data become available, these numbers can be revisited.

Fig. 5 indicates that the HDI rank has no influence on NRED dynamics, as cities with median HDI show similar trends, while the highest difference among NRED characterize cities with the highest HDI. Similarly, specific NRED trends do not emerge for specific clusters, with the exception of cluster G2. This indicates that the variables used in the cluster analysis, as well as the HDI, do not have any particular effect on consumption trends of non-renewable resources per unit area. It is worth noting that the variables considered for the cluster analysis reflect data for 2018–2020, so cluster results refer to the current characteristics of cities, and not to cities characteristics earlier in the time series. None of the cities investigated seems to have entered a stage of degrowth in the pulsing-paradigm curve (PPC; Fig. 1). These findings are in line with Agostinho et al. (2018), who used total emergy of cities to study their growth. The city of Jundiaí shows the highest emergy demand for the entire period. All of the cities investigated are at the growth stage of the PPC, with different growth rates: while Jundiaí increased its demand for non-renewable emergy by 64%, all other cities show an increase between 92% to 222% during 1992–2012. With the exception of Assis, Fig. 5 indicates that cities belonging to the G3 cluster have the highest NRED throughout the time series, which is indicative of 'more urbanized' cities depending on high quality external resources. Clusters G1 and G2 are at a later stage of growth, as compared to G3, so it is expected that their growth rate will slow down once they reach performances similar to those of the cities in G3.

There is no clear evidence of a relationship among clusters and/or HDI with the fractal dimension of the cities investigated (Fig. 6). Although recognizing that reducing the complex dynamics into a single value of fractal dimension could lead to oversimplification and overgeneralization (Chen & Zhou, 2008), some considerations can be drawn from Fig. 6. From 1992 to 2012, fractal's growth rate ranged from 0 to 1.9%. These rates indicate that while cities experienced a fast increase in non-renewable emergy demand (Fig. 5), they did not experience any

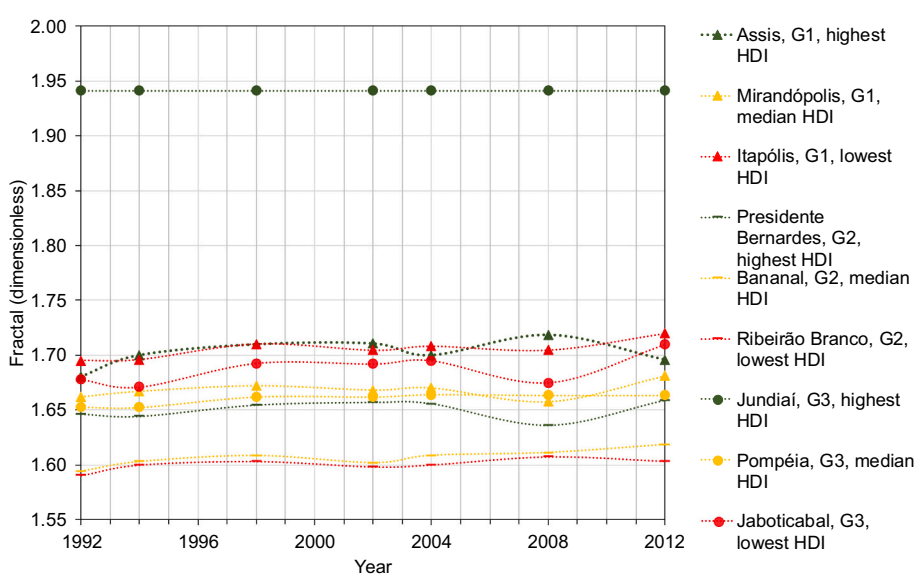

Fig. 6. Fractal dimension time series of the nine cities of the State of São Paulo considered in this study. Raw data are presented in Supplementary material B. HDI: human development index. G: cluster.

significant change in their rate of physical expansion. This indicates that the speed of urban expansion differs from the speed of increasing energy demand in terms of NRED. In particular, the city of Jundaí maintains its fractal dimension of 1.94 from 1992 to 2012, indicating no urban expansion. A constant fractal dimension indicates that a city (i) has achieved its maximum physical expansion (i.e., there is no extra available area to be urbanized), or (ii) there is still potential for urban expansion but this option is not considered in terms of territorial planning. It is worth highlighting that both cases are relevant due to the long-term temporal analysis (20 years) performed in this study, as the same analysis performed over a shorter period could have missed the relatively slow process of urban expansion.

The fractal dimension of cities over time will hardly show similar behavior when compared to that presented by the pulsing-paradigm curve (PPC) of Fig. 1, mainly for the degrowth stage, since a reduction of the fractal dimension implies a reduction of the urbanized area, which is observed in relatively few cases, such as when, for example, urban build-up is replaced by green areas as urban parks, or even due to urban decay. Urban decay or shrinking cities has no single cause, usually it is a result from combinations of socio-economic conditions. As discussed by Reese et al. (2017) and Audirac (2018), external drivers of decay include overreliance on industries coupled with long term structural downturns in these industries, poorly skilled labor available, increasing amount of jobs available in the suburbs, suburbanization process, policies supporting the development of suburbs rather than inner cities, national policies promoting housing development in suburbs and exurbs. Other drivers include tight rent control, the poverty of the local inhabitants, the construction of freeway roads and rail road lines that bypass the inner cities, real estate neighborhood redlining, immigration restrictions, or even just heat cost. Fractal retraction aiming for more positive purposes rather than urban decay can happen, however, it demands a strong socio-political and economic effort, since urban areas are highly valued and priced (i.e. dollars per square-meter), and hardly ever would a green area be developed on an already constructed area. This implies that a constant fractal dimension can be indicative of a climax or a degrowth stage on the PPC (Fig. 1). As the HDI of Jundiai is the highest within its cluster, and its fractal dimension has remained constant since 1992, the hypothesis that Jundiai reached its limits to growth could be established.

According to Chen (2009), both natural and human dominated systems have similar patterns for space-filling properties, which is supported by the statement of Chen and Zhou (2008) that cities are self-organizing systems conforming to certain natural laws, just like many physical systems. However, differently from Chen and Huang (2019), who identified PPC-like behaviors represented by Boltzmann equation, logistic function, and quadratic logistic function, our results from Figs. 5 and 6 did not show the expected growth-degrowth PPC stages for the studied cities.

3.2. Relationship between NRED and fractal dimension

The relationship between NRED and the fractal dimension of the cities under study is assessed to understand to what extent the metabolic (i.e. quantity, quality and distribution of energy use) and the spatial dynamics of cities resemble, or not, one another. From Fig. 7, an increase in both NRED and the fractal dimension over time can be observed, with the former increasing at a faster rate than the latter. While the fractal dimension represents urban expansion by filling a two-dimensional space, the NRED represents the density of systems demand for emergy. Increasing urbanization, including a more vast urbanized space, will likely lead to an increase in NRED, while this is not necessarily true the other way around. In fact, as both variables emergy and fractals were derived from two-dimensional night-time satellite observations, one of the missing elements is the vertical component of urban growth. Further studies are presenting how it is possible to assess vertical growth of cities over time relying on radar, lidar and scatterometer remote sensing data (e.g. Mahtta et al., 2019). Although recognizing that all these characteristics could result in a non-correlation between NRDE and fractal dimension, Fig. 7 shows that for the nine cities considered over 20 years, a positive linear correlation exists (Pearson's correlation coefficient of 0.94). The existing correlation is an important finding of this work because it can be useful in estimating NREDs from fractals, providing such important and scarce data to further emergy synthesis.

The G3 cluster includes 'more urbanized' cities that can be considered in an advanced stage of urbanization whose characteristics are higher GDP and urban population density but at the expense of higher dependence on external resources to support growth and absorb waste. Regarding 'less urbanized' cities, the G2 cluster includes agricultural and extrativism-based economic systems that, although generating lower GDP, live within their own biocapacity. All of the cities studied show the same development pattern for growth based on territorial expansion and increasing NRED, however, at the same time, it seems they have different development stages (Fig. 7).

Another important aspect brought by Fig. 7 is related to temporal

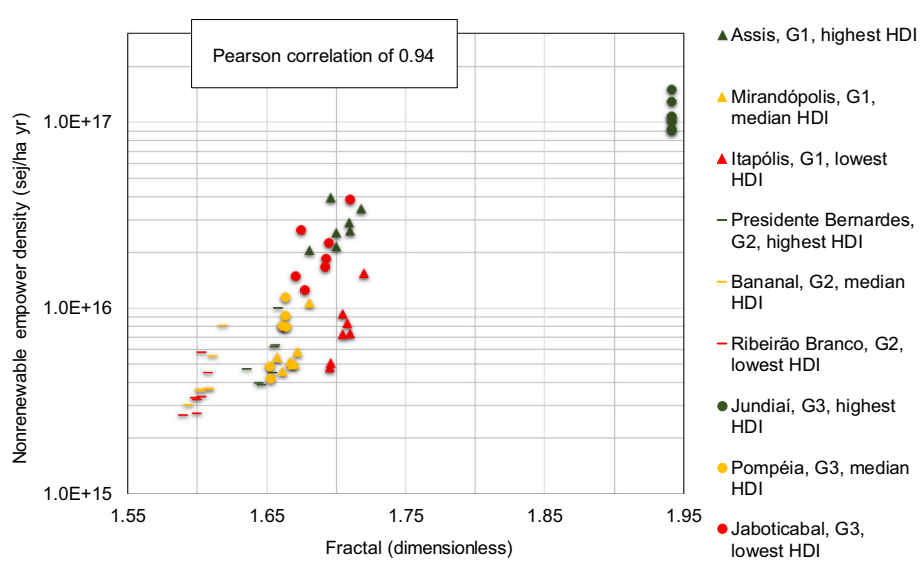

Fig. 7. Scatterplot of nonrenewable empower density (logarithmic scale) and fractal dimensions for the years 1992, 1994, 1998, 2002, 2004, 2008 and 2012 for the nine cities of the State of São Paulo considered in this study. HDI: human development index. G: cluster.

pattern, resulting in the 'attractor' role. Jundiai city has a constant fractal for all the period and it seems that its performance acts as a potential attractor for all other cities. In other words, it seems that all cities are pursuing the performance obtained by Jundiaí city, similarly to a gravitational force pulling bodies. In this sense, it is hypothesized that Jundiai's performance could be understood as a target for all other cities that are currently in a different stage of their own development process and probably, sooner or later, they will reach the same position or stage shown by Jundiai city. Also observed from Fig. 7 is that HDI appears to have no influence on cities' performance, since they are randomly represented; similar results were obtained by Costa (2014) when assessing the relationship between fractals and HDI for eight Brazilian capitals.

Pearson's correlation coefficients for the different clusters and the different HDI ranks across the clusters are presented in Table 2. Results show that G3 and the group with highest HDI (within clusters) are characterized by a strong positive correlation between NRED and the fractal dimension (0.97 and 0.96, respectively), while weak positive correlation coefficients were obtained for the other four groups. This means that urban expansion is reflected by an increase in NRED for those 'more urbanized' cities and for cites with high development (HDI) within each cluster.

The results provide insights on the dynamics of NRED and the fractal dimension that are informative for understanding quantitative aspects of cities growth and degrowth. Our approach constitutes a useful tool for assessing progresses in understanding the limits to growth for cities, that could be complemented by including further indicators on sustainability aspects such as job quality, happiness, community interaction, equal access to essential services, among others, as recognized important by Ulgiati and Zucaro (2019) and Jackson (2019). In addition, the renewable component of empower should also be included in future similar analysis. Further developments of this study will include considering a larger number of cities through a broader period.

After presenting and discussing the obtained results under a critical scientific viewpoint, one can suggest, as takeaway for practice, the use of the proposed method in estimating NREDs from fractals. Besides saving time and money, due to easier satellite imagery processing compared to traditional fractals calculation procedure, the proposed approach will overcome the lack of data on emergy flows for cities scale, and support further additional research focused on understanding the limits to growth for cities through an emergy accounting perspective. The higher the availability and accuracy of data is, the more efficient public policies towards a sustainable future for cities will be.

4. Conclusions

In this study, a novel methodological approach for estimating the fractal dimension of cities over time from night-time lights observations was developed and applied. The method is effective and relies on a smaller amount of data, and consequently faster processing time, as compared to other methods based on land-cover images. Night-time satellite DMSP-OLS and, more recently, VIIRS images are available free-of-charge, and do not require an image classification process. These data can thus be directly used to perform a boxcounting analysis to compute fractal dimension of territorial systems evolving over time.

In considering non-renewable empower density (NRED) trends over nine cities in the State of São Paulo, results highlighted that NRED has a strong positive linear correlation with the extent and shape of urban expansion as represented by the fractal dimension (Pearson's coefficient of 0.94). This finding is important for developing future emergy and/or urban expansion studies when large amounts of data are necessary. We observed that NRDE-fractal correlation is higher in cities with the highest human development index (Assis, Presidente Bernardes and Jundiaí; Pearson of 0.96) and in those belonging to cluster 3 (Jundiaí, Pompéia and Jaboticabal; Pearson of 0, 97), suggesting that the higher the 'urbanization' and 'social development' level of the city, the higher the NRDE-fractal correlation.

As tools for observing and investigating pulsing-paradigm behaviors, fractal dimension and NRED indicate that the cities considered in this study are all at the growing stage, showing no signs that any limit to growth has been considered in territorial planning, with the exception of one city, Jundiaí, which did not experience any urban expansion over the period considered while its demand for non-renewable emergy kept growing. In this vein, our approach gives important insights into the coupling degree of urban area expansion and emergy demand.

Table 2
Pearson correlation coefficient of fractal dimension and nonrenewable empower density for different groups of cities.

Groups based on clusters			
Cluster	G1	G2	G3
Cities	Assis, Mirandópolis and Itápolis	Presidente Bernardes, Bananal and Ribeirão Branco	Jundiaí, Pompéia and Jaboticabal
Pearson's coefficient	0.51	0.60	0.97

Groups based on HDI levels			
HDI level	Highest HDI	Median HDI	Lowest HDI
Cities	Assis, Presidente Bernardes and Jundiaí	Mirandópolis, Bananal and Pompéia	Itápolis, Ribeirão Branco and Jaboticabal
Pearson's coefficient	0.96	0.56	0.54

CRediT authorship contribution statement

Feni Agostinho: Conceptualization, Methodology, Writing (original draft preparation, reviewing and editing). Márcio Costa: Software, Data curation. Luca Coscieme: Writing (reviewing and editing). Cecília M.V. B. Almeida: Writing (review). Biagio F. Giannetti: Conceptualization.

Declaration of competing interest

None.

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Appendix A. Adapted model relating sum of lights (SOL) with non-renewable empower density (NRED)

Table A
Obtaining the SOL-NRED model.

Brazilian states (2007)	Area (ha)	SOL[a]	SOL/ha	Real NRED[b] (sej_{N+F}/ha)	Estimated NRED[c] (sej_{N+F}/ha)	Difference between NREDs[d] (sej_{N+F}/ha)	Corrected NRED[e] (sej_{N+F}/ha)
Amazonas	1.56E+08	8.20E+04	5.26E-04	3.59E+14	2.11E+15	−1.75E+15	3.29E+15
Acre	1.64E+07	2.86E+04	1.74E-03	3.05E+14	2.35E+15	−2.04E+15	3.53E+15
Rondônia	2.38E+07	7.51E+04	3.16E-03	7.99E+14	2.63E+15	−1.83E+15	3.82E+15
Roraima	2.24E+07	2.20E+05	9.81E-03	8.92E+13	3.96E+15	−3.87E+15	5.15E+15
Amapá	1.42E+07	2.26E+04	1.59E-03	2.11E+14	2.32E+15	−2.11E+15	3.50E+15
Pará	1.25E+08	2.21E+05	1.77E-03	1.26E+15	2.35E+15	−1.09E+15	3.54E+15
Tocantins	2.78E+07	6.78E+04	2.44E-03	9.00E+14	2.49E+15	−1.59E+15	3.67E+15
Mato Grosso	9.03E+07	1.65E+05	1.83E-03	3.27E+15	2.37E+15	9.00E+14	3.55E+15
Mato Grosso do Sul	3.57E+07	1.24E+05	3.48E-03	4.14E+15	2.70E+15	1.45E+15	3.88E+15
Goiás	3.40E+07	2.93E+05	8.60E-03	4.85E+15	3.72E+15	1.13E+15	4.90E+15
Distrito Federal	5.76E+05	1.15E+05	2.00E-01	4.51E+16	4.21E+16	3.05E+15	4.33E+16
Rio Grande do Sul	2.82E+07	5.19E+05	1.84E-02	9.34E+15	5.69E+15	3.65E+15	6.87E+15
Santa Catarina	9.57E+06	3.80E+05	3.97E-02	1.30E+16	9.94E+15	3.01E+15	1.11E+16
Paraná	1.99E+07	5.35E+05	2.68E-02	2.17E+16	7.37E+15	1.43E+16	8.55E+15
Minas Gerais	5.87E+07	8.85E+05	1.51E-02	1.35E+16	5.02E+15	8.43E+15	6.20E+15
Rio de Janeiro	4.38E+06	5.45E+05	1.24E-01	3.41E+16	2.69E+16	7.16E+15	2.81E+16
Espirito Santo	4.61E+06	Outlier	Outlier	Outlier	Outlier	Outlier	Outlier
São Paulo	2.48E+07	1.79E+06	7.21E-02	2.96E+16	1.64E+16	1.31E+16	1.76E+16
Maranhão	3.30E+07	1.44E+05	4.38E-03	5.61E+15	2.88E+15	2.74E+15	4.06E+15
Piauí	2.52E+07	9.06E+04	3.60E-03	1.59E+15	2.72E+15	−1.13E+15	3.90E+15
Ceará	1.49E+07	2.85E+05	1.91E-02	5.51E+15	5.82E+15	−3.17E+14	7.01E+15
Rio Grande do Norte	5.28E+06	1.36E+05	2.58E-02	3.60E+15	7.16E+15	−3.56E+15	8.35E+15
Paraíba	5.65E+06	1.88E+05	3.34E-02	4.96E+15	8.67E+15	−3.71E+15	9.85E+15
Pernambuco	9.81E+06	2.74E+05	2.80E-02	6.83E+15	7.59E+15	−7.61E+14	8.78E+15
Alagoas	2.78E+06	1.21E+05	4.33E-02	7.90E+15	1.07E+16	−2.75E+15	1.18E+16
Sergipe	2.19E+06	9.62E+04	4.39E-02	9.12E+15	1.08E+16	−1.65E+15	1.20E+16
Bahia	5.65E+07	4.92E+05	8.72E-03	3.72E+15	3.74E+15	−2.48E+13	4.93E+15
Average value for deviations=						**1.18E+15**	

[a] Sum of lights (SOL) obtained through QGIS® 3.4.2 software as explained in the main text.
[b] Obtained from the study of Demetrio (2011) and calculated on the emergy baseline of 15.83E24 sej/year (Odum et al., 2000).
[c] Estimated through the model presented in Fig. A.
[d] (Real NRED, column #5) − (Estimated NRED, column #6).
[e] Corrected NRED = (Estimated NRED of column #6) + (Average values for deviations).

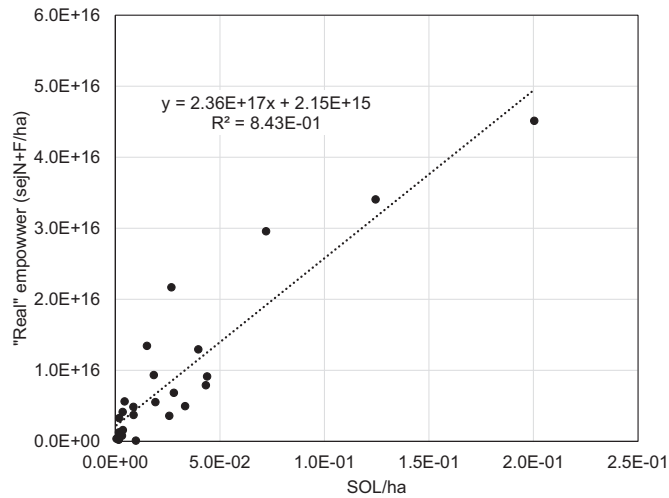

Fig. A. Correlation graph between sum of lights (SOL/ha) and "Real" non-renewable emergy density (sej_{N+F}/ha). Emergy baseline of 15.83E24 sej/year (Odum et al., 2000). Raw data presented in Table A.

The final model (annual basis and referred to an emergy baseline of 15.83E24 sej/year) is obtained by adding the average of deviations of Table A in the model of Fig. A:

$$\text{Adjusted non} - \text{renewable emergy in } sej_{F+N}/\text{ha} = (2.36\ \text{E17}*(\text{SOL/ha})) + 2.15\ \text{E15}$$

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cities.2021.103162.

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