

## Article

# Principles and Applications of the Global Human Settlement Layer as Baseline for the Land Use Efficiency Indicator –SDG 11.3.1

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**Abstract:** The Global Human Settlement Layer (GHSL) produces new global spatial information, evidence-based analytics and knowledge describing the human presence on the planet based mainly on two quantitative factors: i) the spatial distribution (density) of built-up structures and ii) the spatial distribution (density) of resident people. Both factors are observed in the long-term temporal domain and per uniform surface units in order to support the analysis of trends and indicators for monitoring the implementation of international framework agreements. The GHSL uses various input data including global, multi-temporal archives of fine-scale satellite imagery, census data, and volunteered geographic information.

In this paper, we reflect on the characteristics of GHSL information to demonstrate how original frameworks of data and tools rooted on Earth Observation could support Sustainable Development Goals monitoring. In particular, we demonstrate the reach of gridded, open and free, local yet globally consistent, multi-temporal data in filling the data gap for the Sustainable Development Goal 11. Our experiments produce a global estimate for the Land Use Efficiency indicator (SDG 11.3.1) for circa 10,000 urban centers, calculating the ratio of land consumption rate to population growth rate that took place between 1990 and 2015.

The results of our research demonstrate that there is a potential to lift SDG 11.3.1 from a Tier II classification as GHSL provides a global baseline for the essential variables called by the SDG 11.3.1 metadata.

**Keywords:** SDG11; Land Use Efficiency; Open Data, GHSL; Landsat; Urbanization; Urban expansion; Population mapping

## 1. Introduction

With the unanimous adoption of the United Nations (UN) General Assembly resolution 70/1 “Transforming our World: the 2030 Agenda for Sustainable Development” Member States agreed upon a framework of 17 Sustainable Development Goals (SDG) to guide societal development. The action plan, building on the experience of the Millennium Development Goals intertwines aspirational goals with an ambitious monitoring framework composed of 169 targets to monitor progress made in meeting the SDGs. The capacity to monitor such progress is reported to be entangled by the lack of data and statistical capacity to support the monitoring framework [1]–[4].

In this framework, a multi-level governance of information gathering reaching across intergovernmental institutions, national agencies, and civil society has formed. The global partnership articulates from the UN Statistical Commission –with the mandate to coordinate the work to implement the indicator framework and the review of SDG and targets [3], the Inter-Agency Expert Group on SDG Indicators, the UN Statistical Division hosting the Committee of Experts on Global Geospatial Information Management (UN-GGIM), and Non-Governmental Organizations. This latter major group of stakeholders includes the Group on Earth Observations and the Committee

on Earth Observation Satellites that work to promote the integration of statistical, geospatial and other big data to equip the SDG monitoring framework with the necessary data and making SDG reporting possible and as complete as possible. In order to map the capacity to monitor SDG indicators, the Inter-Agency Expert Group on SDG Indicators developed a 3 Tier classification for the indicators. The classification criteria are based on the simultaneous availability of an internationally agreed methodology and standard to monitor the indicator, and the presence of data produced by countries covering at least half the countries and representing half the population of a region. As result of the 7<sup>th</sup> Inter-Agency Expert Group on SDG Indicators meeting in spring 2018 (<https://unstats.un.org/sdgs/iaeg-sdgs/tier-classification/>), 93 indicators are classified Tier I, 72 Tier II and 62 Tier III. Alternative and innovative sources of data, especially derived Earth Observation (EO) offer significant information, and especially data to support the SDG reporting [5]–[7]. Since the early XXI century, the human society is predominantly urban as more than half of global population lives in cities [8]. In recognition of this trait of human development, the 2030 Development Agenda devoted to cities a specific Goal, SDG 11 that aspires to “Make cities and human settlements inclusive, safe, resilient and sustainable”. Despite the human nature is so intertwined with the urban condition [9], mankind is currently able to monitor less than half of the SDG 11 indicators for its own man-made artificial environment. Many SDG 11 indicators require fine scale local data that are to be sourced locally, making it more difficult to reach adequate data availability –especially in countries in transitions and data-poor territories.

Against this condition, remote sensing and EO are capable to collect information, at a large scale, at high degree of spatial resolution, repeatedly over time, and over wide geographical areas serving multiple applications [10], [11], especially in the SDG framework [6], [12], [13], or for generic urban development indicators [14].

In this contribution we reflect on the ways in which the above support can be enacted. In the paper we reflect on the principles and the architecture of the Global Human Settlement Layer (GHSL) and the application of GHSL in service to the SDG 11.3. The GHSL is a framework of data and tools developed from EO, census data and volunteered geographic information that produces global maps of built-up areas, resident population and settlement typologies for four epochs (1975, 1990, 2000 and 2015). GHSL layers have global coverage and are released as open and free data. GHSL data and derived scientific information to inform policy were released in 2016 at the Habitat III conference with the auspice to support the 2030 Development Agenda and its thematic agreements (Sendai Framework for Disaster Risk Reduction, United Nations Framework Convention on Climate Change, and the New Urban Agenda). GHSL information are particularly salient in the disciplinary contexts of disaster risk reduction, urbanization and human settlements dynamics, where fine scale information on the presence of people and built-up areas are of high importance [15]. GHSL data served to quantify the process of urbanization [16], observe population density [17], and inform policy making on 40 years of human settlements development [18] and exposure to natural hazards [19]. In this paper the GHSL is applied to estimate SDG 11.3.1 that aims at measuring the “ratio of land consumption rate to population growth rate”. This indicator requires data on the spatial extent of the settlement and its population. Furthermore, information is needed with a fine scale level of detail, and most of all it has to be consistent across places of the world and epochs to make a comprehensive global overview possible. The article focuses on the Tier II nature of SDG 11.3.1, for which an agreed methodology exists. However, it is not implemented as data to run it are not established. With the use of GHSL data we provide evidences to suggest that SDG 11.3.1 could be lifted from its Tier II classification.

## 2. Materials and Methods

In section 2.1 we briefly introduce the GHSL concept, its three geospatial layers that map built-up areas (GHS-BUILT), resident population (GHS-POP) and settlement typologies (GHS-SMOD), and recall salient GHSL derived analytics. In section 2.2 we present the methodology applied in this study to estimate SDG 11.3.1 according to the internationally agreed methodology.

## 2.1 The Global Human Settlement Layer Data

The GHSL concept was introduced by the European Commission (EC), Joint Research Centre (JRC) during the years 2008–2011, in the frame of the program named “*Information Support for Effective and Rapid External Action*” (ISFEREA), developing new image information mining technologies in support to geo-spatial information analysis for global security and stability [20]. The notion of the basic categories and information abstractions used by the GHSL, such as the notion of “built-up area” were introduced after a critical revision of the available satellite-derived information products (land-use/land-cover) when applied to the quantification of the presence of built-up structures in support to spatial modelling and assessment activities [21], [22]. In particular, the application areas setting the requirements for the GHSL were identified as post-natural-disaster and post-conflict damage, needs and reconstruction assessment, including refugee camps and temporary, rapidly-changing human settlement monitoring [23]–[25]. The data and semantic requirements of these initial application areas largely influenced the design of the GHSL information production system. In particular, regarding the attention devoted to providing automatic image information mining methods designed under pragmatic assumptions: a) of robustness against real-world big data scenarios involving large-volume, largely heterogeneous/unstructured data sources (incl. remote sensing and other data) and rapidly changing data specifications, b) of robustness against multi-stakeholder scenarios potentially leading to irreconcilable data-derived outputs, focused on different political/economic priorities, c) of effectiveness in providing output analytics in the severe time constraints and limited computational resources as the ones set by crisis management applications.

In parallel to the Post-2015 process the experience made in mapping global human settlements using European medium resolution ENVISAT ASAR for the delineation of built-up surfaces was transferred to prototype automatic recognition of built-up areas over more than 50 millions square kilometers of Earth land surface, using in input a heterogeneous set of data collected from optical sensors ranging from 0.5 to 10 meters of spatial resolution, with a large variety of sensor spectral characteristics demonstrating the sensor-agnostic nature of the GHSL remote sensing data processing paradigm [22] –the workflow was tasked to produce the first seamless pan-European settlement layer at 2.5 m of spatial resolution in support to the European Cohesion policy [26].

The aim of the GHSL was to provide a prototype of an open, public platform that facilitates the knowledge sharing and the discussion in complex, multilateral processes. In order to achieve this, the GHSL information production system was set-up in a full open and free domain in line with the suggestions of the inter-ministerial Group of Earth Observation (GEO) and the Global Earth Observation System of Systems (GEOSS) [27]. During 2015 a refined (beta) release of the Landsat-derived GHSL was produced and shared among the GEO partners together with new GHSL population grids produced through a partnership with the Center for International Earth Science Information Network (CIESIN –<http://www.ciesin.org/>) of the Columbia University [28], [29]. The first public release of the GHSL was announced at the Habitat III conference of Quito, in October 2016. The data is freely accessible from the JRC Open Data Portal (<https://data.jrc.ec.europa.eu/>) and the GEOSS portal (<http://www.geoportal.org>). Since 2017, the GHSL data and tools contribute to the GEO Human Planet Initiative, supporting the GEO Strategic Plan 2016–2025.

### 2.1.1 GHSL data layers

The GHSL suite contains three main grid-based layers (Table 1) that cover four epochs: 1975–1990–2000–2015. GHS-BUILT [30] (Figure 1, a) is an EO derived product, mapping built-up areas (density). The information is extracted from 40 years of Landsat imagery archives [31], through Symbolic Machine Learning workflows [22], [29], [32]. The process is based on a training set owning heterogeneous completeness (geographical and temporal coverage), thematic definitions and reliability. The training set includes MERIS Globe Cover [33], LandScan population grids [34], Open Street Map, GeoNames and MODIS 500 [35]. The result is a series of global maps of built-up areas in grid format for the four epochs in World Mollweide projection (EPSG: 54009):

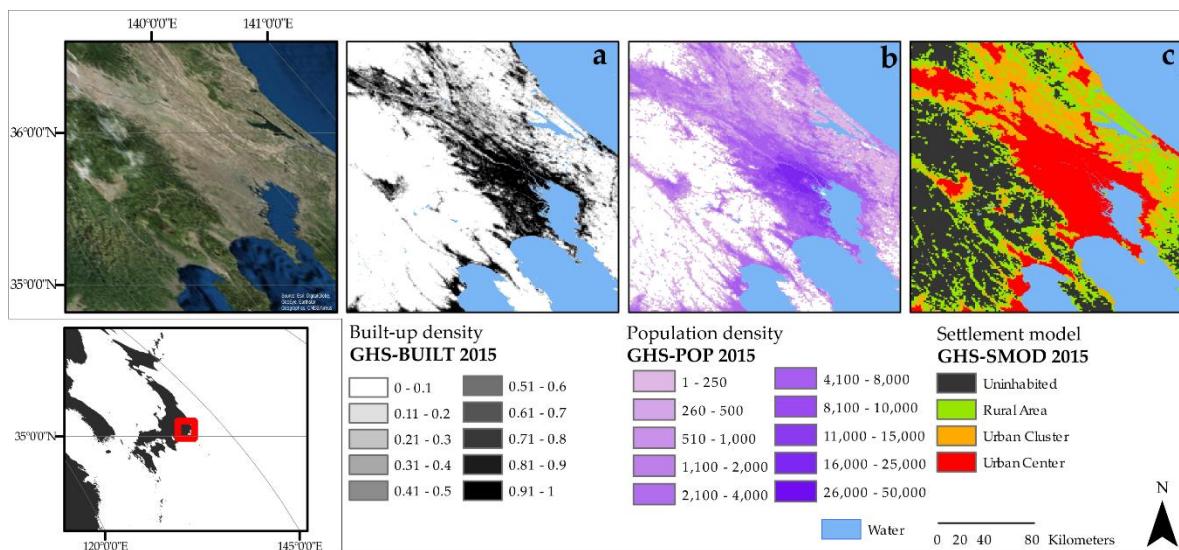
- at 250m resolution in which values are expressed as decimals from 0 to 1 (density);

- at 1km resolution in which values are expressed as decimals from 0 to 1 (density);
- at 38m resolution in Spherical Mercator (EPSG: 3857), a multi-temporal layer where the presence of built-up areas per epoch is classified in numbers ranging 6 (built-up area mapped 1975) to 3 (built-up area mapped in 2015) with additional classes for the non-built-up land (2), presence of water (1) and no data (0).

**Table 1.** Synthesis and features of GHSL data

Name	Semantic	Grid Resolution	Epoch <sup>1</sup>	Main Input Data
GHS-BUILT	Density of built-up area per grid cell	30m, 250m, 1km	2015,	Satellite imagery
GHS-POP	Population counts per grid cell	250m, 1km	2000, 1990,	Census data, GHS-BUILT
GHS-SMOD	Classification of each grid cell into one of the Settlement Model classes: high density cluster, low density cluster, and rural cells	1-km	1975	GHS-BUILT, GHS-POP

<sup>1</sup> Temporal dimension



**Figure 1.** Example of GHSL data, GHS-BUILT (a), GHS-POP (b), GHS-SMOD (c) displayed at 1km spatial resolution in the area of Tokyo (Japan) and compared to the imagery base map.

GHS-POP [36] maps estimated resident population on the basis of built-up areas presence (Figure 1, b). It is based CIESIN GPWv4 to source demographic data (derived from census or administrative units) and population is distributed using GHS-BUILT. GHS-POP is available at two resolutions for the four epochs in World Mollweide (EPSG: 54009):

- at 250m resolution;
- at 1km resolution. In both layers the value of each grid cell reports the absolute number of inhabitants in the cell (density, as float).

GHS-SMOD (Figure 1, c) [37] combines GHS-BUILT and GHS-POP to port the *Degree of Urbanisation* [38] into the GHSL environment. In the GHS-SMOD grid cells are classified in three classes: *Urban Centre*, *Urban Cluster*, *Rural Area* according to population density and population thresholds (of individual cells and group of cells) [39]. GHS-SMOD is accessible at 1km resolution for the four epochs, in World Mollweide (EPSG: 54009). In the layer cells are classified as rural cells (1), urban cluster (2), and urban centers (3). In particular, urban centers are the human settlements with

more than 50,000 inhabitants. The population of our dataset consists of the circa 10,000 urban centers from the GHS-SMOD layer for the epoch 2015.

In 2017, a revised image processing workflow was implemented in the JRC Earth Observation Data and Processing Platform (JEODPP), and applied to the Landsat multi-temporal imagery collection. As a result, an updated version of the GHSL (GHS-BUILT, GHS-POP and GHS-SMOD) [40] was released in the community of the GEO Human Planet Initiative and it has been tested in this study.

The GHSL framework serves multiple applications and analytics methods. GHSL baseline data, GHS-BUILT and GHS-POP are especially used as exposure layers in the disaster risk reduction sector in support to emergency management services (i.e. Copernicus EMS) [41], alert systems [42], risk management decision support indexes (i.e. INFORM) [43]. GHS-POP and GHS-SMOD were applied to estimate carbon footprints of human settlements [44], travel time to major cities [45] and global patterns of human domination [46] and presence on the planet [18]. Through these applications GHSL has established as source to support studies on the human interaction with and modification of the environment over time. More importantly the GHSL baseline data, comprehensively GHS-BUILT, GHS-POP and GHS-SMOD can be injected in Sustainable Development Goals metadata to estimate SDG indicators. Below we explore the use of GHSL to estimate the SDG 11.3.1.

## 2.2 SDG 11.3.1 methodology

The methodology for SDG 11.3.1 is established and referenced in the SDG indicators Metadata Repository managed by UNDESA (<https://unstats.un.org/sdgs/metadata>). To perform our experiments we applied the established methodology using GHSL as input data. LUE monitors the “Ratio of land consumption rate to population growth rate” and it is entrusted to quantify the wise use of land consequence of urban expansion pressures [47] –demographic and economic ones [48]. To estimate LUE, first it is necessary to quantify the rate of land consumption (LCR) and the population growth rate (PGR) in a given spatial unit over a time span. The two rates (LCR and PGR) are computed as follows:

$$\text{LCR} = \frac{\ln(\text{Urb}_{t+n}/\text{Urb}_t)}{y} \quad \text{PGR} = \frac{\ln(\text{Pop}_{t+n}/\text{Pop}_t)}{y} \quad (1)$$

where  $\text{Urb}_t$  and  $\text{Urb}_{t+n}$  reflect the total areal extent of the land consumed (extent of the human settlement) at the initial reference year ( $t$ ) and at the final reference year ( $t+n$ ) respectively,  $\text{Pop}_t$  and  $\text{Pop}_{t+n}$  input the total population of the spatial unit at the initial reference year ( $t$ ) and at the final reference year ( $t+n$ ) respectively, and  $y$  is the number of years between  $t$  and  $t+n$ . The estimate of the ratio of land consumption rate to population growth rate (LCRPGR or LUE), is obtained with:

$$\text{LUE (LCRPGR)} = \frac{\text{LCR}}{\text{PGR}} \quad (2)$$

In our research we used GHS-SMOD to delineate the extent of urban areas in 2015 (using grid cells classified as *Urban Centres*), in GIS environment we injected GHS-BUILT epoch 1990 and 2015 to generate statistics of built-up areas for the corresponding epochs and to derive the LCR value. Similarly we injected GHS-POP epoch 1990 and 2015 to derive PGR. Then we statistically computed LUE (LCRPGR) as presented in equation 2.

GHSL derived urban centers were classified in regions of the world according to the aggregation of countries from the Global Administrative Map (V2.8 –<https://gadm.org/data.html>) following the categories (Region) of the UN World Urbanization Prospects 2018 [49]. The extraction of statistics on built-up areas and population was implemented in Geographic Information System environment (ArcGIS) through zonal statistics operations.

## 3. Results

The analysis of spatial expansion and demographic change in urban centers focuses on three aspects addressed in specific sub-sections below. First, the extent and demographics of urban centers is reported between 1990 and 2015 (in 3.1); second, the latter development trajectory is analyzed with the Land Use Efficiency indicator sourcing the LUE value at urban centers level (in 3.2); third, we propose some considerations on the differentiation of built-up areas per capita across regions of the world clustering urban centers in classes LUE value (in 3.3). LUE has been estimated in circa 10,000 urban centers defined in the GHS-SMOD. As comprehensive overview of the SDG 11.3.1 quantified with GHSL data over the 25 years between 1990 and 2015, it results that urban centers follow a development trajectory in which the rate of population growth prevailed over that of spatial expansion, with a LUE equivalent to 0.72. In absolute terms urban centers expanded globally over a land surface equivalent to almost 67,800 km<sup>2</sup> (approximately the surface of Ireland) to settle about 1.1 billion new people (almost the population of India in 2015).

### 3.1 Spatial expansion and demographic growth in urban centers

According to GHSL data, urban centers account in 2015 a population exceeding 3.53 billion people and their built-up areas extend over almost 295 thousand km<sup>2</sup> (Figure 3). In urban centers built-up areas expanded in 25 years (1990-2015) by 30% and population increased by 44%. Trajectories of growth follow clear regional dynamics whereas: the highest demographic change in size and absolute spatial expansion takes place in Asia (+637 million inhabitants and +35.7 thousand km<sup>2</sup>), while most significant population growth has occurred in Africa (population of urban centers has almost doubled).

The interdependence between spatial expansion and demographic change manifests in terms of change in population density in urban centers. Population density has globally increased by 11% moving from 10,800 inhabitants per km<sup>2</sup> to 12,000 inhabitants per km<sup>2</sup> in 2015. Most significant processes of densification took place in Africa (+40%) and Oceania (+36%). Population density is stable in Asia (+1% and equivalent to 17,000 inhabitants per km<sup>2</sup> in 2015). Modest changes towards density reduction took place in Europe (-6% and 6,300 inhabitants per km<sup>2</sup> in 2015) and towards density increase in Northern America (+4% and 2,500 inhabitants per km<sup>2</sup>) and Latin America and the Caribbean (+8% and 12,192 inhabitants per km<sup>2</sup>).

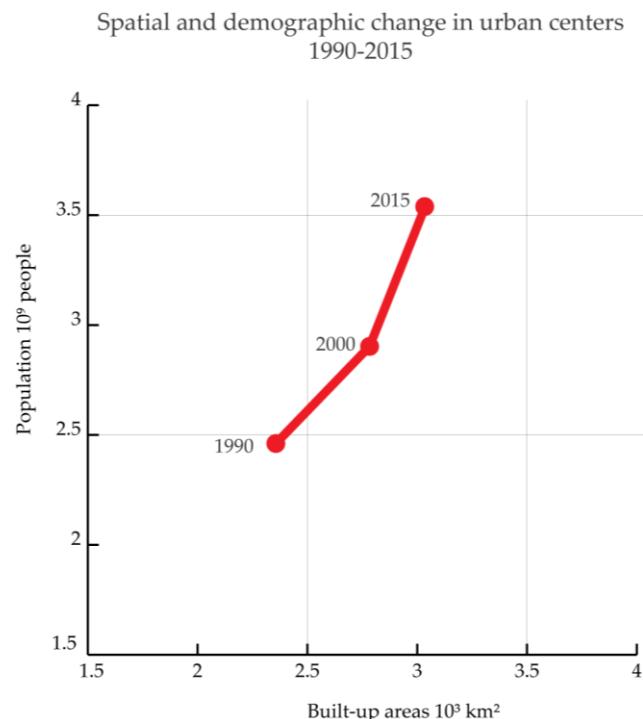


Figure 2. Multi-temporal global extent of built-up areas and population in urban centers at corresponding epochs as estimated from GHSL data (GHS-POP and GHS-BUILT)

### 3.2 LUE in 10,000 urban centers

To synthetically report on the LUE trajectories of this vast dataset, we clustered urban centers in 5 classes of LUE:  $\text{LUE} \leq -1$ ;  $-1 < \text{LUE} \leq 0$ ;  $0 < \text{LUE} \leq 1$ ;  $1 < \text{LUE} \leq 2$ ;  $\text{LUE} > 2$ . Figure 3 below displays the geographical distribution of urban centers and their related LUE class (1990-2015). It emerges that 13% of the centers in the globe developed between 1990 and 2015 with a substantially negative LUE value ( $<-1$ ) in particular in countries in central and western Europe, central China and south India. Values in the range  $-1 < \text{LUE} \leq 0$  are accounted in 6% of urban centers of the globe, this share reaches 21% in Europe (especially in Eastern Europe and Russia), and 18% in Asia (mainly Japan). Most frequent LUE class across the globe is the one ranging  $0 < \text{LUE} \leq 1$  (39% of the centers in the dataset). On a regional basis, this class represents 65% of the centers in Africa, more than half the ones in Latin America and the Caribbean, 39% the centers in Oceania, and almost 1/3 the ones in Asia and Europe. The class  $1 < \text{LUE} \leq 2$  includes 20% of the centers in the globe, but almost 1/3 the ones in Latin America and the Caribbean, 1/4 the ones in Northern America and 22% of the ones in Africa. The last class ( $\text{LUE} > 2$ ) globally accounts 22% of the centers, the share increases in Asia –31% especially including centers in India and north-east and south China.

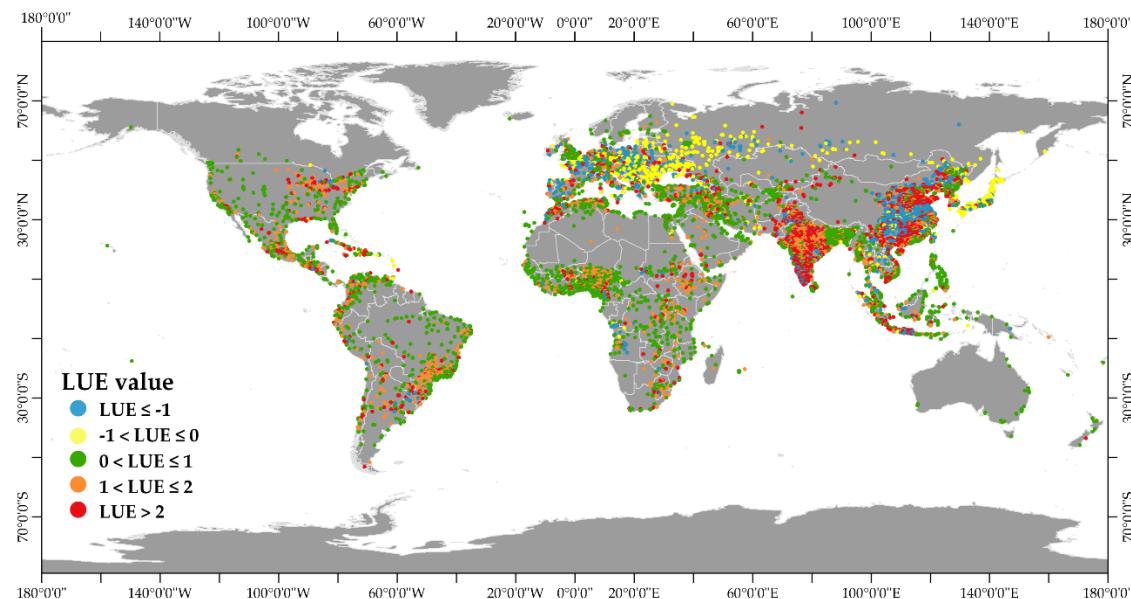


Figure 3. Comprehensive visualization of the LUE value in the circa 10,000 urban centers computed in the period 1990-2015.

### 3.3 Built-up areas per capita and Land Use Efficiency

The LUE indicator (that is a dimensionless value) has been further characterized observing the built-up area per capita in the year 2015 in the LUE classes considered in the previous sub-section, this operation presents an example of the spatial implications of the LUE indicator (Figure 4). The following arguments are based on the average built-up areas per capita calculated for each of the 10,000 urban centers and then averaged by regional collocation of the center. Results demonstrate that in regions like Europe and Northern America in the class of  $\text{LUE} > 2$ , in which spatial expansion takes place at a rate at least double the one of population growth, built-up areas per capita exceed respectively 180 and 490  $\text{m}^2$  per inhabitant. Great variations are also observed comparing the built-up area per capita in the same LUE class across regions. In the case of a development trajectory of population densification ( $0 < \text{LUE} < 1$ ), built-up areas per capita range from almost 450  $\text{m}^2$  per person in Northern America, 175  $\text{m}^2$  per person in Europe, and it drops by almost half in Latin America and the Caribbean (90  $\text{m}^2$  per person), to almost 70  $\text{m}^2$  per person in Asia and to 52  $\text{m}^2$  per person in centers in Africa.

In terms of average change of built-up areas per capita between 1990 and 2015, values are also diverse. In the class  $0 < \text{LUE} < 1$ , built-up areas per capita shrink between 10% (in Europe) and 26% (in Africa). In the class of  $\text{LUE} > 2$  built-up areas per capita more than doubled in Latin America and the Caribbean, Asia and Africa, increased by half in Northern America, by 15% in Europe and by 6% in Oceania.

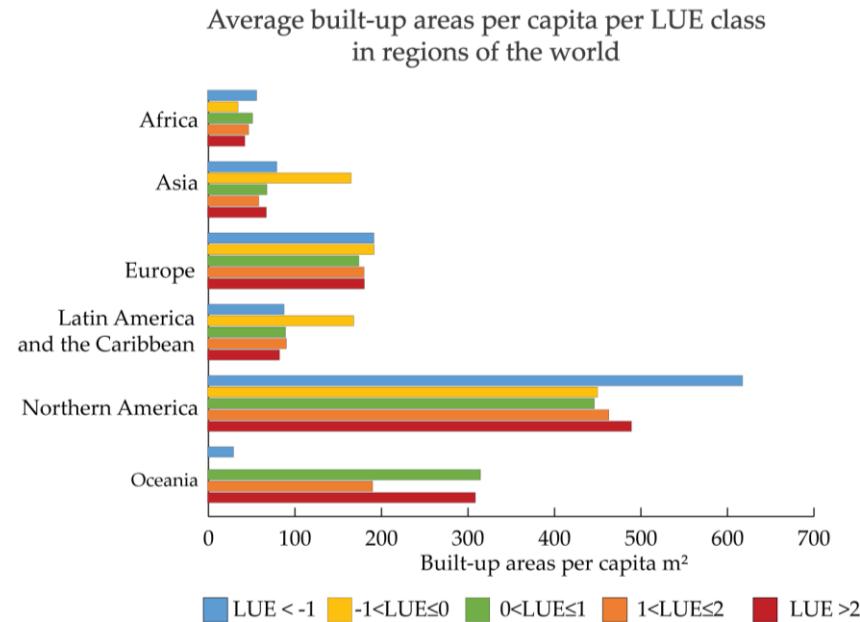


Figure 4. Regional comparison of built-up areas per capita

#### 4. Discussion

In the following section we develop two main strands of arguments. One reflects on the principles and architecture of GHSL and its fitness for purpose to support SDG indicators and intergovernmental agreements with open data to fill present gaps. In 4.1 we discuss about the GHSL architecture and design features that enable an action-oriented support to SDG monitoring, in particular thanks to a full open and free data cycle (input data, methods, output/results), and the capacity to handle and make sense of big-data scenarios harmonizing data across space and time.

The other argument focuses on the implications of the empirical findings of this research in contributing to selected intergovernmental policy literature on urban development (4.2).

##### 4.1 GHSL principles

The GHSL concept is framed around three general goals or requirements: a) operation in an open and free data and methods access policy (open input, open method, open output); b) aim for reproducible, scientifically defendable, fine-scale, synoptic, complete, planetary-size, and cost-effective information production; and c) aim to facilitate information sharing and multilateral democratization of the information production, and collective knowledge building. The general requirements b and c, call for automatic information production methods being able to process systematically the large mass of baseline data (satellite imagery, and population census information) supporting the output analytics and to lower down the cost of the information production.

GHSL framework production was enabled by the definition of a new artificial intelligence approach for the satellite data classification process named “Symbolic Machine Learning” (SML), and working with the similar principles used in genomics for the DNA sequences characterization [32]. The SML approach allows machines to learn efficiently new association rules between satellite data instances and target abstraction classes used by the GHSL as for example “built-up areas”. Through the SML it was possible to design a robust supervised data classification process using available

global data as training examples just approximating the scale and thematic requirements of the information retrieval tasks. This fact allowed a drastic reduction of the human labor traditionally needed for the training set collection tasks.

#### 4.1.1 Real-world (big) data scenario

The GHSL approach was developed with real-world big-data scenarios calling for a pragmatic, adaptive approach in complex data, information and stakeholder/users scenarios with planetary-size, multi-temporal, fine-scale data that generate large volumes of information. These complex scenarios coupled with fast technological development generates rapidly changing data specifications and contradictory semantics and assumptions. Furthermore, and paradoxically, more detailed data produce larger relative inconsistencies: assuming any given level of effort/cost for data harmonization, the relative across-data inconsistencies grow by a multiplicative pattern when the spatial and thematic detail of the data is increased linearly. In these conditions, the adoption of a strict normative approach would easily lead to irrelevance and failure of the system with respect to the reality check. The GHSL takes instead a pragmatic adaptive perspective. Artificial intelligence is used to find relevant associations between different data streams at different level of abstraction/semantics and different scales with the minimal set possible of assumptions. In this perspective, the whole universe of data shall be used for testing hypothesis and efficient computational machine learning methods should allow to discover on-the-fly association between any given data and information at any collected sensor/data parameters conditions, with no need for model transfer [22], [29], [50], [51].

#### 4.1.2 Evidence-based output analytics

Global policy frameworks outcome of the Post-2015 process such as the New Urban Agenda, the Sendai Framework for Disaster Risk Reduction, the United Nations Framework Convention on Climate Change, and the overarching 2030 Development Agenda architecture is linked to national and multi-national (as in the case of the European Union) policy processes driven by decision makers operating at various levels of governance. Data and evidences are sought to inform this policy process [52] by providing indicators that focus on measurable outcomes and allow to evaluate, compare and benchmark alternative programs of action (i.e. policy and plans). Policy processes are negotiation processes [53]. With data and the data-derived analytics becoming relevant in the policy process, monitoring frameworks become integrated with the negotiation [54]. As a consequence, data, the data-derived information and the devolution of influence to epistemic communities may lead to prejudice in support to specific political and/or economical interest [55]. This condition may lead to a situation where most of the human efforts are devoted to the scrutiny and discussion about the assumptions embedded in the system generating the analytical results, and in the collective discussion about the possible way forward, in lieu of understanding the results. In order to mitigate that risk, the output categories generated by the GHSL system are designed with a modular abstraction schema [21].

At the basis of the GHSL classification schema there are low-level-of-abstraction categories as for instance “built-up areas”. They include a minimal set of expert assumptions [29] and are derived from the most independent, consistent and extensive data handled by the system, i.e. the remote sensing imagery, making the concept prone for consideration as “evidence” from the different stakeholders involved in the policy processes. At the top of the GHSL classification schema there are high-level-of-abstraction categories as “urban vs. suburban vs. rural” areas discrimination (as provided in the GHS-SMOD). These include the maximum level of theoretical assumptions and have a direct impact on the calculation of indicators. The ways in which urban areas are defined directly affect the sourcing of data, and so the results. This argument is evident observing data on urban demography that are compiled by the United Nations Department for Economic and Social Affairs (UNDESA) in the periodic updates of the World Urbanization Prospects. The Prospects UNDESA produces include data sourced from member States that are often compiled using heterogeneous motives to classify urban areas [56]–[59], so to report about urban population, making consistency of the data across territories limited. While alternative ways to define urban areas are being proposed

[38], [60], [61] it is of high disciplinary and policy relevance to reaffirm that the definition of boundaries for spatial information collection is a key step for the measurement [62] [63]. Data framework that are grid based and possess high spatial resolution (of 250m and 1km) –like GHSL, are capable to adapt to a great variety of spatial aggregations (cities, small regions, large geographical areas, till the wall to wall global coverage).

#### 4.1.3 Full repeatability

Repeatability of measurements refers to the ability to repeat measurements made on the same subject under identical conditions [64]. Variability in measurements made on the same subject under identical conditions can be attributed to errors originated by the measurement process itself. The measurements generated by the GHSL system are fully repeatable. The same input data and the same information extraction method produces identical numerical result. This is a requirement needed to maintain full control of data, methods and results lineages in the “Real-word (Big) Data Scenarios” as described in the first principle above. Moreover, full repeatability increases trust in the new data/analytics generated by new technologies, especially if non-experts are involved in the evaluation of the results. A corollary of this principle is that GHSL avoids the use of Artificial Intelligence methods based on random iterative optimization processes.

#### 4.1.3 Multi-temporal and spatial harmonization of information

GHSL layers are continuous global raster with information on the spatial footprint of settlements –built-up areas, that are processed using Landsat imagery at corresponding epochs and population that is modelled on the basis of the Gridded Population of the World (GPW). The information on built-up areas is extracted through the open workflow [29] and it is fed with multi-temporal imagery from Landsat at corresponding epochs [31], [65]. Information on population is derived from GPW that is a fine scale spatially disaggregated layer produced from population and housing censuses from which estimates for past epochs are derived and made consistent with and adjusted to United Nations World Population Prospects [66]. The availability of consistent and harmonized data across the globe and epochs makes possible to analyze the long term process of human settlement changes (1975 – 2015) providing valuable tools for urban development analytics including a new lens to observe planetary urbanization [16].

#### 4.1.4 Open data and tools filling gaps of a Tier II indicator

The action oriented outcome of the GHSL framework architecture demonstrated by our results is that indicator 11.3.1 was estimated for the year 0 of the 2030 Development Agenda (2015) against 25 years of spatial and demographic change in urban centers.

In practice, using open and free data it could be possible to lift SDG 11.3.1 from its Tier II status using the GHSL approach to fill the present data gap. With respect to UNDESA metadata, the GHSL operationalization of the SDG 11.3.1 estimation has been performed with two key premises. First, the adoption of the *Degree of Urbanisation* people based “Global Harmonized Definition of Cities and Settlements” allowed to delineate the spatial units of analysis (the urban centers). Second, LCR and PGR were defined respectively as the change in the built-up areas (from GHS-BUILT derived from Landsat) and in population (from GHS-POP) between epochs in these spatial units.

This is a pragmatic (evidence based, replicable and multi-temporal) approach to implement the conceptual definition of “land consumption” intended as “the expansion of built-up area which can be directly measured” (SDG 11.3.1 metadata, p.2). Further to the above motives, the GHSL framework offers a suite of free tools, especially the MASADA (Massive Spatial Automatic Data Analytics), DUG (Degree of Urbanisation Grid) and LUE (Land Use Efficiency) tools. The MASADA Tool is developed to support production of local and regional settlement layers by automatic classification of satellite imagery (both high and very high resolution data). Using as training set a land cover information or a coarse settlement map (to incorporate in the workflow radiometric, textural and morphological features) a supervised classification of remotely sensed data (through SML classifier) extracts built-

up areas information. The tool is primarily devoted to the extraction of built-up areas with a preset of workflows for SPOT-5, SPOT-6/7, RapidEye and CBERS-4, yet it can be applied to other imagery sources (i.e. GeoEye-1, WorldView-2/3, Pléiades and Quickbird) to derive other land cover maps – provided that the appropriate training set is given in input. The second tool supporting SDG estimate is dedicated to the delineation of urban areas as defined in the *Degree of Urbanisation* definition [38]. Urban centers, urban clusters and rural areas can be delineated using the DUG tool. The tool is designed to work with GHS-BUILT and GHS-POP but other spatial and demographic layers could also be used. With this tool the user is free to use proprietary data on built-up and population and set ad hoc population criteria and threshold to define settlement typologies. The LUE Tool (a Qgis plugin) [67] enables the estimation of the SDG 11.3.1 in GIS environment with an input of spatial multi-temporal information on the spatial extent of the settlement and its demography at the corresponding epochs.

The GHSL suite of data and tools seems to encompass a wide spectrum of functionalities to support the SDG monitoring, both within its own resources (especially data) but also by offering free tools to users empowering them to use third party or proprietary information sources, especially in the context of SDG 11.3.1. In particular, the GHSL architecture retains potential for the estimation of LUE to 2030. With the entry into service of the Sentinel-1 and Sentinel-2 constellations and the conception of workflows to process their data for built-up areas extraction in GHSL environment [68], [69] it is to foresee a community-based capacity to periodically update LCR estimates for the entire Earth.

#### 4.2 EO derived information on human settlements

In recent times the remote sensing and EO technology to acquire, process and manage data has significantly improved. In particular, significant advances took place in the instruments to source information from space, whereas the spatial resolution of new sensors has increased. Early EO derived products to map the extent of human settlement did rely on coarse resolution imagery (MODIS or Landsat 1-3 MSS) or on a combination of the latter and night time lights (i.e. DMSP/OLS). Recent platforms equipped high-resolution (i.e. Sentinel-2) and very-high-resolution optical (i.e. SPOT) or synthetic-aperture radar technology (i.e. TerraSAR-X and Sentinel-1) were proved effective for delivering maps of human settlements [26], [68] [69], [70].

This new generation of information support researchers and policymakers in the understanding of the new geographies of human settlements in the era of a predominantly urban society. Our research findings support rationales on urbanization that allege that urban areas are efficient in terms of use of land resources [71], and that urban development is considerably unequal across regions of the world [72]. Estimating a LUE<1 corresponding to 25 years of urban development (1990-2015) we empirically illustrate that the rate of demographic growth in urban centers has been dominant over the growth in space. Although this value could validate a dense/compact pattern of development that imply population densification, the diversity of LUE values across regions of the world and the corresponding built-up areas per capita may reinforce the signals of widening urban divide, in terms of inequality in development. In particular the comparison of built-up areas per capita in 2015 broken-down into LUE classes and regions of the world manifests the traits of unfairness. Considering the least efficient LUE class (LUE>2) built-up areas per capita in urban centers in Northern America is 10 times the one of that in centers in Africa. Similar patterns are found in the other LUE classes too. This fact implies substantially heterogeneous patterns of development to be captured by comparable –yet same- LUE values. By formulation the LUE indicator does not retain a spatially explicit nature (dimensionless) it could be a proxy for a spatial and demographic trajectory of change. The Land Use Efficiency estimates seem to suggest that several territories encountering extensive population growth (i.e. Sub-Saharan Africa, and South-East Asia) develop with LUE values between 0 and 1, corresponding to population densification, while negative LUE values (LUE<-1) is frequent in countries with low –or even negative- population growth rates (i.e. Eastern Europe, Japan and some converging regions of the European Union).

## 5. Conclusion

In this article we provide a concrete example of the contribution of Earth Observation and innovative geospatial-remote sensing derived data in support to the Sustainable Development Goals. The SDG were negotiated in parallel to a comprehensive and ambitious monitoring framework. This framework is currently pressured by shortcomings in data availability and statistical capacity for its monitoring, with only 93 indicators with a Tier I classification. Earth Observations set out as a key source of information to service SDG monitoring: by improving the availability of required data, supplying suitable and accurate data that cover long time series, have wide/planetary geographical scope are compatible/complimentary with traditional statistical methods.

To provide a practical application of this service we estimated at global level Land Use Efficiency (SDG indicator 11.3.1) currently classified as Tier II indicator due to the presence of an internationally agreed methodology but in absence of data. The GHSL serves the purpose as it offers harmonized data in space and time on the spatial distribution of built-up areas (GHS-BUILT), population (GHS-POP) and settlement typologies (GHS-SMOD) fulfilling the UNDESA metadata requirements for the indicator. In addition to the above, we also discussed the principles and architecture of the Global Human Settlement Layer that by design embraces an open input, open method, open output policy, has a modular hierarchical structure of information, tests and applies real-word (big) data scenarios, produces evidence based output analytics, and facilitates the repeatability of results. In particular, we emphasize the role of multi-temporal and spatial harmonization of information to enable comparative studies and analyses on development trajectories.

The quantitative results of the experimental application of GHSL data in support to SDG indicator 11.3.1 show that urban centers developed between 1990 and 2015 with a LUE equivalent to 0.72, whereas the rate of population growth has been higher than the one of spatial expansion. In absolute terms urban centers expanded over a land surface equivalent to almost 67,800 km<sup>2</sup> (approximately the surface of Ireland) to settle almost 1.1 billion new people (almost the population of India in 2015). To further characterize LUE, we compared built-up areas per capita in the epoch 2015 achieved in centers that developed in common LUE classes in various regions of the world. It emerges that there might be inequalities in the trajectories of development of centers that develop with comparable LUE values but are located in different geographical areas. This is perceived in particular comparing the changes in built-up areas per capita between 1990 and 2015.

With the estimate of the LUE, we enacted UNGGIM instruction to test GHSL for the purpose. In this context it is to reaffirm that while GHSL data could support data-poor territories, they could also back data-rich parties for harmonization and comparison purposes. Our research concludes that the GHSL framework, with its tools and data enables users to generate built-up areas layers that could be used directly with UNDESA compiled demographic data to quantify LUE. A further perspective is proposed by new satellites (Sentinel constellation) and the workflows generated in GHSL environment that open the possibility to secure the estimation of the Land Consumption Rate to 2030 with open data and open tools.

**Author Contributions:** Conceptualization, M.M and M.P; Data curation, A.F and C.C; Formal analysis, M.M and A.F; Funding acquisition, T.K; Methodology, M.M, M.P and C.C; Project administration, T.K; Software, A.F; Supervision, M.P and T.K; Validation, A.F, C.C and T.K; Writing – original draft, M.M and M.P; Writing – review & editing, M.M, M.P, A.F, C.C and T.K.

**Funding:** This work has been carried out in the frame of the institutional work program of the Joint Research Centre (JRC, European Commission) and supported by the administrative arrangement No. 33994 between the JRC and the Directorate General for Regional and Urban Policies (DG REGIO, European Commission).

**Conflicts of Interest:** The authors declare no conflict of interest.

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