



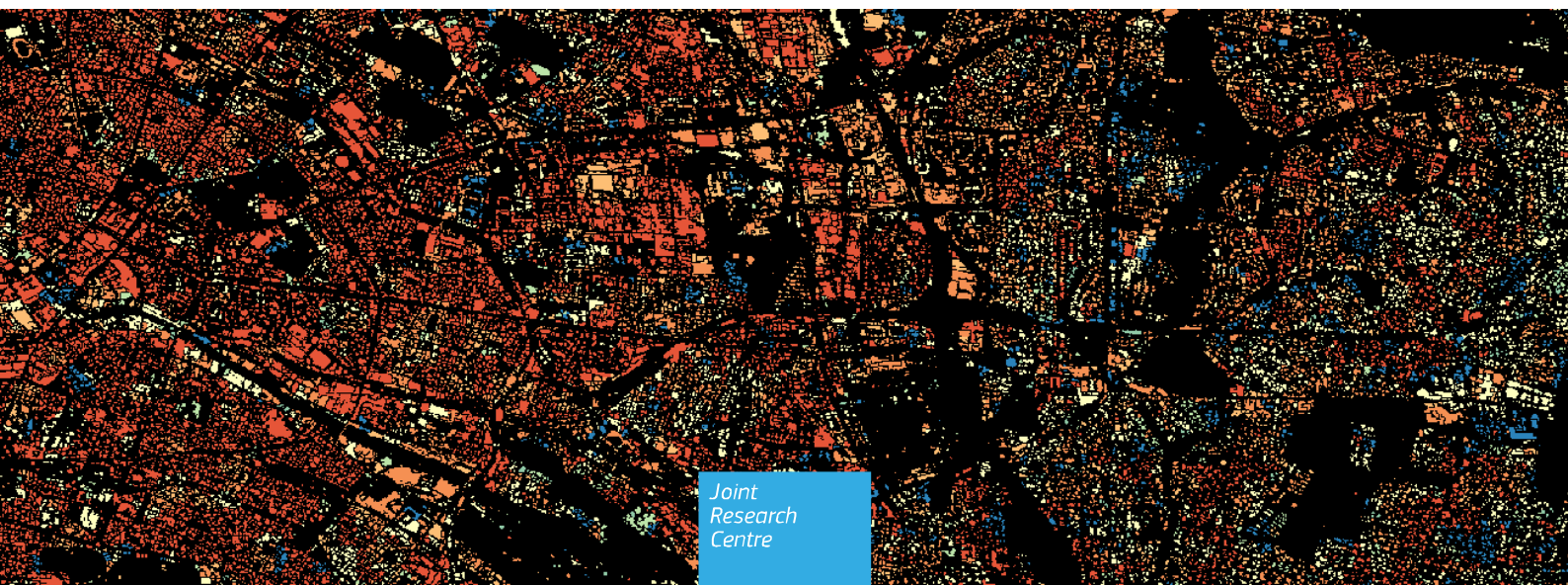
European
Commission

JRC Scientific Information Systems and Databases Report

GHSL Data Package 2023

Public release
GHSL P2023

2023



Joint
Research
Centre

This publication is a Scientific Information Systems and Databases report by the Joint Research Centre (JRC), the European Commission's science and knowledge service. It aims to provide evidence-based scientific support to the European policymaking process. The contents of this publication do not necessarily reflect the position or opinion of the European Commission. Neither the European Commission nor any person acting on behalf of the Commission is responsible for the use that might be made of this publication. For information on the methodology and quality underlying the data used in this publication for which the source is neither Eurostat nor other Commission services, users should contact the referenced source. The designations employed and the presentation of material on the maps do not imply the expression of any opinion whatsoever on the part of the European Union concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries.

Contact information

Name: Thomas Kemper
Address: Via Fermi, 2749 21027 ISPRA (VA) - Italy - TP 267
European Commission - DG Joint Research Centre
Space, Security and Migration Directorate
Disaster Risk Management Unit E.1
Email: thomas.kemper@ec.europa.eu
Tel.: +39 0332 78 5576

GHSL project: JRC-GHSL@ec.europa.eu
GHSL Data: JRC-GHSL-DATA@ec.europa.eu

EU Science Hub

<https://joint-research-centre.ec.europa.eu>

JRC133256

PDF ISBN 978-92-68-02341-9 [doi:10.2760/098587](https://doi.org/10.2760/098587) KJ-03-23-103-EN-N

Luxembourg: Publications Office of the European Union, 2023

© European Union, 2023



The reuse policy of the European Commission documents is implemented by the Commission Decision 2011/833/EU of 12 December 2011 on the reuse of Commission documents (OJ L 330, 14.12.2011, p. 39). Unless otherwise noted, the reuse of this document is authorised under the Creative Commons Attribution 4.0 International (CC BY 4.0) licence (<https://creativecommons.org/licenses/by/4.0/>). This means that reuse is allowed provided appropriate credit is given and any changes are indicated.

All content © European Union, 2023

How to cite this report: European Commission, *GHSL Data Package 2023*, Publications Office of the European Union, Luxembourg, 2023, doi:10.2760/098587, JRC133256

Contents

Contents	i
Abstract	1
1 Introduction	2
1.1 Overview	2
1.2 Rationale	3
1.3 History and Versioning	3
1.4 Main Characteristics	5
2 Products	6
2.1 GHS-BUILT-S R2023A - GHS built-up surface spatial raster dataset, derived from Sentinel-2 composite and Landsat, multi-temporal (1975-2030)	6
2.1.1 Definitions	7
2.1.1.1 The building	7
2.1.1.2 The built-up surface (BUSURF)	7
2.1.1.3 The built-up fraction (BUFRAC)	7
2.1.1.4 The residential (RES) domain	7
2.1.1.5 The “non-residential domain” (NRES)	7
2.1.2 Expected Errors	12
2.1.2.1 Errors in the 2018 predictions	12
2.1.2.2 Errors in the multi-temporal predictions	17
2.1.3 Improvements compared to the previous release	20
2.1.4 Input Data	22
2.1.4.1 Remotely sensed image data	22
2.1.4.2 High-level semantic abstraction data	22
2.1.5 Technical Details	23
2.1.6 Summary statistics	24
2.1.7 How to cite	24
2.2 GHS-BUILT-H R2023A - GHS building height, derived from AW3D30, SRTM30, and Sentinel-2 composite (2018)	26
2.2.1 Definitions	26
2.2.2 Input data	27
2.2.3 Expected errors	30
2.2.4 Technical Details	31
2.2.5 How to cite	31
2.3 GHS-BUILT-V R2023A - GHS built-up volume spatial raster datasets derived from joint assessment of Sentinel-2, Landsat, and global DEM data, for 1975-2030 (5yrs interval)	33
2.3.1 Input Data	33
2.3.2 Technical Details	33
2.3.3 Summary statistics	34
2.3.4 How to cite	34

2.4	GHS-BUILT-C R2023A - GHS Settlement Characteristics, derived from Sentinel-2 composite (2018) and other GHS R2023A data.....	36
2.4.1	Input data	43
2.4.2	Technical Details	43
2.4.3	How to cite	44
2.5	GHS-POP R2023A - GHS population spatial raster dataset multi-temporal (1975-2030).....	45
2.5.1	Improvements compared to the previous release	46
2.5.2	Input Data.....	47
2.5.3	Technical Details	48
2.5.4	Summary statistics.....	48
2.5.5	How to cite	48
2.6	GHS-SMOD R2023A - GHS settlement layers, application of the Degree of Urbanisation methodology (stage I) to GHS-POP R2023A and GHS-BUILT-S R2023A, multitemporal (1975-2030).....	49
2.6.1	Improvements compared to the previous release	50
2.6.2	GHS-SMOD classification rules	50
2.6.3	GHS-SMOD L2 spatial raster dataset and L1 aggregation	53
2.6.4	Input Data.....	57
2.6.5	Technical Details	57
2.6.5.1	GHS-SMOD raster spatial raster dataset.....	58
2.6.5.2	GHS-SMOD urban centre entities.....	58
2.6.5.3	GHS-SMOD dense urban cluster entities.....	58
2.6.6	Summary statistics.....	59
2.6.7	How to cite	61
2.7	GHS-DUC R2023A - GHS Degree of Urbanisation Classification, application of the Degree of Urbanisation methodology (stage II) to GADM 3.6 layer, multitemporal (1975-2030).....	62
2.7.1	Improvements compared to previous release.....	63
2.7.2	GHSL Territorial Units Classification.....	63
2.7.2.1	Territorial units classification Level 1	63
2.7.2.2	Territorial units classification Level 2	64
2.7.2.3	Classification workflow	65
2.8	A consistent nomenclature for the Degree of Urbanisation.....	65
2.8.1	How to use the statistics tables	66
2.8.2	Input Data.....	66
2.8.3	Technical Details	67
2.8.3.1	GHS-DUC Summary Statistics Table.....	67
2.8.3.2	GHS-DUC Admin Classification layers.....	68
2.8.4	Summary statistics.....	74
2.8.5	How to cite	76
2.9	GHS-BUILT-LAUSTAT R2023A - GHS built-up surface statistics in European LAU, multitemporal (1975-2020).....	77
2.9.1	Input data	77

2.9.2	Technical Details	77
2.9.3	How to cite	77
2.10	GHS-SDATA R2023A - GHSL data supporting the production of R2023A Data Package (GHS-BUILT, GHS-POP)	78
2.10.1	Technical Details	78
2.10.2	How to cite	79
3	Conclusions.....	80
	References	81

Abstract

The Global Human Settlement Layer (GHSL) project produces new global spatial information, evidence-based analytics and knowledge describing the human presence on Earth. It operates in a fully open and free data and methods access policy. The knowledge generated with the GHSL is supporting the definition, the public discussion and the implementation of European policies and the monitoring of international frameworks such as the 2030 Development Agenda. The GHSL is the core data set of the Exposure Mapping Component under the Copernicus Emergency Management Service. GHSL data continue to support the GEO Human Planet Initiative that is committed to developing a new generation of measurements and information products providing new scientific evidence and a comprehensive understanding of the human presence on the planet and that can support global policy processes with agreed, actionable and goal-driven metrics.

This document describes the public release of the GHSL Data Package 2023 (GHS P2023). This release provides improved built-up (including surface, volume and height) and population products as well as a new settlement model and classification of administrative and territorial units according to the “Degree of Urbanisation” framework.

Prior to cite this report, please access the updated version available at:

http://ghsl.jrc.ec.europa.eu/documents/GHSL_Data_Package_2023.pdf

1 Introduction

1.1 Overview

The Global Human Settlement Layer (GHSL) project produces global spatial information, evidence-based analytics, and knowledge describing the human presence on the planet. The GHSL relies on the design and implementation of spatial data processing technologies that allow automatic data analytics and information extraction from large amounts of heterogeneous geospatial data including global, fine-scale satellite image data streams, census data, and crowd sourced or volunteered geographic information sources.

This document accompanies the public release of the GHSL Data Package 2023 (GHS P2023) and describes its contents.

Each product is named according to the following convention:

GHS-<name>_<spatial extent>_<release>

For example, a product name GHS-BUILT-V_GLOBE_R2023A indicates the built-up volume (BUILT-V) produced globally in the release R2023A.

Each product can be made by one or more datasets and layers. A layer is named with a unique identifier according to the following convention:

GHS_<name>_<Epoch>_<spatialExtent>_<release>_<projection>_<resolution>_<version>

For example, a layer name GHS_BUILT_V_E2030_GLOBE_R2023A_54009_100_V1_0 indicates the built-up volume (GHS_BUILT_V) in the epoch 2030 (E2030), included in the release R2023A, in World Mollweide projection (ESRI:54009) at 100m of spatial resolution, version 1.0.

The GHSL Data Package 2023 contains the following products:

GHS-BUILT-S R2023A - GHS built-up surface spatial raster dataset, derived from Sentinel-2 composite (2018) and Landsat, multitemporal (1975-2030)

GHS-BUILT-H R2023A - GHS building height, derived from AW3D30, SRTM30, and Sentinel-2 composite (2018)

GHS-BUILT-V R2023A - GHS built-up volume spatial raster datasets derived from joint assessment of Sentinel-2, Landsat, and global DEM data, for 1975-2030 (5 years interval)

GHS-BUILT-C R2023A - GHS Settlement Characteristics, derived from Sentinel-2 composite (2018) and other GHS R2023A data

GHS-POP R2023A - GHS population spatial raster dataset multitemporal (1975-2030)

GHS-SMOD R2023A - GHS settlement layers, application of the Degree of Urbanisation methodology (stage I) to GHS-POP R2023A and GHS-BUILT-S R2023A, multitemporal (1975-2030)

GHS-DUC R2023A - GHS Degree of Urbanisation Classification, application of the Degree of Urbanisation methodology (stage II) to GADM ¹4.1 layer, multitemporal (1975-2030)

GHS-SDATA R2023A - GHS release R2023A supporting data

GHS-BUILT-LAUSTAT R2023A - GHS built-up surface statistics in European LAU, multitemporal (1975-2020)

¹ Global Administrative boundaries layer: <https://gadm.org/>

1.2 Rationale

Open data and free access are core principles of the GHSL (Melchiorri et al., 2019). They are aligned with the Directive on the re-use of public sector information (Directive 2003/98/EC²). The free and open access policy facilitates the information sharing and collective knowledge building, thus contributing to a democratisation of the information production.

The GHSL Data Package 2023 contains the new GHSL data produced at the European Commission Directorate General Joint Research Centre in the Directorate for Space, Security and Migration in the Disaster Risk Management Unit (E.1) in the period 2022-2023.

1.3 History and Versioning

Previous GHSL releases relied on the processing of Landsat imagery for producing the GHS-BUILT information layer. The Landsat satellite platforms collect Earth observation data since the beginning of the civilian space programs in the 1970s. In January 2008, Barbara Ryan, the Associate Director for Geography at the U.S. Geological Survey (USGS), and Michael Freilich, NASA's Director of the Earth Science Division, signed off a Landsat Data Distribution Policy that made Landsat images free to the public. The USGS announced the free-and-open data policy on April 21, 2008. The Global Land Survey (GLS) data sets were created as a collaboration between NASA and the USGS from 2009 through 2011.³ Each of these collections were created using the primary Landsat sensor in use at the time for each collection epoch. Early global experiments on the GHS-BUILT production by the European Commission's Joint Research Centre (JRC) date back to 2014, using as input GLS1975, GLS1990, GLS2000, and a collection of Landsat 8 imagery of the year 2014, autonomously selected and downloaded by the JRC from the USGS portal. These data constitute the first set of data evidences used to support the GHSL epochs 1975, 1990, 2000, and 2014 (Pesaresi, Ehrlich, et al., 2016).

Copernicus, previously known as GMES (Global Monitoring for Environment and Security), is the European Union's Earth observation programme. It relies as well on a free-and-open data access policy. Sentinel-1 is the first of the Copernicus Programme satellite constellation using active radar sensor technology. The first satellite, Sentinel-1A, was launched on 3 April 2014, and Sentinel-1B was launched on 25 April 2016. In December 2016 the JRC successfully completed the first experiment of Sentinel-1 global data processing in the frame of the Global Human Settlement Layer (GHSL) project (Corbane et al., 2017). Sentinel-2 (S2) is an Earth observation mission from the Copernicus Programme that systematically acquires optical imagery at high spatial resolution (10 m to 60 m) over land and coastal waters. The launch of the first satellite, Sentinel-2A, occurred 23 June 2015. Sentinel-2B was launched on 7 March 2017. In 2018, the JRC produced the first Sentinel-2 cloud-free global pixel based image composite from L1C data for the period 2017-2018 for public use, leveraging on the Google Earth Engine platform (Corbane, Politis, et al., 2020). In October 2020, the JRC successfully completed the first public release of global built-up areas assessment from these Sentinel-2, 10m-resolution Copernicus imagery data (Corbane, Syrris, et al., 2020).

In 2016, the first public GHSL Data Package was released (GHS P2016). It consisted in several multi-temporal and multi-resolution raster products, including built-up area spatial raster datasets (GHS-BUILT), population spatial raster datasets (GHS-POP), a settlement model (GHS-SMOD) and selected quality spatial raster datasets. The first GHS-BUILT product included in that release was generated from Landsat image data using the URBAN class generated from MODIS 500m-resolution data as learning set (Pesaresi, Ehrlich, et al., 2016), (Schneider et al., 2010). The population spatial raster datasets (GHS_POP_GPW41MT_GLOBE_R2016A) were produced in collaboration with Columbia University (New York City, USA), Center for International Earth Science Information Network (CIESIN) in 2015. The GHS-SMOD spatial raster datasets (GHS_SMOD_POP_GLOBE_R2016A) present an implementation of the Degree of Urbanization (DEGURBA)⁴ model using as input the population grid cells (European Commission & Statistical Office of the European Union, 2021) .

In 2018, the second version of the multi-temporal GHS-BUILT was released (GHS R2018), re-processing the same Landsat images, but with an improved learning set obtained by the introduction of the built-up areas collected from the classification of Sentinel-1 Synthetic-aperture radar (SAR) data at 20m-resolution (Corbane

² <http://eur-lex.europa.eu/legal-content/en/ALL/?uri=CELEX:32003L0098>

³ <https://www.usgs.gov/landsat-missions/global-land-survey-gls>

⁴ <https://ghsl.jrc.ec.europa.eu/degurba.php>

et al., 2017). In the GHS P2019 release the GHS-POP and GHS-SMOD data derived from these improved GHS-BUILT datasets were distributed.

In 2020, a new single-epoch GHS-BUILT dataset was released (GHS R2020) by processing of 10m-resolution Sentinel-2 imagery data of year 2018 and by introducing as improvement of the learning set new data on building footprints or human settlement delineation made available from open efforts of Microsoft and Facebook on classification of VHR image data (Corbane, Syrris, et al., 2020).

In 2022, the JRC released GHS P2022, which builds upon the past experience and data with two main objectives: A) augment the thematic contents of the built-up area information; and B) reconnect and rebuild the historical information contained in the GHSL rooting on the historical Landsat imagery with the new, recent data coming from the Sentinel mission at higher spatial resolution. Several innovative aspects are included in the new GHS-BUILT of the GHS P2022.

After the publication of the GHS P2022 new independent data showed an anomaly in the performance of the multi-temporal model that was not visible during the model development⁵. According to the JRC internal tests, the anomaly was expected to introduce a positive bias in predicted change rates of built-up surfaces and built-up volumes after the year 2000. The positive bias is especially remarkable in the rural domain as set by the GHS-SMOD R2022A.

The new release GHS P2023 fixes the anomaly in the multi-temporal modelling mechanism and recalculates the multi-temporal built-up surfaces, built-up volumes, population, and degree of urbanization spatial raster datasets (SMOD) accordingly. Moreover, some other improvements are applied in the POP estimates and downscaling mechanisms. The 10m-resolution products directly derived from the Sentinel-2 image composite of the year 2018 remains substantially the same in the GHS P2023 as compared to the GHS P2022, with some marginal improvements. The GHS-LAND product is not affected by the introduced changes and therefore it remains as a R2022 dataset. Here below some of the key features of the GHS P2023:

1. sub-pixel built-up surface fraction estimates at 10m-resolution
2. a Boolean classification of the built-up surfaces in residential (RES) vs. non-residential (NRES) semantic abstractions at 10m-resolution
3. average building height estimates at 100m-resolution
4. spatial-temporal interpolations of the built-up surface information at 100m-resolution and in equal time (5-year) intervals from 1975 to 2030.
5. Population distribution at spatial resolution of 100m in 5-year intervals between 1975 and 2030.
6. allocation of population according to the presence of residential (RES) built-up volume
7. country total population time series aligned to the latest UN World Population Prospects 2022 (United Nations, Department of Economic and Social Affairs, Population Division, 2022)
8. temporal population estimates anchored to the UN “urban agglomeration” population time series of the latest UN World Urbanization Prospects 2018 (United Nations, Department of Economic and Social Affairs, Population Division, 2018)

The settlement classification layer (GHS-SMOD) benefits from improvements in built-up surface and population spatial raster datasets and is based on the specifications of the Degree of Urbanisation (stage I) framework (European Commission & Statistical Office of the European Union, 2021).

This new GHS-SMOD layer and the new GHS-POP spatial raster datasets are used to update the GADM 4.1 Degree of Urbanisation Classification (GHS-DUC), the classification of territorial units according to the stage II of the Degree of Urbanisation framework (European Commission & Statistical Office of the European Union, 2021).

As in all previous releases, the GHS P2023 is available at the GHSL download portal (<https://ghsl.jrc.ec.europa.eu/download.php>) and as GHSL collection in JRC Open Data Repository (<http://data.jrc.ec.europa.eu/collection/ghsl>). The current data release contains the most up-to-date products and

⁵ <https://ghsl.jrc.ec.europa.eu/p2022Release.php>

datasets, and thus, data users should be aware that the quality of the GHS P2023 data exceeds the quality of the estimates published in previous releases.

1.4 Main Characteristics

In order to facilitate data analytics - as it was done in previous issues - the release includes a set of multi-resolution products created by aggregation of the main products. Additionally, the density spatial raster datasets are produced in an equal-area projection using grid cells of 100 m and 1 km spatial resolution. For example, the multi-temporal population spatial raster datasets were produced based on grid cells of 100 m spatial resolution, and they were then aggregated to 1 km². Most of the datasets will be provided also in a warped version to WGS84 coordinate system, at 3 arcsec and 30 arc sec resolutions.

The differences between the products in the previous GHS P2019 and those in the current GHS P2023 release are substantial. They include new and more precise 10m-resolution sub-pixel fraction built-up surface estimations, new semantics (i.e., residential vs. non-residential), building height estimates, and new seamless interpolated spatial raster datasets at 100m-resolution with equal time intervals of 5 years from 1975 to 2030.

Moreover, an improved approach for the production of population spatial raster datasets was applied. Total population time series by country are aligned to the latest UN World Population Prospects 2019 (United Nations, Department of Economic and Social Affairs, Population Division, 2019). The local temporal population estimates (i.e. at census polygon level) are derived using a new model that takes into account the UN 'city' population time series of the latest UN World Urbanization Prospects 2018 (United Nations, Department of Economic and Social Affairs, Population Division, 2018). Finally, the population distribution takes advantage of the residential (RES) vs. non-residential (NRES) semantic abstractions by weighting the dasymetric population disaggregation according to the presence of residential (RES) and non-residential (NRES) built-up volume.

The subsections of Section 2 introduce briefly each product (including more details on differences with the corresponding past version). Dedicated reports are under preparation.

Terms of Use

The data in this data package are provided free-of-charge © European Union, 2023. Reuse is authorised, provided the source is acknowledged. The reuse policy of the European Commission is implemented by a Decision of 12 December 2011 (2011/833/EU). For any inquiry related to the use of these data please contact the GHSL data producer team at the email address: JRC-GHSL-DATA@ec.europa.eu

Disclaimer: The JRC data are provided "as is" and "as available" in conformity with the JRC [Data Policy](#)⁶ and the [Commission Decision on reuse of Commission documents](#) (2011/833/EU). Although the JRC guarantees its best effort in assuring quality when publishing these data, it provides them without any warranty of any kind, either express or implied, including, but not limited to, any implied warranty against infringement of third parties' property rights, or merchantability, integration, satisfactory quality and fitness for a particular purpose. The JRC has no obligation to provide technical support or remedies for the data. The JRC does not represent or warrant that the data will be error free or uninterrupted, or that all non-conformities can or will be corrected, or that any data are accurate or complete, or that they are of a satisfactory technical or scientific quality. The JRC or as the case may be the European Commission shall not be held liable for any direct or indirect, incidental, consequential or other damages, including but not limited to the loss of data, loss of profits, or any other financial loss arising from the use of the JRC data, or inability to use them, even if the JRC is notified of the possibility of such damages.

Prior to cite this report, please access the updated version available at:
http://ghsl.jrc.ec.europa.eu/documents/GHSL_Data_Package_2023.pdf

⁶ JRC Data Policy <https://doi.org/10.2788/607378>

2 Products

2.1 GHS-BUILT-S R2023A - GHS built-up surface spatial raster dataset, derived from Sentinel-2 composite and Landsat, multi-temporal (1975-2030)

The GHS-BUILT-S spatial raster dataset depicts the distribution of the built-up (BU) surfaces estimates between 1975 and 2030 in 5 year intervals and two functional use components a) the total BU surface and b) the non-residential (NRES) BU surface. The data is made by spatial-temporal interpolation of five observed collections of multiple-sensor, multiple-platform satellite imageries: Landsat (MSS, TM, ETM sensor) data supports the 1975, 1990, 2000, and 2014 epochs, while a Sentinel-2 (S2) image composite (GHS-composite-S2 R2020A) supports the 2018 epoch.

The sub-pixel built-up fraction (BUFRAC) estimate at 10m resolution is produced from the 10m-resolution Sentinel-2 image composite, using as learning set a composite of data from GHS-BUILT-S2 R2020A, Facebook settlement delineation, Microsoft, and Open Street Map (OSM) building delineation. The inferential engine is a multiple-quantization-minimal-support (MQMS) generalization of the symbolic machine learning (SML) approach (Pesaresi, Syrris, et al., 2016). The SML for the classification of the Sentinel-2 data uses in input both radiometric and multi-scale morphological image descriptors (Pesaresi, Corbane, et al., 2016), including functional (i.e. RES, NRES) delineation of the built-up areas. In particular, the multiscale decomposition of the image information it is supported by the characteristic-saliency-levelling (CSL) model (Pesaresi et al., 2012) from generalization of the image segmentation based on the derivative of the morphological profile (DMP) (Pesaresi & Benediktsson, 2001). The multi-scale CSL it is solved by using a computationally efficient approach (Ouzounis et al., 2012). The inference is computed in data tiles of 100×100 km size.

The non-residential (NRES) built-up surface domain is predicted from S2 data by observation of radiometric, textural, and morphological features in a multi-faceted image processing framework merging global unsupervised rule-based reasoning and inductive locally-adaptive methods leveraging on pixel-wise spectral indexes, textural assessments, and object-oriented shape analysis. Textural analysis is performed by multi-scale, anisotropic and rotation-invariant contrast measurements using increasing displacement vectors of the co-occurrence matrix selecting the areas where contrast of large objects dominate the textural contrast generated by smaller image structures (Gueguen et al., 2012, Pesaresi et al., 2008). The connected component (“object”) image analysis is solved by a segmentation of salient image structure based on the watershed of the inverse of the saliency layer as defined in the “characteristics-saliency-levelling” CSL (Pesaresi et al., 2012).

As in previous GHSL releases (Corbane et al., 2019; Pesaresi, Ehrlich, et al., 2016), the multi-temporal (MT) process works stepwise from recent epochs to past epochs, deleting the BU information if the decision is supported by empirical evidences from satellite data of the specific epoch. By definition, the process can only decrease the amount of built-up surface going from recent to past epochs. In this release, a similar logic generalized to the continuous prediction domain is applied within an object-oriented image processing framework. Salient spatial units are delineated by the watershed of the inverse of the continuous BUFRAC function at 10m resolution. This is done in order to increase the robustness of the change detected by the system, vs. the changing sensor data geometry (origin of the grid, resolution, projection) of the supporting image data in the various epochs. For each evaluated epoch and available Landsat scene, the probability Φ that any specific sensor sample (pixel or grid cell) can be associated to the foreground “built-up” (BU) vs. the background “non-built-up” (NBU) information semantic is evaluated, by observing the statistical association between the combinations of the quantized reflectance values and the training data. This inferential process is solved by multiple-quantization-minimal-support (MQMS) generalization of the symbolic machine learning (SML) approach (Pesaresi, Syrris, et al., 2016). The semantic Φ extracted at the pixel level of the different Landsat scenes in arbitrary geometries is aggregated to the data segments using a surface-weighted average. The final prediction on the amount of built-up surface change for each segment is solved by a multiple decision support approach evaluating ensemble linear regression model predictions from the semantic association of Φ to the BU vs. NBU class abstraction hypothesis, stratified in different data domains characterized by different expected sensor bias in discrimination of BU vs. NBU classes, that are cumulated and maximized from all the available input satellite scenes in the various epochs. Finally, the predictions on built-up surface change are aggregated by averaging at a uniform sample size of 100m grid cells and are used to build the final raster data.

In the intermediate epochs not covered by direct satellite observations, in areas not covered by satellite imageries (i.e. satellite data gaps in the 1975 epoch), or in the future epochs 2025 and 2030, the BU prediction it is solved by spatial-temporal interpolation or extrapolation based on a rank-optimal spatial allocation method. This supporting spatial optimization function combines static and dynamical components: the static component

is determined by the observation of the empirical association between the occurrence of specific land form combinations (slope, elevation, water) and the occurrence of human settlement development from remotely sensed data. The dynamical component is based on the spatial dynamics of the BU surface in the observed epochs, decomposed in a change (growth, or shrink) vs inertial (i.e. unchanged) BU dynamical field components.

2.1.1 Definitions

2.1.1.1 The building

Since the initial concept of the GHSL (Pesaresi et al., 2013) the adopted definition is the same as the INSPIRE “building” abstraction (<https://inspire.ec.europa.eu/id/document/tg/bu>), limited to the above-ground case, and without the “permanent” characterization of the built-up structures, allowing to be inclusive to temporary settlements as associated to slums, rapid migratory patterns, or displaced people because of natural disasters or crisis. “... *Buildings are constructions above (and/or underground) which are intended or used for the shelter of humans, animals, things, the production of economic goods or the delivery of services and that refer to any structure (permanently) constructed or erected on its site...*”. In short, and taking in to account the remote-sensing technology characteristics and limitations, the implicit GHSL abstraction of the “building” can be summarized as: “any roofed structure erected above ground for any use”.

2.1.1.2 The built-up surface (BUSURF)

The built-up surface is the gross surface (including the thickness of the walls) bounded by the building wall perimeter with a spatial generalization matching the 1:10K topographic map specifications, that it also informally called “building footprint”.

2.1.1.3 The built-up fraction (BUFRAC)

The built-up fraction (BUFRAC) is the share of the raster sample (i.e. pixel or grid cell) surface that is covered by the built-up surface.

2.1.1.4 The residential (RES) domain

The RES domain is defined as the built-up surface dedicated prevalently for residential use. The residential use is defined as from INSPIRE: “...*Areas used dominantly for housing of people. The forms of housing vary significantly between, and through, residential areas. These areas include single family housing, multi-family residential, or mobile homes in cities, towns and rural districts if they are not linked to primary production. It permits high density land use and low density uses. This class also includes residential areas mixed with other non-conflicting uses and other residential areas...*”⁷

2.1.1.5 The “non-residential domain” (NRES)

The “non-residential domain” (NRES) is defined as the domain of the BUFRAC>0 complement of the RES domain. This can be worded also as “any built-up surface not included in the RES class”. As a logical corollary of the fact that in the RES domain definition also mixture with other not conflicting uses is allowed, the complement NRES domain is characterized by uses not compatible with the human residence.

Examples:

Let assume a 100m resolution spatial raster dataset with a $100 \times 100 = 10,000$ square meters of surface per spatial sample (pixel, or cell grid) of this spatial raster dataset. Moreover, let be the built-up surface predicted at the sample X of this grid $BUSURF_x = 750$ square meters.

The corresponding built-up fraction estimate will be : $BUFRAC_x = 750 / 10,000 = 0.075$

Let assume in the sample x of $100 \times 100m$ resolution the total $BUSURF_x = 4380$ square meters, while the NRES $BUSURF_x = 850$ square meters. Then the residential built-up surface RES $BUSURF_x$ can be predicted as $RES\ BUSURF_x = 4380 - 850 = 3530$ square meters.

⁷ https://inspire.ec.europa.eu/codelist/HILUCSValue/5_ResidentialUse

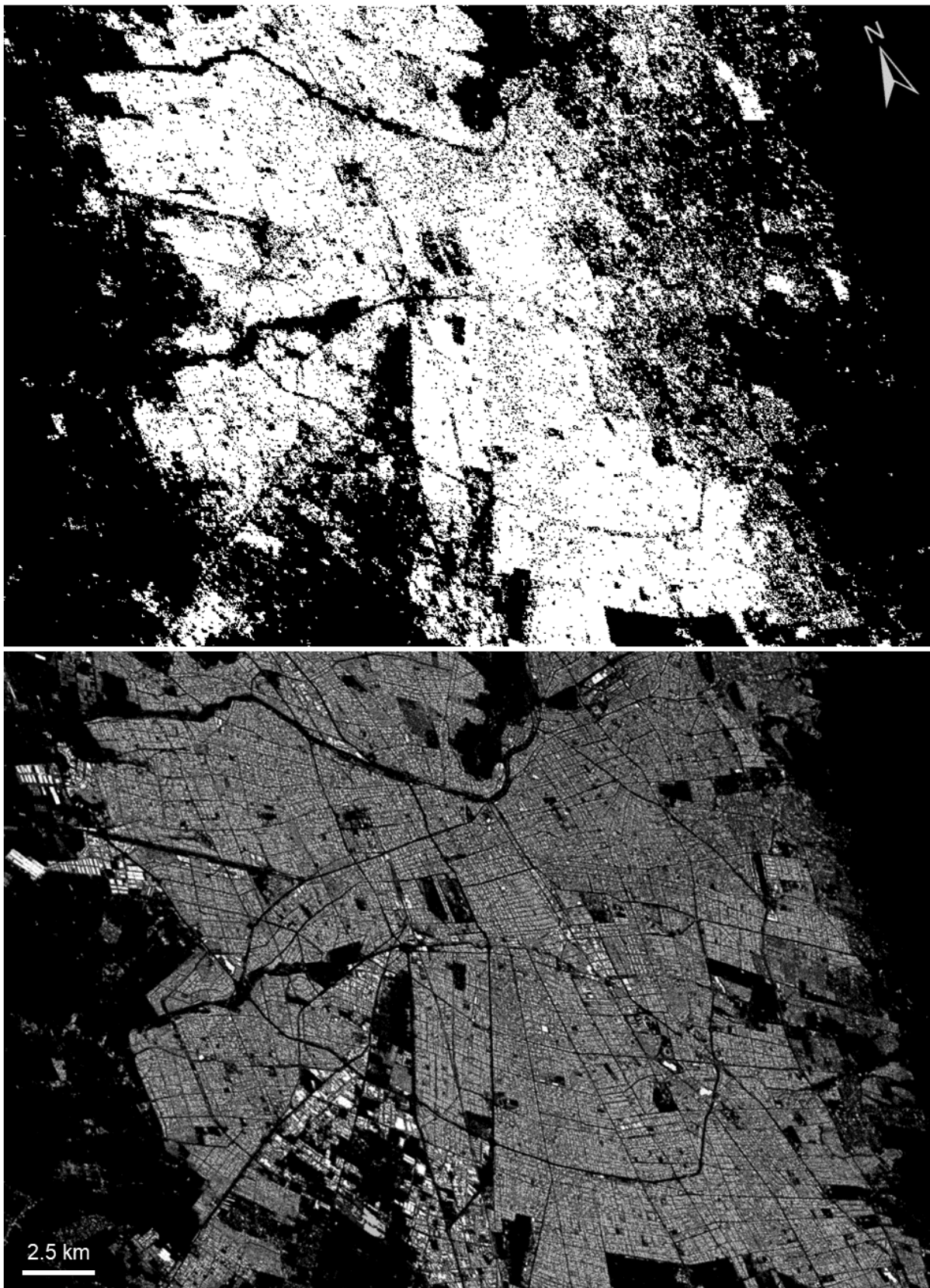


Figure 1 - Santiago de Chile: comparison of the built-up surfaces as assessed by the previous GHS_BUILT_LDSMT_GLOBE_R2018A for the epoch 2014 from Landsat image data with a Boolean 30m-resolution method (upper), vs the new GHS-BUILT-S_GLOBE_R2023A for the epoch 2018 from Sentinel-2 image data with a continuous 10m-resolution method (lower).

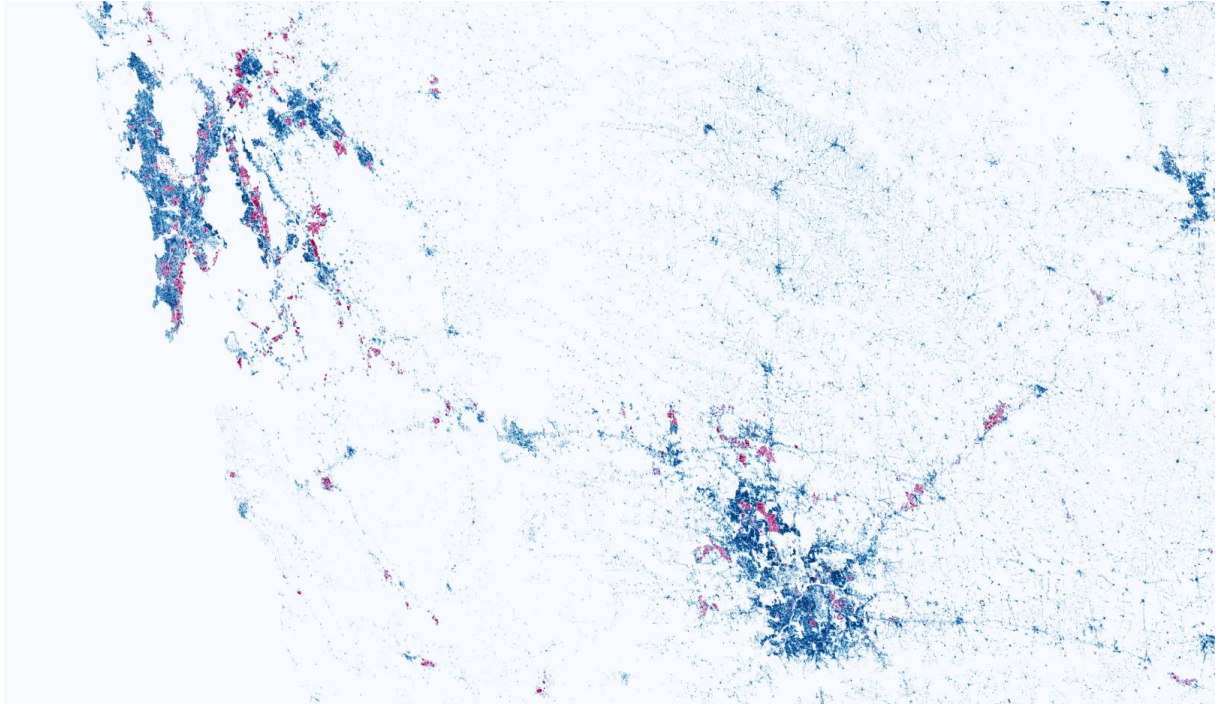


Figure 2 - Mumbai-Pune (India): residential (RES) and non-residential (NRES) components of the built-surfaces estimated for the GHSL 2020 epoch. RES and NRES are represented with blue and magenta, respectively.

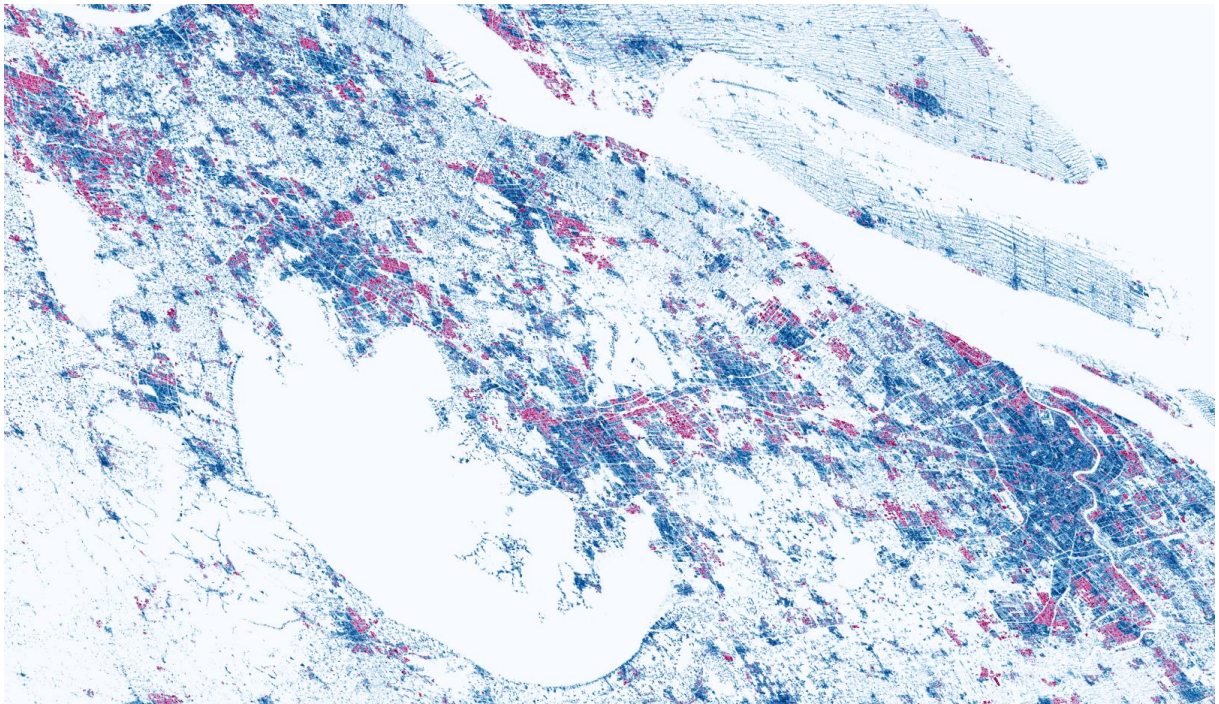


Figure 3 - Shanghai-Changzhou (China): residential (RES) and non-residential (NRES) components of the built-surfaces estimated for the GHSL 2020 epoch. RES and NRES are represented with blue and magenta, respectively.

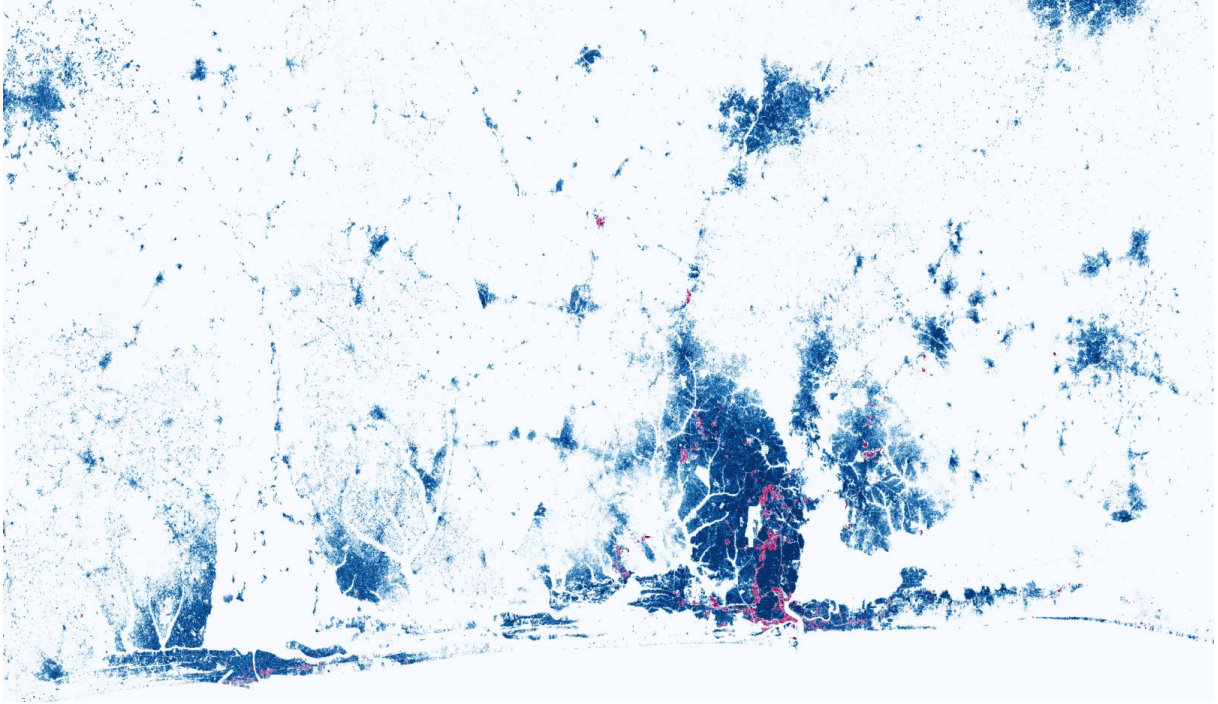


Figure 4 - Lagos-Porto Novo-Abeokuta (Nigeria): residential (RES) and non-residential (NRES) components of the built-surfaces estimated for the GHSL 2020 epoch. RES and NRES are represented with blue and magenta, respectively.

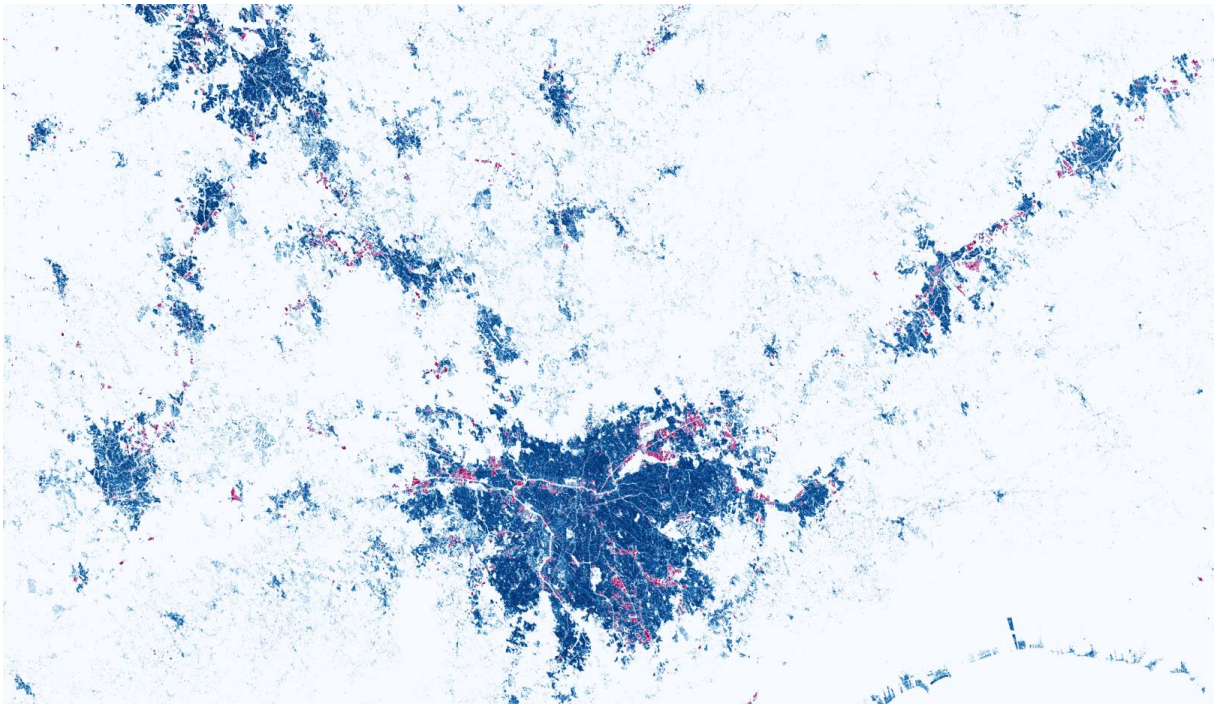


Figure 5 - Sao Paulo- Campinas - Sao Jose dos Campos (Brazil): residential (RES) and non-residential (NRES) components of the built-surfaces estimated for the GHSL 2020 epoch. RES and NRES are represented with blue and magenta, respectively.

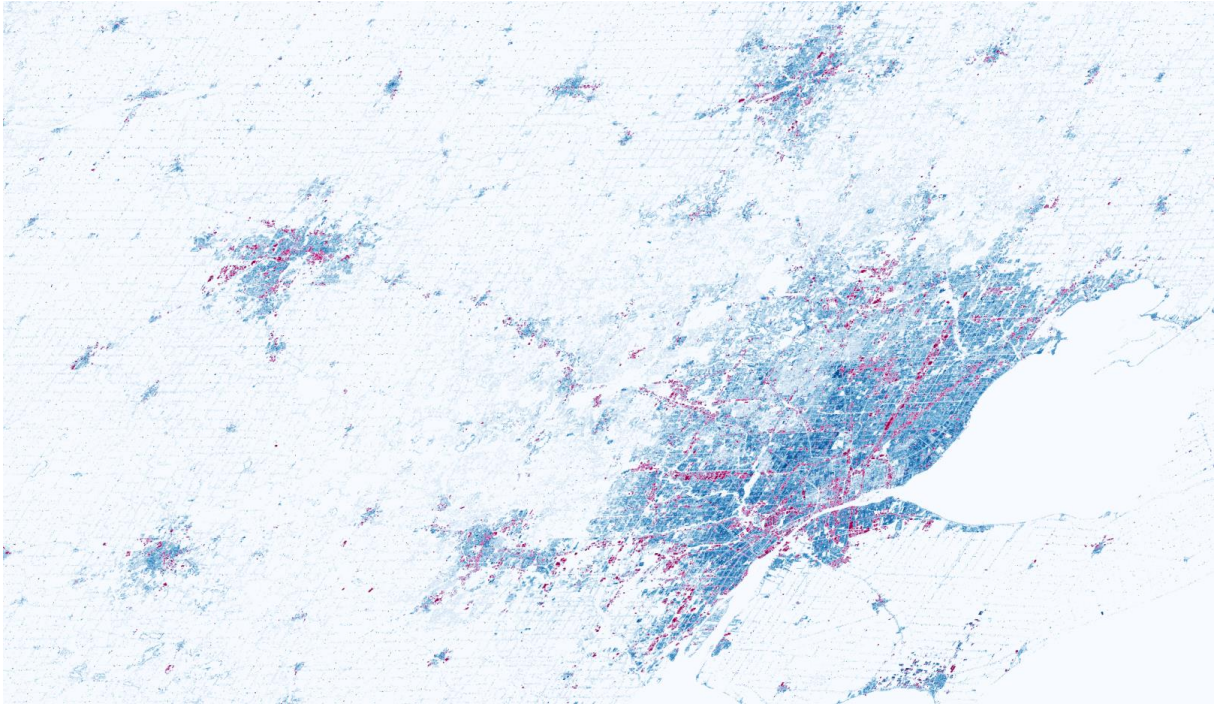


Figure 6 - Detroit-Lansing-Flint (United States): residential (RES) and non-residential (NRES) components of the built-surfaces estimated for the GHSL 2020 epoch. RES and NRES are represented with blue and magenta, respectively.

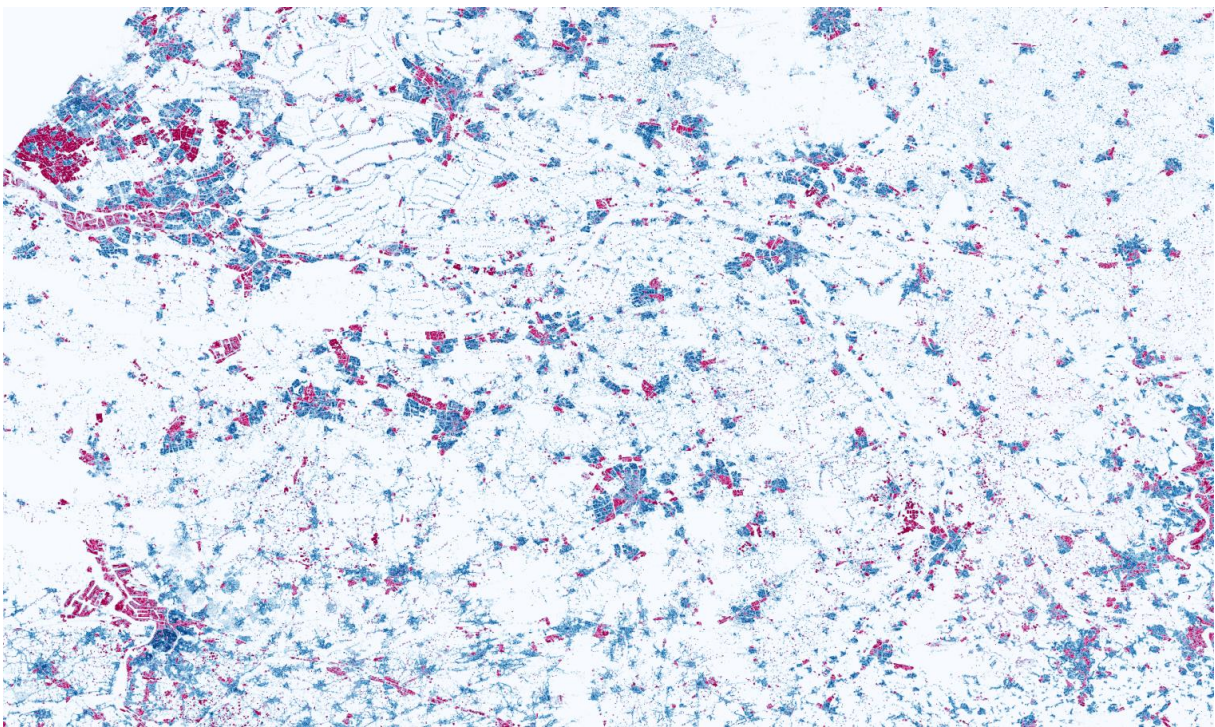


Figure 7 - The Hague - Rotterdam- Antwerp (The Netherlands): residential (RES) and non-residential (NRES) components of the built-surfaces estimated for the GHSL 2020 epoch. RES and NRES are represented with blue and magenta, respectively.

2.1.2 Expected Errors

The estimation of the GHS-BUILT-S errors is currently ongoing, and will be delivered in peer-reviewed publications targeting the different GHS-BUILT-S thematic aspects possibly in 2023-2024.

The ongoing error assessment is solved by two complementary approaches a) comparing model predictions with human visual inspection of the same imagery data input, and b) comparing model predictions with other data of presumably higher accuracy after passing consistency and completeness checks. In the following, it is adopted a pragmatic approach by considering synonyms “accuracy metrics” or “agreement metrics”, both measuring the agreement between the reference data and the model predictions, in both (a) and (b) approaches.

2.1.2.1 Errors in the 2018 predictions

On the error assessment approach (a) a total of 1 million sample points is under assessment for the four Boolean classes listed below:

1. NBU_WATER : non built-up water surfaces
2. NBU_LAND: non built-up land surfaces
3. BU_RES: residential built-up surfaces
4. BU_NRES: non-residential built-up surfaces

A stratified uniform random sampling schema is applied targeting an equalized number of samples for the four considered classes, uniformly distributed across the whole global landmass with the exception of Antarctica. Each random sample was visually inspected in three independent inspection campaigns (trials), performed by nine distinct professional photo-interpreters that were randomly assigned to each sample interpretation task. Each human labelling decision was accompanied by a high (H) vs. low (L) score of the confidence in the label assignment.

The results summarized here are aggregated from the first tranche of 250,000 validation points, which were available at the date of the report.

The class assignment from the different trials in each random sample is not necessarily the same, reflecting possibly different opinions of the human interpreters on the same sample. These uncertainties can be solved by two approaches: a) a voting schema and b) subsampling of the observations minimizing the human disagreement domain. This subsampling is done by using a metric called the Joint Agreement High Confidence (JAHC), which is defined as the domain where all the three independent human interpretations provide the same class answer, all of them with a high confidence score, so it represents the domain with the highest confidence of the human interpretation results. Among the 250,000 considered points, 155,649 (62.26%) are JAHC points, accordingly to the first tranche of 250,000 observed points discussed here. Observing the geographic distribution, the JAHC share ranges from 57.1% to 70.1% of Europe and Oceania, respectively (Table 1).

Table 1 – Total and JAHC samples per Region, sorted by decreasing Joint Agreement High Confidence share of the human interpretation of S2 data.

Region	N Samples (All)	N Samples JAHC (*)	JAHC share
Oceania	13,542	9,505	70.19%
America	78,061	50,094	64.17%
Africa	38,779	24,596	63.43%
ALL	250,000	155,649	62.26%
Asia	71,279	43,821	61.48%
Europe	48,339	27,633	57.17%

(*) Joint Agreement High Confidence (JAHC) samples

Table 2 and Table 3 show the confusion matrix and the accuracy metrics for the 4-class classification scenario, by solving the human uncertainty using the voting schema, and the subsampling to the JAHC universe, respectively. In both cases, per-class Precision and Recall scores (also called Producer and User accuracy) are summarized in the horizontal and vertical highlighted rows, respectively. The voting approach including both High and Low confidence scores of the human labelling, yields an overall accuracy of 82.6% on the 250,000 reference points (Table 2), while the subsampling on the high confidence high agreement of the JAHC domain yields an overall accuracy of 90.5% on the 155,649 reference points passing the agreement and confidence tests (Table 3).

Table 4 shows the summary of the 4-class agreement metrics by sub-regions of the world⁸ ordered by decreasing accuracy scores, focusing the attention on the optimal JAHC human interpretation domain. Significant positive accuracy extrema are collected in South East Asia (94.8%) and Melanesia (95.2%), while the worst region is the Central Africa and Southern Africa, yielding an 86.4% and 83.8% accuracy, respectively.

Table 2 – Reference set by voting schema, any confidence level: confusion matrix and accuracy or agreement metrics

Label		OBSERVED NBU_WATER	OBSERVED NBU_LAND	OBSERVED BU_RES	OBSERVED BU_NRES	Total predicted	Total predicted [%]	Metrics	
		99.5%	56.8%	88.7%	83.3%				
PREDICTED NBU_WATER	95.5%	52,323	2,401	1	43	54,768	21.9%	Precision	82.1%
PREDICTED NBU_LAND	98.6%	215	30,575	75	159	31,024	12.4%	Recall	86.2%
PREDICTED BU_RES	73.3%	2	11,446	63,750	11,746	86,944	34.8%	Accuracy	82.6%
PREDICTED BU_NRES	77.4%	31	9,389	8,037	59,807	77,264	30.9%	Specificity	94.3%
Total observed		52,571	53,811	71,863	71,755	250,000		F1 score	82.5%
Total observed [%]		21.0%	21.5%	28.7%	28.7%				

Table 3 – Reference set by subsampling in the JAHC domain: confusion matrix and accuracy or agreement metrics

Label		OBSERVED NBU_WATER	OBSERVED NBU_LAND	OBSERVED BU_RES	OBSERVED BU_NRES	Total predicted	Total predicted [%]	Metrics	
		99.9%	73.5%	95.0%	91.9%				
PREDICTED NBU_WATER	98.0%	47,873	994	0	0	48,867	31.4%	Precision	90.1%
PREDICTED NBU_LAND	99.8%	60	28,439	5	0	28,504	18.3%	Recall	90.6%
PREDICTED BU_RES	85.3%	0	3,344	34,761	2,633	40,738	26.2%	Accuracy	90.5%
PREDICTED BU_NRES	79.3%	2	5,933	1,824	29,781	37,540	24.1%	Specificity	97.0%
Total observed		47,935	38,710	36,590	32,414	155,649		F1 score	89.6%
Total observed [%]		30.8%	24.9%	23.5%	20.8%				

⁸ Sub-regions are drafted accordingly to the UN world population prospect 2022 definitions (<https://population.un.org/wpp/>)

Table 4 – Agreement metrics by sub-region in the JAHC domain, ordered by decreasing overall accuracy. Precision and Recall are also called “Producer Accuracy” and “User Accuracy”, respectively.

Region	Precision	Recall	Overall Accuracy	Specificity	F1 Score	N Samples
Polynesia	91.9%	95.7%	98.0%	99.4%	93.5%	355
Micronesia	73.2%	70.5%	97.4%	99.2%	71.6%	352
Melanesia	88.5%	84.2%	95.2%	98.5%	85.6%	1,653
South Eastern Asia	94.1%	93.9%	94.8%	98.3%	93.7%	10,794
Seven seas open ocean	74.2%	62.5%	94.8%	97.8%	66.9%	193
Western Europe	91.5%	96.1%	94.3%	98.2%	93.3%	2,270
Middle Africa	92.0%	85.3%	93.8%	97.9%	87.1%	5,527
Central America	92.3%	94.6%	93.7'	98.0%	93.2%	4,514
Caribbean	92.2%	94.1%	93.7%	98.0%	92.76	1,487
Australia and New Zealand	91.7%	91.7%	93.5%	97.9%	91.4%	6,952
Eastern Europe	92.4%	90.3%	92.8%	97.7%	90.7%	18,060
Eastern	90.2%	92.3%	91.7%	97.4%	90.3%	15,631
Western Africa	92.1%	85.8%	91.5%	97.0%	87.2%	4,380
Southern Asia	90.3%	91.76	90.8%	96.9%	90.2%	9,009
ALL	90.1%	90.6%	90.5%	97.0%	89.6%	155,649
Northern Africa	88.7%	86.9%	89.5%	96.4%	87.4%	4,782
Northern Europe	87.4%	89.9%	89.3%	96.6%	87.8%	3,533
South America	88.0%	88.2%	89.1%	96.6%	86.8%	21,434
Eastern Africa	88.9%	34.5%	88.5%	96.3%	84.7%	6,989
Southern Europe	85.4%	91.8%	87.7%	96.3%	86.4%	3,770
Northern America	88.6%	84.0%	87.1%	95.8%	84.3%	22,659
Western Asia	87.0%	88.9%	86.6%	95.5%	87.3%	5,019
Central Asia	88.0%	83.6%	86.4%	95.7%	83.9%	3,368
Southern Africa	85.2%	85.7%	83.8%	94.9%	83.5%	2,918

Table 5 shows the 2-class agreement in model detection of (a) the BU vs. NBU and (b) the WATER vs. LAND abstraction semantics from the S2 data as compared with human visual inspection of the same image data in the high confidence JAHC domain. The performances are aggregated by regions in the world and ordered by accuracy value added of the R2023 vs. the previous R2019 GHSL release if evaluated using the same reference samples. Noticeable is the increase in the BU vs. NBU accuracy of the new release in Asia and Africa (+23.54%, + 22.69%, respectively), while the least increase in accuracy is yielded in Europe (+13.55%).

Table 5 - Accuracy performances in model detection as compared with human visual inspection of the same image data. Jaccard similarity (also called intersection-over-union), Overall Accuracy, Commission Error and Omission Error. (a) the BU vs. NBU and (b) the WATER vs. LAND abstraction semantics. (right) the new GHSL release R2023, (left) the previous GHSL release R2019 tested vs. the same reference data

		GHSL R2019 / LDS_SML2019				GHSL R2023 / S2_SML2023				Increase of Overall Accuracy
		Jaccard similarity	Overall accuracy	Commission error	Omission error	Jaccard similarity	Overall accuracy	Commission error	Omission error	
(a) BU vs NBU	N samples									
Asia	43,821	42.71%	70.51%	0.08744	0.55314	88.29%	94.05%	0.11702	0.00013	23.54%
Africa	24,596	34.77%	70.37%	0.10282	0.63797	86.53%	93.06%	0.13466	0.00000	22.69%
Oceania	9,505	19.54%	76.95%	0.58935	0.72184	91.43%	98.04%	0.08568	0.00000	21.09%
ALL	155,649	48.38%	75.47%	0.12162	0.48148	88.14%	94.04%	0.11854	0.00007	18.56%
America	50,094	56.83%	78.34%	0.09401	0.38766	88.87%	94.48%	0.11124	0.00003	16.14%
Europe	27,633	65.53%	80.53%	0.13341	0.27412	89.62%	94.09%	0.10379	0.00000	13.55%
(b) WATER vs LAND										
Oceania	9,505	74.33%	85.82%	0.05663	0.22095	99.00%	99.43%	0.00303	0.00700	13.61%
Africa	24,596	53.87%	88.01%	0.00353	0.46030	97.17%	99.21%	0.02826	0.00000	11.21%
Asia	43,821	62.55%	89.59%	0.00967	0.37088	98.78%	99.68%	0.01105	0.00117	10.10%
ALL	155,649	68.07%	90.00%	0.02445	0.30746	97.84%	99.32%	0.02034	0.00129	9.32%
America	50,094	77.78%	92.99%	0.02270	0.20552	98.30%	99.41%	0.01580	0.00123	6.42%
Europe	27,633	82.39%	94.83%	0.00272	0.17420	99.23%	99.73%	0.00698	0.00069	4.90%

On the error assessment approach (b) the preliminary error scores in prediction of the BUFRAC were estimated vs. observed built-up surfaces from building footprints available in vector format at scale 1:10K. The test set is made by the global collection of building footprints used for quality control during the GHSL production.

Table 6 shows the expected errors of the new GHS-BUILT-S R2023A release at 10m resolution stratified by class of the Copernicus Global Land cover at 100m resolution (Buchhorn et al., 2020).

Table 7 shows the expected errors of the new GHS-BUILT-S R2023A release at 100m resolution as compared to the previous GHSL release made from Boolean classification of Landsat data (GHS-BUILT R2018A) and as compared to the predictions included in the continuous “urban cover fraction” (UCF) of the Copernicus Global Land cover at 100m resolution (Buchhorn et al., 2020). The test data are subdivided in two geographical strata (“non-US” and “US”) in order to control the performances of the model in different settlement pattern conditions.

The capacity of GHS-BUILT-S R2023A to predict the BUFRAC (quasi continuous, 64 levels) in a globally-representative set of almost 50,000 test cases of 80x80 meter size visually inspected with a Boolean interpretation schema at 10m resolution (See et al., 2022), yield a Pearson Correlation Coefficient of the linear least square regression equal to 0.81363. To be noticed that the correlation is systematically decreased by the fact that the reference data is not spatially aligned with the GHSL data, and by the fact that the GHSL uses a continuous classification schema of the 10m-res raster samples, while the reference data used in See et al. applies a human interpretation schema based on Boolean classification.

Table 8 shows the amount of total built-up surface and NRES built-up surface assessed by the GHS-BUILT-S R2023A data (epoch 2020) stratified by land use classes in United States (NLUD⁹; Theobald, 2014), and Europe

9 Land Use Classification and Map for the US http://csp-inc.org/public/NLUD2010_20140326.zip

(CLC¹⁰), ordered by the GHSL NRES surface share. The table shows the empirical association between the NRES class and the land use classes. To be noticed that the measured association is only indicative and systematically decreased by the fact that the GHSL data is derived from 10m-resolution imagery and consequently has a much higher spatial precision as compared to the land use data used as reference, which is defined with a minimal mapping unit in the order of hectares.

Table 6 – Expected errors of the new GHS-BUILT-S R2023A release at 10m resolution stratified by class of the Copernicus Global Land cover at 100m resolution (Buchhorn et al., 2020).

CODE	LABEL	RMSE	MAE	NSAMPLES
0	Not Classified	0.122	0.070	7,509
20	Shrubs	0.120	0.056	555,261,719
30	Herbaceous vegetation	0.136	0.060	1,310,171,720
40	Cultivated and managed vegetation agriculture cropland	0.071	0.020	914,235,915
50	Urban / built up	0.296	0.218	337,089,799
60	Bare soil or sparse vegetation	0.192	0.111	123,557,016
70	Snow and Ice	0.001	0.000	13,447,153
80	Permanent water bodies	0.028	0.005	116,262,034
90	Herbaceous wetland	0.062	0.019	63,299,127
100	Moss and lichen	0.006	0.001	347,875
111	Closed forest, evergreen needle leaf	0.071	0.025	573,176,106
112	Closed forest, evergreen, broad leaf	0.012	0.002	575,661,481
113	Closed forest, deciduous needle leaf	0.069	0.018	19,610
114	Closed forest, deciduous broad leaf	0.035	0.007	751,956,669
115	Closed forest, mixed	0.027	0.006	145,625,305
116	Closed forest, unknown	0.071	0.026	142,841,787
121	Open forest, evergreen needle leaf	0.101	0.042	111,872,259
122	Open forest, evergreen broad leaf	0.023	0.005	2,599,647
123	Open forest, deciduous needle leaf	0.000	0.000	181
124	Open forest, deciduous broad leaf	0.067	0.021	168,233,648
125	Open forest, mixed	0.048	0.012	1,299,363
126	Open forest, unknown	0.107	0.043	839,029,693
200	Open sea	0.072	0.025	144,012,925
	Total	0.075	0.034	6,890,008,541

Table 7 – Expected error scores in prediction of the built-up surface fraction (BUFRAC) at the aggregated 100m and 1km resolution.

	Non-US			US			Total		
Prediction at 100m resolution	RMSE	MAE	N Samples	RMSE	MAE	N Samples	RMSE	MAE	N Samples
GHS-BUILT-S R2022	0.062	0.035	32,418,503	0.062	0.035	35,886,736	0.062	0.035	68,305,239
GHS-BUILT R2018A	0.194	0.129	32,418,503	0.308	0.213	35,886,736	0.258	0.177	68,305,239
Copernicus Global Land Service UCF	0.255	0.173	32,418,503	0.285	0.195	35,886,736	0.272	0.186	68,305,239
Prediction at 1km resolution	RMSE	MAE	N Samples	RMSE	MAE	N Samples	RMSE	MAE	N Samples
GHS-BUILT-S R2022	0.036	0.026	301,940	0.038	0.030	329,121	0.037	0.028	631,061
GHS-BUILT R2018A	0.144	0.110	301,940	0.259	0.209	329,121	0.213	0.170	631,061
Copernicus Global Land Service UCF	0.195	0.148	301,940	0.242	0.193	329,121	0.223	0.175	631,061

10 Corine Land Cover European seamless 100m raster database (Version 20b2)

<https://land.copernicus.eu/pan-european/corine-land-cover/clc2018?tab=metadata>

Table 8 – The amount of total built-up surfaces, the NRES built-up surfaces assessed in the GHS-BUILT-S R2023A data and the NRES built-up surface share stratified by land use classes in United States (NLUD) and Europe (CLC), ordered by decreasing NRES surface share.

LUSOURC	LUCCLASS	LABEL1	LABEL2	LABEL3	BUTOT m2	BUNRES m2	NRES_shai
NLUD	251	Built-up	Transportation	Airports (developed)	371014506	253357093	68.29%
CLC	121	Artificial surfaces	Industrial, commercial and transport units	Industrial or commercial units	7649839186	5056391057	66.10%
CLC	123	Artificial surfaces	Industrial, commercial and transport units	Port areas	327183968	215970214	66.01%
NLUD	231	Built-up	Industrial	Factory, plant	1619490370	1045588694	64.56%
NLUD	223	Built-up	Commercial	Entertainment (stadiums, amusement, etc.)	53632078	33581582	62.61%
NLUD	221	Built-up	Commercial	Office	1614791936	978439733	60.59%
NLUD	222	Built-up	Commercial	Retail/shopping centers	1742663387	1039508683	59.65%
CLC	124	Artificial surfaces	Industrial, commercial and transport units	Airports	170180711	98086496	57.64%
NLUD	233	Built-up	Industrial	Confined animal feeding	88703844	50398369	56.82%
NLUD	249	Built-up	Institutional	Prison/penitentiary	16152586	8924402	55.25%
NLUD	241	Built-up	Institutional	Schools (dev)	225846287	123608473	54.73%
NLUD	242	Built-up	Institutional	Schools (undeveloped)	598016804	326285150	54.56%
NLUD	243	Built-up	Institutional	Medical (hospitals, nursing home, etc.)	367951278	196239687	53.33%
NLUD	244	Built-up	Institutional	Government/public	86726621	44112906	50.86%
CLC	212	Agricultural areas	Arable land	Permanently irrigated land	622458355	268234717	43.09%
CLC	132	Artificial surfaces	Mine, dump and construction sites	Dump sites	40734981	12866115	31.58%
NLUD	261	Built-up	Transportation	Rural buildings, cemetery	1242246217	391906221	31.55%
NLUD	341	Production	Timber	Timber harvest	165945723	46319990	27.91%
CLC	122	Artificial surfaces	Industrial, commercial and transport units	Road and rail networks and associated land	224903444	57729502	25.67%
CLC	133	Artificial surfaces	Mine, dump and construction sites	Construction sites	94362978	22856256	24.22%
NLUD	255	Built-up	Transportation	Undeveloped	173761477	39555968	22.76%
CLC	213	Agricultural areas	Arable land	Rice fields	32328402	6089237	18.84%
CLC	131	Artificial surfaces	Mine, dump and construction sites	Mineral extraction sites	142861969	24980523	17.49%
NLUD	330	Production	Mining	Mining strip mines, quarries, gravel pits	8185807	1420084	17.35%
NLUD	245	Built-up	Institutional	Military/DOD/DOE (dev)	104554407	17490907	16.73%
NLUD	246	Built-up	Institutional	Military/DOD (training)	217411481	31391901	14.44%
CLC	211	Agricultural areas	Arable land	Non-irrigated arable land	7385826240	982409064	13.30%
CLC	141	Artificial surfaces	Artificial, non-agricultural vegetated areas	Green urban areas	165087965	20670163	12.52%
NLUD	252	Built-up	Transportation	Highways, railways	1042336050	121981507	11.70%
CLC	111	Artificial surfaces	Urban fabric	Continuous urban fabric	2160143750	194234820	8.99%
CLC	222	Agricultural areas	Permanent crops	Fruit trees and berry plantations	398088530	33459968	8.41%
NLUD	411	Recreation	Developed park	Urban park	202120970	16703263	8.26%
CLC	142	Artificial surfaces	Artificial, non-agricultural vegetated areas	Sport and leisure facilities	586211113	45131809	7.70%
CLC	231	Agricultural areas	Pastures	Pastures	4571276116	337410401	7.38%
NLUD	310	Production	General	General agricultural	158011938	11520002	7.29%
NLUD	313	Production	Cropland	Orchards	71453036	4800693	6.72%
CLC	112	Artificial surfaces	Urban fabric	Discontinuous urban fabric	30206040355	1990977548	6.59%
NLUD	314	Production	Cropland	Sod & switch grass	14887041	933461	6.27%
NLUD	311	Production	Cropland	Cropland/row crops	3107157034	190204508	6.12%
CLC	242	Agricultural areas	Heterogeneous agricultural areas	Complex cultivation patterns	4975196695	283937849	5.71%
NLUD	213	Built-up	Residential	Suburban (1–2.5 ac)	9335940633	520592660	5.58%
CLC	243	Agricultural areas	Heterogeneous agricultural areas	Land principally occupied by agriculture, with si	2121377478	109108914	5.14%
NLUD	321	Production	Rangeland	Grazed	3116664551	160096140	5.14%
CLC	221	Agricultural areas	Permanent crops	Vineyards	391114177	19693622	5.04%
NLUD	214	Built-up	Residential	Exurban (2.5–10 ac)	8778472493	408859021	4.66%
NLUD	211	Built-up	Residential	Dense urban (>0.1 ac)	1461479361	64398593	4.41%
CLC	223	Agricultural areas	Permanent crops	Olive groves	436848677	17939775	4.11%
NLUD	415	Recreation	Developed park	Resort/ski area	43570356	1739805	3.99%
NLUD	410	Recreation	Undifferentiated park	General park	201511693	7926588	3.93%
NLUD	421	Recreation	Natural park	Natural park	144612371	5448426	3.77%
NLUD	417	Recreation	Developed park	Campground/ranger station	20170842	710508	3.52%
CLC	244	Agricultural areas	Heterogeneous agricultural areas	Agro-forestry areas	44227686	1378654	3.12%
CLC	241	Agricultural areas	Heterogeneous agricultural areas	Annual crops associated with permanent crops	149655325	4474819	2.99%
NLUD	412	Recreation	Developed park	Golf course	202243104	5893655	2.91%
NLUD	312	Production	Cropland	Pastureland	3456950217	91632160	2.65%
NLUD	212	Built-up	Residential	Urban (0.1–1)	16435713363	399274360	2.43%
NLUD	215	Built-up	Residential	Rural (10–40 ac)	5350324389	111117959	2.08%
NLUD	422	Recreation	Natural park	Designated recreation area	203351	2066	1.02%

2.1.2.2 Errors in the multi-temporal predictions

Preliminary error assessment results in the multi-temporal domain include the comparison of model-predicted built-up surfaces vs. observed built-up surfaces as deduced from the rasterization of vector building footprint data including the year of construction that are available in France, Spain, the Netherlands, Switzerland and the US (Uhl & Leyk, 2022). Table 9 shows the number of valid samples used in the preliminary multi-temporal test by country and by degree of urbanization spatial raster dataset (GHS-SMOD 1km epoch 2020) URBAN vs. RURAL stratification.

Table 9 – number of valid samples used in the MT test

	RURAL	URBAN	ALL
France	2,862,465	658,771	3,521,236
Netherlands	207,186	309,022	516,208
Spain	929,967	550,710	1,480,677
Switzerland	6,244	17,600	23,844
USA	87,947	132,451	220,398
Grand Total	4,093,809	1,668,554	

Figure 8 shows the time series of agreement measures estimated by a generalized version of the Jaccard similarity index to the continuous numerical domain (Costa, 2022) of the built-up surface predictions at 100m of spatial resolution in the temporal domain 1975-2015 in 5 year intervals. Besides the aforementioned rural-urban stratification, some alternative products were used, assessing similar information as the GHS-BUILT-S. In particular, the BENCHMARK(R2022A) case is the GHSL data released in June 2022, the GHSL R2023A is the current release, the PRIOR(GHS_B_P2019) is the previous GHSL release (Corbane et al., 2019), the PRIOR(GISA) is the Global Impervious Surface Area (Huang et al., 2022), and the PRIOR(WSF_EVO) is the World Settlement Footprint Evolution product (Marconcini et al., 2021). According to these empirical evidences, the new R2023A discussed here i) improves the accuracy of the previous release R2022A in both the URBAN and RURAL application domains in all the predicted epochs, and ii) among the considered alternative sources, it is the best predictor of the built-up surfaces at 100m resolution in both the URBAN and RURAL application domains in all the predicted epochs.

Figure 9 and Figure 10 show the temporal evolution of the predicted and observed (REF) normalized built-up surfaces in the considered test areas, in the URBAN 2020 and RURAL 2020 stratum, respectively, in three different GHSL models: The R2019, the R2022A, and the current R2023A. The built-up surfaces are normalized by the respective average in all the considered epochs. According to these results i) the new R2023A release is more sensitive to the change in URBAN domain as compared to the previous releases R2019, R2022 (Figure 9) and ii) the new release R2023 fixes the issue on the unrealistic change rates in the RURAL domain observed in the R2022 (Figure 10).

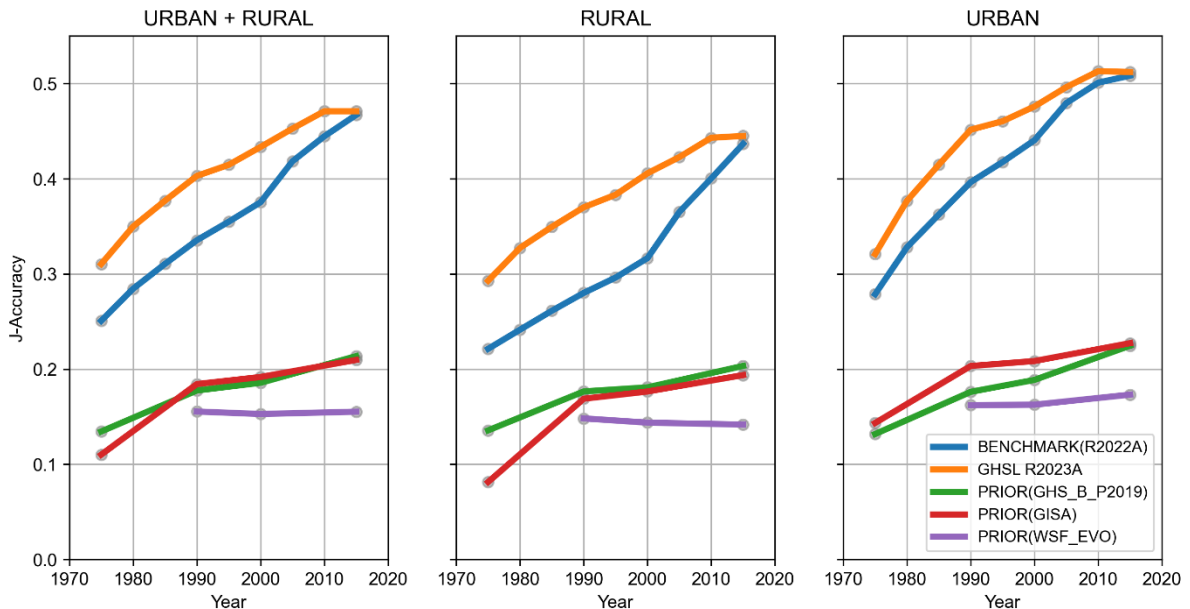


Figure 8 – Multi-temporal accuracy estimations in URBAN and RURAL domains, and across both domains. J-Accuracy is the generalized version of the Jaccard similarity index to the continuous numerical domain (Costa, 2022)

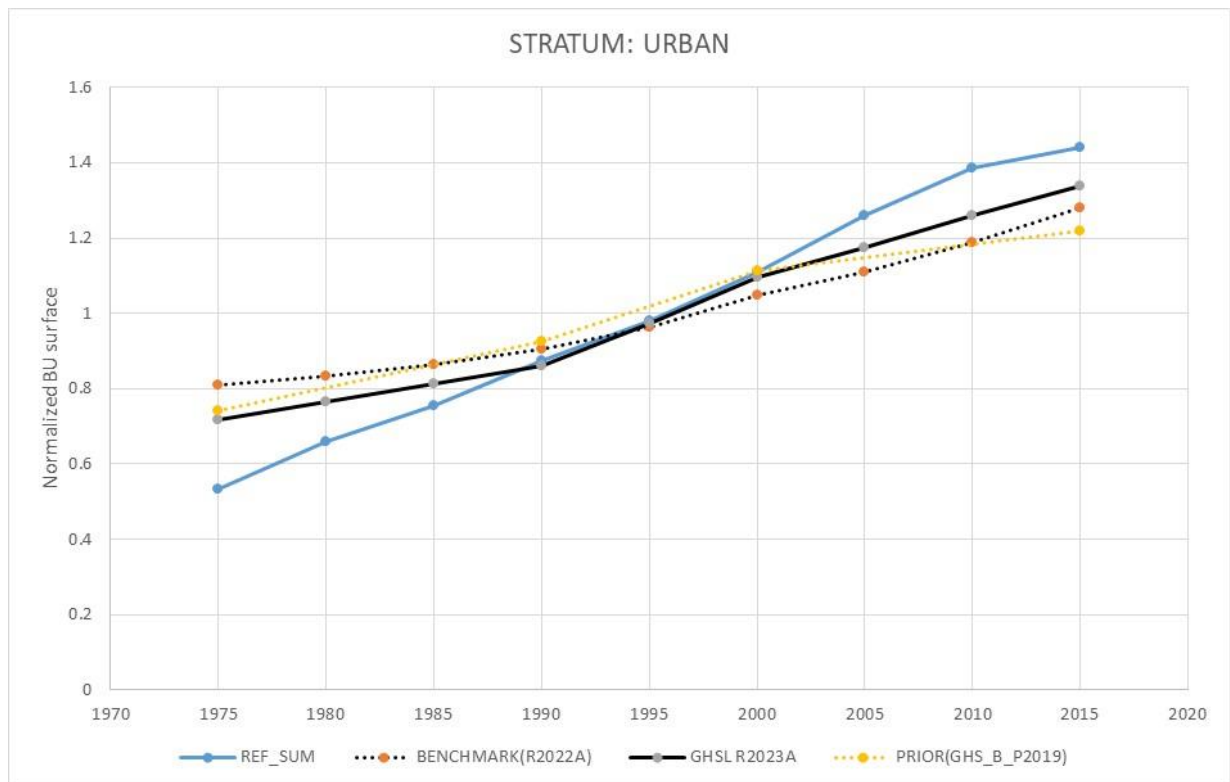


Figure 9 – Temporal evolution of the predicted and observed (REF_SUM) normalized built-up surfaces in the considered test areas, URBAN 2020 stratum.

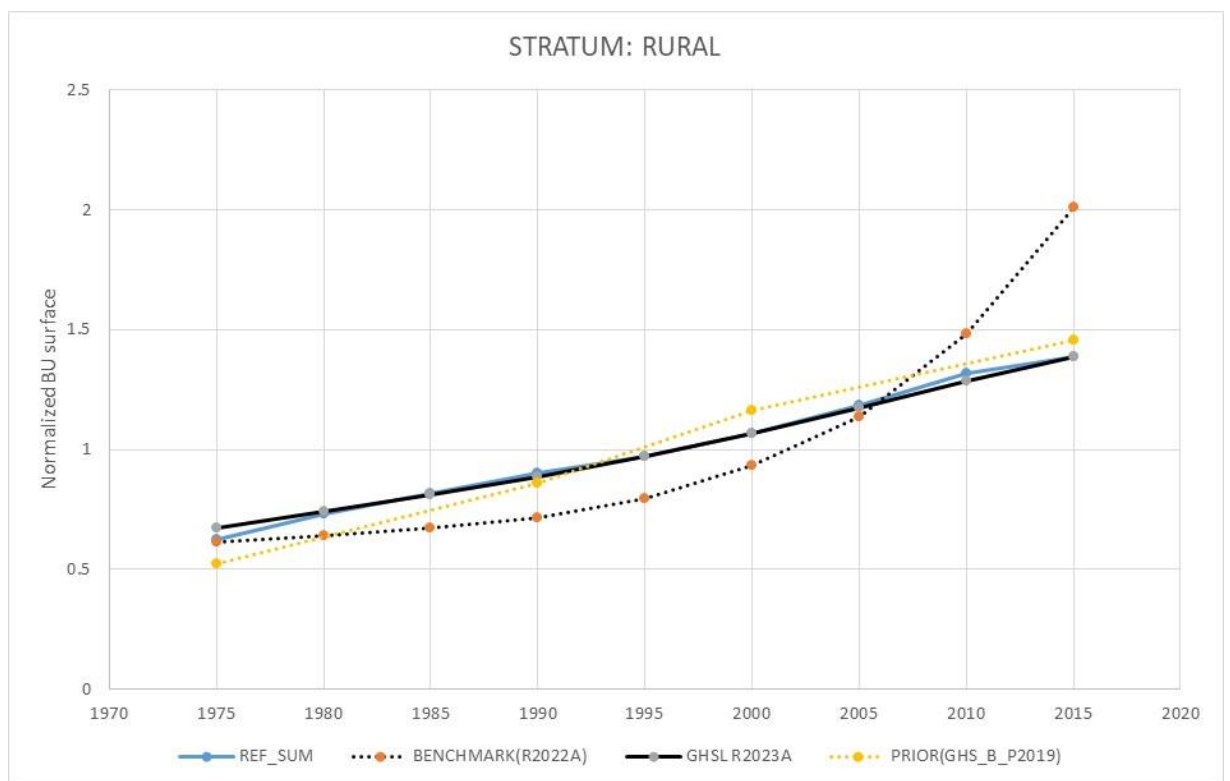


Figure 10- Temporal evolution of the predicted and observed (REF_SUM) normalized built-up surfaces in the considered test areas, RURAL 2020 stratum.

2.1.3 Improvements compared to the previous release

Improved input

Improved input data used in this release includes: improved satellite imagery and new prior knowledge and learning set.

Regarding improved satellite imagery we have included a more populated historical Landsat data series, a new epoch 2018 from Sentinel-2 with 10m spatial resolution vs. previous 30m Landsat data.

Regarding new prior knowledge and learning set we have included new BU labels as i) the GHS-BUILT-S2 R2020A¹¹ that is a probability to the BU class spatial raster dataset derived from Sentinel-2 global image composite for reference year 2018 using Convolutional Neural Networks (GHS-S2Net; Corbane, Syrris, et al., 2020) and ii) the buildings and the settlement delineation derived from VHR imagery by Microsoft¹² and Facebook¹³ open efforts, the new BU change map as included in the GHS-BUILT R2018A, GHS built-up spatial raster dataset, derived from Landsat, multi-temporal (1975-1990-2000-2014), and Land Use and other information included in National land use data (US NLCD¹⁴, EU CORINE¹⁵) and Volunteered geographical information by Open Street Map (OSM)¹⁶ on LANDUSE, ROADS, RIVER, STREAMS.

List of Countries where Microsoft building footprint data were available during the GHSL production: USA, Canada, Australia, Uganda, Tanzania, Nigeria, Kenya, Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Guyana, Paraguay, Peru, Uruguay, Venezuela.

List of Countries where high resolution settlement layer (HRSL) data from Facebook were available during the GHSL production: Albania, Algeria, American Samoa, Andorra, Angola, Anguilla, Antigua and Barbuda, Argentina, Aruba, Australia, Austria, Bahamas, Bahrain, Bangladesh, Barbados, Belarus, Belgium, Belize, Benin, Bhutan, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, British Virgin Islands, Brunei, Bulgaria, Burkina Faso, Burundi, Cabo Verde, Cambodia, Cameroon, Cayman Islands, Central African Republic, Chad, Chile, Colombia, Comoros, Congo, Cook Island, Costa Rica, Cote d'Ivoire, Croatia, Czechia, Democratic Republic of the Congo, Djibouti, Dominica, Dominican Republic, Ecuador, Egypt, El Salvador, Equatorial Guinea, Eritrea, Estonia, Federated States of Micronesia, Fiji, France, French Guiana, French Polynesia, Gabon, Gambia, Gibraltar, Georgia, Germany, Ghana, Greece, Grenada, Guadeloupe, Guam, Guatemala, Guinea, Guinea Bissau, Guyana, Haiti, Honduras, China Hong Kong Special Administrative Region, Hungary, Iceland, Indonesia, Iraq, Ireland, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Kingdom of Eswatini, Kiribati, Kuwait, Kyrgyzstan, Laos, Latvia, Lebanon, Lesotho, Liberia, Libya, Liechtenstein, Lithuania, Luxemburg, China Macao Special Administrative Region, Madagascar, Malawi, Malaysia, Maldives, Mali, Malta, Marshall Islands, Mauritania, Mauritius, Mayotte, Mexico, Moldova, Monaco, Mongolia, Montserrat, Mozambique, Namibia, Nauru, Nepal, Netherlands, New Caledonia, New Zealand, Nicaragua, Niger, Nigeria, The former Yugoslav Republic of Macedonia, Northern Mariana Islands, Oman, Palau, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Portugal, Puerto Rico, Qatar, Reunion, Romania, Rwanda, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and the Grenadines, Samoa, San Marino, Sao Tome and Principe, Saudi Arabia, Senegal, Serbia, Seychelles, Sierra Leone, Singapore, Slovakia, Slovenia, Solomon Islands, South Africa, South Korea, Spain, Sri Lanka, Suriname, Switzerland, Taiwan, Tajikistan, Thailand, Timor Leste, Togo, Tonga, Trinidad and Tobago, Tunisia, Turkmenistan, Turks and Caicos, Tuvalu, Uganda, United Arab Emirates, United Kingdom, United Republic of Tanzania, Uruguay, US Virgin Islands, United States of America, Uzbekistan, Vanuatu, Vietnam, Wallis and Futuna Islands, Zambia, Zimbabwe

Improved Output

Several improvements regarding the assessment of the built-up surfaces are included in this new release, as compared to the previous GHSL data. They may be summarized in the following points:

¹¹ <https://ghsl.jrc.ec.europa.eu/download.php?ds=buS2>

¹² <https://github.com/microsoft/USBuildingFootprints>

¹³ <https://research.fb.com/downloads/high-resolution-settlement-layer-hrsl/>

¹⁴ <https://www.mrlc.gov/data>

¹⁵ <https://land.copernicus.eu/pan-european/corine-land-cover/clc2018>

¹⁶ <https://www.openstreetmap.org/>

The accuracy of the Boolean prediction of BU vs. NBU surfaces has improved from the 75.47% of the previous R2019 to the 94.04% of the current R2022/R2023 using the same reference data. Accuracy improvements are remarkable in Asia and Africa (Table 5). The WATER vs. LAND Boolean discrimination has also improved significantly as compared to the previous release R2019 (Table 5).

The prediction of the continuous built-up surface improved considerably with a MAE at 100m-resolution that drops from 0.117 of the previous release to the 0.035 of the current release (Table 7).

The new GHSL release includes a new classification of the non-residential (NRES) built-up surfaces that was not available in the previous releases. This feature will improve the usability of the new GHSL data in applications requiring a functional classification of the built environment.

The new GHSL release produces data at equal intervals in the time period 1975-2030 using a spatial-temporal interpolation process, while previous GHSL releases were reporting data in arbitrary points in time where satellite images were available. This will further enhance the usability of the new GHSL data in trend and projection analysis requiring consistent time intervals (see section 2.1).

The accuracy of the multi-temporal built-up surface prediction of the new release R2023A has improved with respect to all previous releases (R2022, R2019) in all epochs (Figure 8). The unrealistic built-up surface change rate in RURAL domain noticed in the R2022 has been fixed in the new release R2023 (Figure 10).

Table 10 - Summary of the characteristics of the new GHS-BUILT data vs. the previous releases

Data Characteristics	GHS-BUILT R2018A	GHS-BUILT-S R2023A
Definition of the built-up class abstraction	INSPIRE “BUILDING” roofed structure above ground for any use	INSPIRE “BUILDING” roofed structure above ground for any use
Definition of the NRES vs. RES class abstraction	Not available	Derived from INSPIRE “residential” use definition
Built-up surface : class	Boolean	Continuous
Built-up surface : RES vs. NRES class	Not available	Boolean
Built-up surface : spatial resolution	30m	10m
Built-up surface : observed epochs	4 (1975,1990,2000,2014)	5 (1975,1990,2000,2014,2018)
Built-up surface : change map	Pixel-based	Segment-based
Building height : measurement	Not available	Continuous
Building height : spatial resolution	Not available	100m
Building height : observed epoch	Not available	2018
Built-up surface : spatial resolution of the generalized grids	250m	100m
	1km	1km
Built-up volume : spatial resolution of the generalized grids	Not available	100m
		1km
Equal-time-interval spatial-temporal interpolated grids of built-up surfaces and volume	Not available	12 epochs (1975, 1980, 1985, 1990, 1995, 2000, 2005, 2010, 2015, 2020, 2025, 2030)
Future grids projections	Not available	2025 and 2030

2.1.4 Input Data

2.1.4.1 Remotely sensed image data

The remotely sensed image data supporting this GHSL release are collected by the Landsat and the Sentinel platforms, organized in five epochs: 1975, 1990, 2000, 2014, and 2018.

The Landsat data used in input include 35479 individual scenes organized in four epochs 1975, 1990, 2000, and 2014. The average absolute time tolerance of the image data collection time vs. the nominal time barycentre of the epoch is 2.0, 2.2, 1.2, and 0.8 years for the 1975, 1990, 2000, and 2014 epochs, respectively. The aggregated time precision of all the data in the four epochs is of 1.5 years. The empirical time barycentre for the epochs 1975, 1990, 2000, and 2014 is the year 1975.1, 1989.4, 2000.8, and 2013.2, respectively.

Table 11 - Summary of the Landsat Image data used in input

Row Labels	Count of YEAR	Average of YEAR	Average of ABS_TimeTolerance
1975	7355	1975.1	2.0
L1	4403	1973.4	1.6
L2	1880	1976.8	1.8
L3	1072	1979.3	4.3
1990	8011	1989.4	2.2
L4	258	1983.5	6.5
L5	7475	1989.4	2.0
L6	278	1994.3	4.3
2000	9774	2000.8	1.2
L5	459	2004.7	5.7
L6	8827	2000.4	0.7
L7	488	2005.5	5.5
2014	10339	2013.2	0.8
L5	638	2009.6	4.4
L7	259	2009.5	4.5
L8	9442	2013.5	0.5
Grand Total	35479	1996.5	1.5

The epoch 2018 is derived from the GHS_composite_S2_L1C_2017-2018_GLOBE_R2020A¹⁷ that represents a global, cloud-free pixel-based composite created from the Sentinel-2 data archive (Level L1C) available in Google Earth Engine¹⁸ for the period January 2017 - December 2018.

2.1.4.2 High-level semantic abstraction data

Several high-level semantic datasets are used in the process with the function of prior knowledge supporting the various phases of data classification to obtain BU surface fraction estimates, the historical change detection in the BU surfaces, and the land use classification of RES vs. NRES BU surfaces.

BU class abstraction labels: i) the GHS-BUILT-S2 R2020A¹⁹ that is a probability to the BU class spatial raster dataset derived from Sentinel-2 global image composite for reference year 2018 using Convolutional Neural Networks (GHS-S2Net) and ii) the buildings derived from VHR imagery by Microsoft²⁰ and the settlement delineation from Facebook²¹ open efforts

¹⁷ <https://ghsl.jrc.ec.europa.eu/download.php?ds=compositeS2>

¹⁸ https://developers.google.com/earth-engine/datasets/catalog/COPERNICUS_S2

¹⁹ <https://ghsl.jrc.ec.europa.eu/download.php?ds=buS2>

²⁰ <https://github.com/microsoft/USBuildingFootprints>

²¹ <https://research.fb.com/downloads/high-resolution-settlement-layer-hrsl/>

Multi-temporal assessments: i) the BU change map GHS built-up spatial raster dataset, derived from Landsat, multi-temporal (1975-1990-2000-2014) of the GHSL R2019 (Corbane et al., 2019), ii) GISA the Global Impervious Surface Area (Huang et al., 2022), and WSF_EVO the World Settlement Footprint Evolution product (Marconcini et al., 2021).

Land Use and other: information included in National land use data (US NLUD²², EU CORINE²³) and Volunteered geographical information by Open Street Map (OSM)²⁴ on LANDUSE, ROADS, RIVER, STREAMS

2.1.5 Technical Details

Author: Pesaresi, Martino; Politis Panagiotis

Product name: GHS-BUILT-S_GLOBE_R2023A

Spatial extent: Global

Temporal extent: from 1975 to 2030, 5 years interval

Coordinate Systems: World Mollweide (ESRI:54009), WGS84 (EPSG:4326)

Spatial resolution available: 10 m, 100 m, and 1 km, 3ss, 30ss

Encoding: integer (Byte, UInt16, UInt32), unit: built square meters in the grid cell

Data organisation: GeoTIFF file (10 m, 100m, 1km, 3 ss, 30 ss) with overview images (OVR). Data tiles of 100x100 km size in GeoTIFF format (10 m, 100 m, 1 km, 3 ss, 30 ss). Tile schema in shapefile format

Table 12 outlines the technical characteristics of the datasets released in this data package.

Disclaimer: the re-projection of the World Mollweide version of the GHS-BUILT-S_GLOBE_R2023A to coordinate systems requires specific technical knowledge. No responsibility is taken for workflows developed independently by users.

Table 12 - Technical details of the datasets in GHS-BUILT-S_GLOBE_R2023A

GHS-BUILT-S_GLOBE_R2023A		
ID	Description	Resolution (projection)
GHS_BUILT_S_E<epoch>_GLOBE_R2023A_<proj>_<res>_V1_0	BU surface <epoch> 1975-2030; <proj> 54009, 4326; <res> 100, 1000 Encoding: UInt16 (100 m), UInt32 (1 km) Values range: 0-10000 (100 m, 3ss), 0-1000000 (1 km, 30ss) NoData: 65535 (100 m, 3ss), 4294967295 (1 km, 30ss)	100 m, 1 km World Mollweide (ESRI:54009)
GHS_BUILT_S_E2018_GLOBE_R2023A_54009_10_V1_0	BUFRAC at 10m spatial resolution for E2018 Encoding: Byte Values range: 0-100 NoData: 255	10 m World Mollweide (ESRI:54009)

²² <https://www.mrlc.gov/data>

²³ <https://land.copernicus.eu/pan-european/corine-land-cover/clc2018>

²⁴ <https://www.openstreetmap.org/>

GHS-BUILT-S_NRES_GLOBE_R2023A		
ID	Description	Resolution (projection)
GHS_BUILT_S_NRES_E<epoch>_GLOBE_R2023A_<proj>_<res>_V1_0	Non-residential BU surface <epoch> 1975-2030; <proj> 54009, 4326; <res> 100m, 1000 Encoding: UInt16 (100 m), UInt32 (1 km) Values range: 0-10000 (100 m, 3ss), 0- 1000000 (1 km, 30ss) NoData: 65535 (100 m, 3ss), 4294967295 (1 km, 30ss)	100 m, 1 km World Mollweide (ESRI:54009)
GHS_BUILT_S_NRES_E2018_GLOBE_R2023A_54009_10_V1_0	NRES 10m (boolean) at 10m spatial resolution for E2018 Encoding: Byte Values range: 0:non-NRES ; 1:NRES NoData: 255	10 m World Mollweide (ESRI:54009)

2.1.6 Summary statistics

Table 13 - Summary statistics of predicted surface (square meters) of built-up total (BUTOT) and the built-up non-residential (BUNRES) component, per years of prediction

YEAR	BUTOT	BUNRES	NRES SHARE
1975	173,579,688,013	14,851,659,436	8.56%
1980	194,287,591,836	15,786,940,488	8.13%
1985	220,083,865,086	16,824,775,584	7.64%
1990	249,833,100,538	17,952,331,271	7.19%
1995	280,112,957,342	20,040,927,733	7.15%
2000	315,676,641,605	22,572,549,796	7.15%
2005	345,785,691,160	24,500,768,168	7.09%
2010	382,248,138,896	26,910,963,662	7.04%
2015	422,815,687,372	29,654,448,253	7.01%
2020	464,586,276,041	32,175,346,993	6.93%
2025	491,637,335,418	34,010,908,125	6.92%
2030	509,277,184,552	35,391,231,420	6.95%

2.1.7 How to cite

Dataset:

Pesaresi, Martino; Politis, Panagiotis (2023): GHS-BUILT-S R2023A - GHS built-up surface grid, derived from Sentinel2 composite and Landsat, multitemporal (1975-2030). European Commission, Joint Research Centre (JRC) [Dataset] doi: 10.2905/9F06F36F-4B11-47EC-ABB0-4F8B7B1D72EA PID: <http://data.europa.eu/89h/9f06f36f-4b11-47ec-abb0-4f8b7b1d72ea>

Concept & Methodology:

European Commission, GHSL Data Package 2023, Publications Office of the European Union, Luxembourg, 2023, ISBN 978-92-68-02341-9, doi:10.2760/098587, JRC133256

Essential methodological background:

Pesaresi M, Corban C, Julea A, Florczyk A, Syrris V, Soille P. Assessment of the Added-Value of Sentinel-2 for Detecting Built-up Areas. Remote Sensing 8 (4); 2016. p. 299. JRC99996

Pesaresi M; Syrris V; Julea A. A New Method for Earth Observation Data Analytics Based on Symbolic Machine Learning. *Remote Sensing* 8 (5); 2016. p. 399. JRC99747

Pesaresi M. Global fine-scale information layers: the need of a paradigm shift. In: Soille P, Marchetti PG, editors. *Proceedings of the 2014 conference on Big Data from Space (BiDS'14)*. Luxembourg (Luxembourg): Publications Office of the European Union; 2014. p. 8-11. JRC92345

Pesaresi M, Ouzounis G, Gueguen L. A new compact representation of morphological profiles: report on first massive VHR image processing at the JRC. In *Conference Proceedings: Sylvia S. Shen, Paul E. Lewis, editors. Algorithms and Technologies for Multispectral, Hyperspectral, and Ultraspectral Imagery XVIII*. Vol. 8390. SPIE; 2012. JRC70542

Gueguen L, Soille P, Pesaresi M. A New Built-Up Presence Index Based On Density of Corners. In *Conference Proceedings: Geoscience and Remote Sensing Symposium (IGARSS), 2012 IEEE International*. Piscataway (USA): IEEE; 2012. p. 5398-5401. JRC68582

Ouzounis G, Pesaresi M, Soille P. Differential area profiles: decomposition properties and efficient computation. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 34 (8); 2012. p. 1533-1548. JRC59388

Pesaresi M, Gerhardinger A, Kayitakire F. A Robust Built-up Area Presence Index by Anisotropic Rotation-invariant Textural Measure. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 1 (3); 2008. p. 180-192. JRC37845

Pesaresi M, Benediktsson J. A New Approach for the Morphological Segmentation of High-Resolution Satellite Imagery. *IEEE Transactions on Geoscience and RS* 39 (2); 2001. JRC19264

2.2 GHS-BUILT-H R2023A - GHS building height, derived from AW3D30, SRTM30, and Sentinel-2 composite (2018)

This spatial raster dataset depicts the distribution of the building heights generalized at the resolution of 100m, and referred to the year 2018. The input data used to predict the building heights are the ALOS Global Digital Surface Model "ALOS World 3D - 30m (AW3D30)"²⁵, the NASA Shuttle Radar Topographic Mission data - 30m (SRTM30)²⁶, and the Sentinel-2 global pixel based image composite from L1C data for the period 2017-2018²⁷ that is the support of the year 2018 in this release.

The first global attempt to produce an estimate of the building heights was done in the so called "GHSL_LABEL" product as described in (Pesaresi, Ehrlich, et al., 2016) and tested in (Bechtel et al., 2018) in support to the urban local climate zones (LCZ) taxonomy. The use of the global DEM for prediction of building heights using linear regression techniques was introduced in (Pesaresi et al., 2021). In the application of those techniques included in the GHS-BUILT-H R2023A, the building heights are first predicted from the filtering of a composite of the AW3D30 and SRTM30 global DEMs, by generalization of the linear regression to a multiple-objective case targeting different estimates of 100m-res generalized vertical components of built surfaces: Average of the Net Building Height (ANBH), Average of the Gross Building Height (AGBH) and volume total (VOL) that are linked by analytical relations. They independently estimate the same variable (ANBH) from different filtering of the same DEMs and different regression coefficients, in conjunction with the BUSURF included in the GHS-BUILT-S R2023A data. The different independent estimates of the ANBH generated by the global DEMs are composed by minimization of the expected error, and they are used to estimate the linear regression coefficient predicting the ANBH from the density of shadow markers as observed in 10m-resolution Sentinel-2 image data, of each specific data tile (100×100km). These last ANBH predictions from the S2 data are used to update the final ANBH prediction included in this GHSL release.

2.2.1 Definitions

The built-up volume (BUVOL) is the volume of the built space above ground, expressed in cubic meters

Be S_x , the surface of the grid sample x

The Average of the Net Building Height of the sample x ($ANBH_x$) is defined as:

$$ANBH_x = BUVOL_x / BUSURF_x$$

$$BUVOL_x = BUSURF_x * ANBH_x$$

The Average of the Gross Building Height of the sample x ($AGBH_x$) is defined as:

$$AGBH_x = BUVOL_x / S_x$$

$$BUVOL_x = S_x * AGBH_x$$

Developing the above, the $BUFRAC_x$ can be derived as

$$AGBH_x / ANBH_x = BUSURF_x / S_x = BUFRAC_x$$

Examples

Let assume a sample x of a grid with 100m of spatial resolution, then $S_x = 10,000$ square meters. The built-up surface in this sample it is predicted as $BUSURF_x = 750$ square meters, corresponding to a $BUFRAC_x = 0.075$. Moreover, in the same sample the $ANBH_x$ is predicted as $ANBH_x = 11.5$ meters.

The total built-up volume in this sample will be $BUVOL_x = BUSURF_x * ANBH_x = 750 * 11.5 = 8625$ cubic meters. In the same sample x , the $AGBH_x$ will be predicted as 0.8625 meters.

The total built-up volume in this sample will be $BUVOL_x = S_x * AGBH_x = 10,000 * 0.865 = 8625$ cubic meters. While the ratio $AGBH_x / ANBH_x = 0.075$, corresponds to the $BUFRAC_x$ in the same sample x

²⁵ https://www.eorc.jaxa.jp/ALOS/en/dataset/aw3d30/aw3d30_e.htm

²⁶ https://cmr.earthdata.nasa.gov/search/concepts/C1000000240-LPDAAAC_ECS.html

²⁷ GHS-composite-S2 R2020A <https://ghsl.jrc.ec.europa.eu/download.php?ds=compositeS2>

2.2.2 Input data

The input data for the GHS-BUILT-H R2023A are: the ALOS Global Digital Surface Model "ALOS World 3D - 30m" (AW3D30), the NASA Shuttle Radar Topographic Mission data - 30m (SRTM30), and the global, pixel-based Sentinel-2 image composite from L1C data for the period 2017-2018.

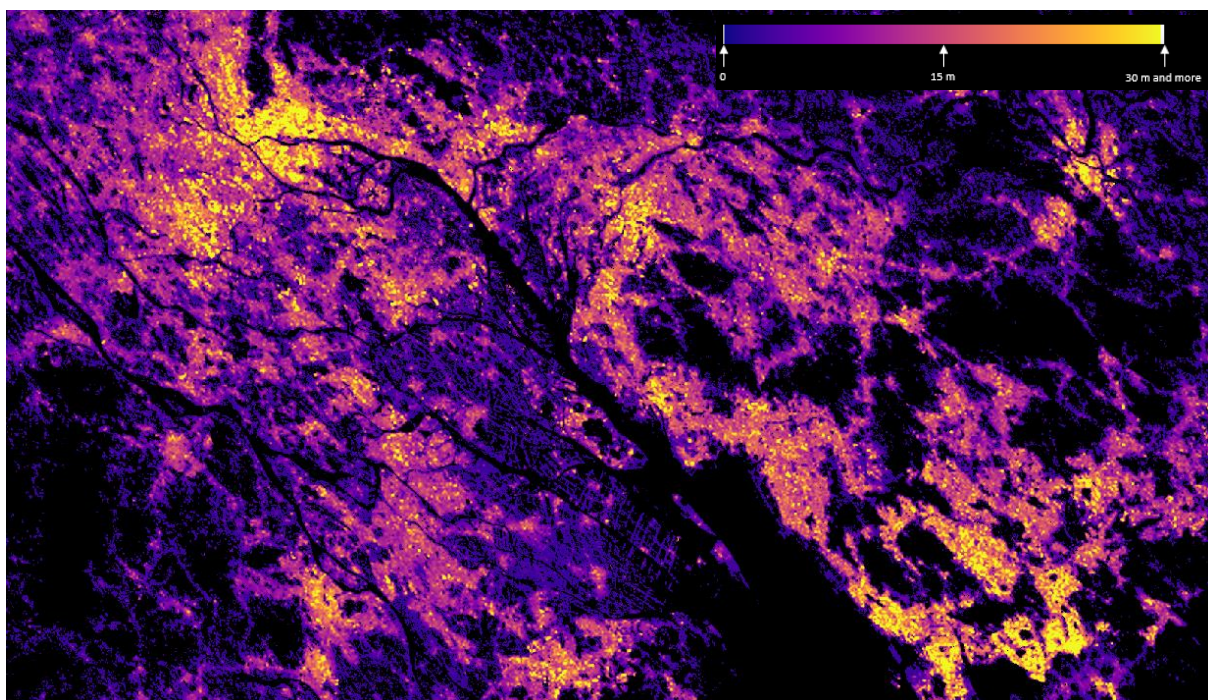


Figure 11 – Average building height (ANBH 100m) estimates in Guangzhou - Shenzhen (China).

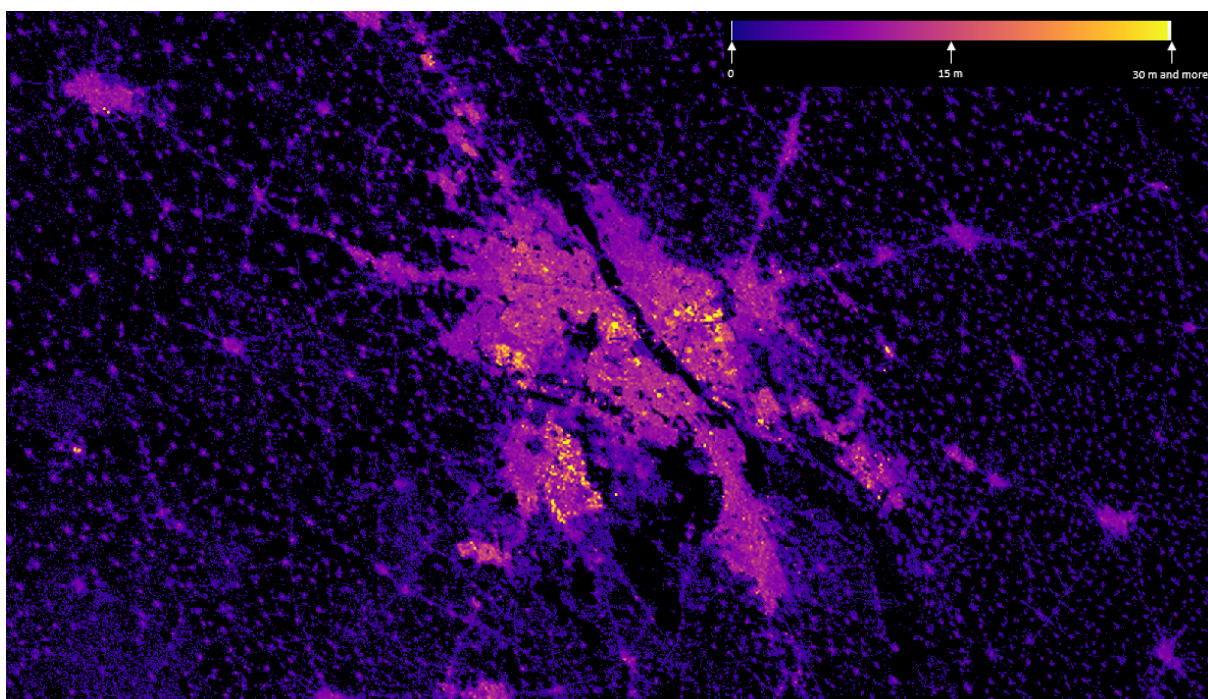


Figure 12 - Average building height (ANBH 100m) estimates in Delhi (India).

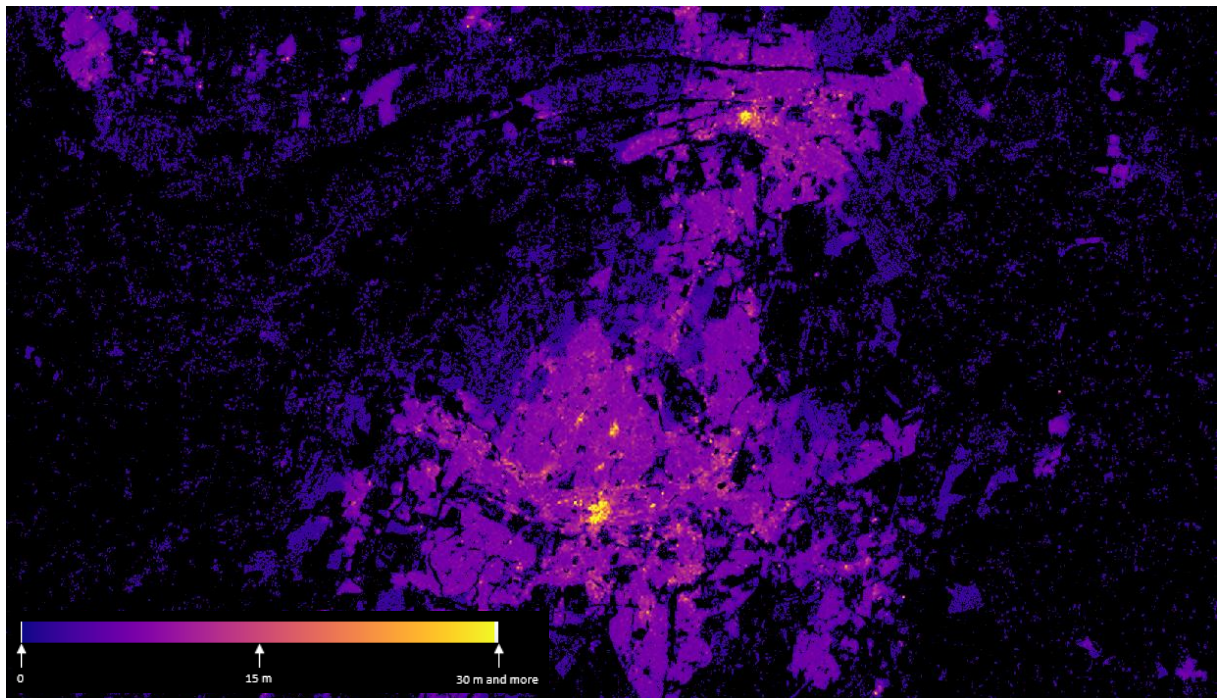


Figure 13 - Average building height (ANBH 100m) estimates in Pretoria – Johannesburg (South Africa).

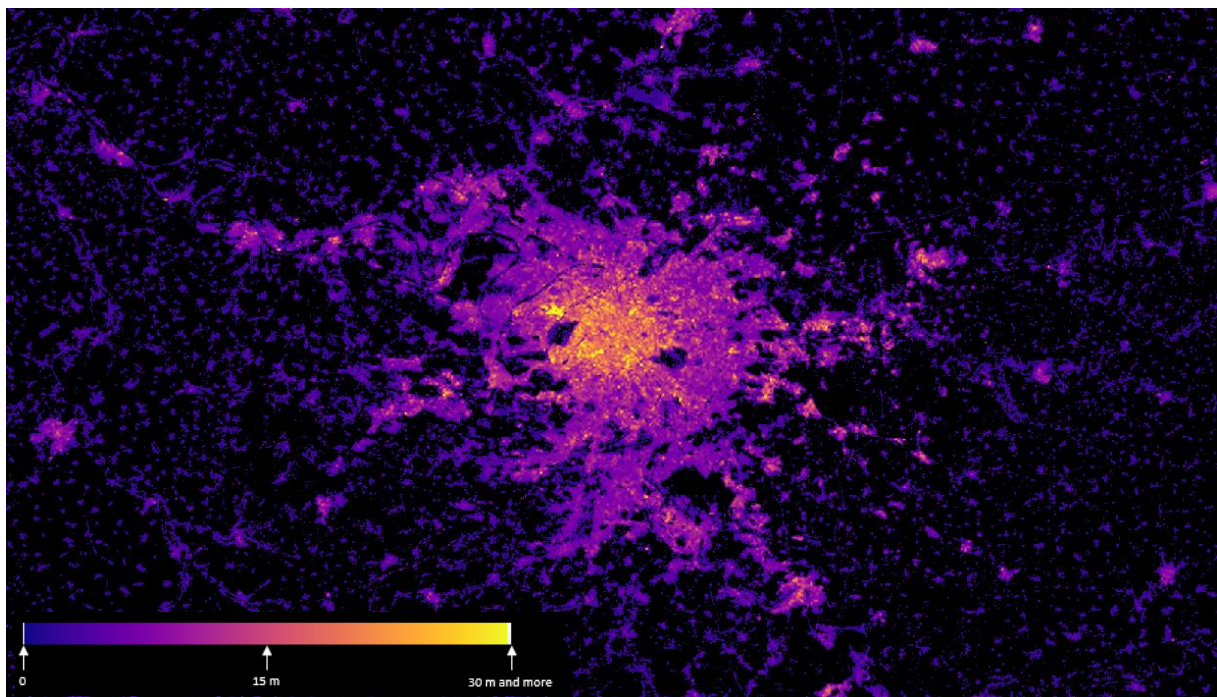


Figure 14 - Average building height (ANBH 100m) estimates in Paris (France).

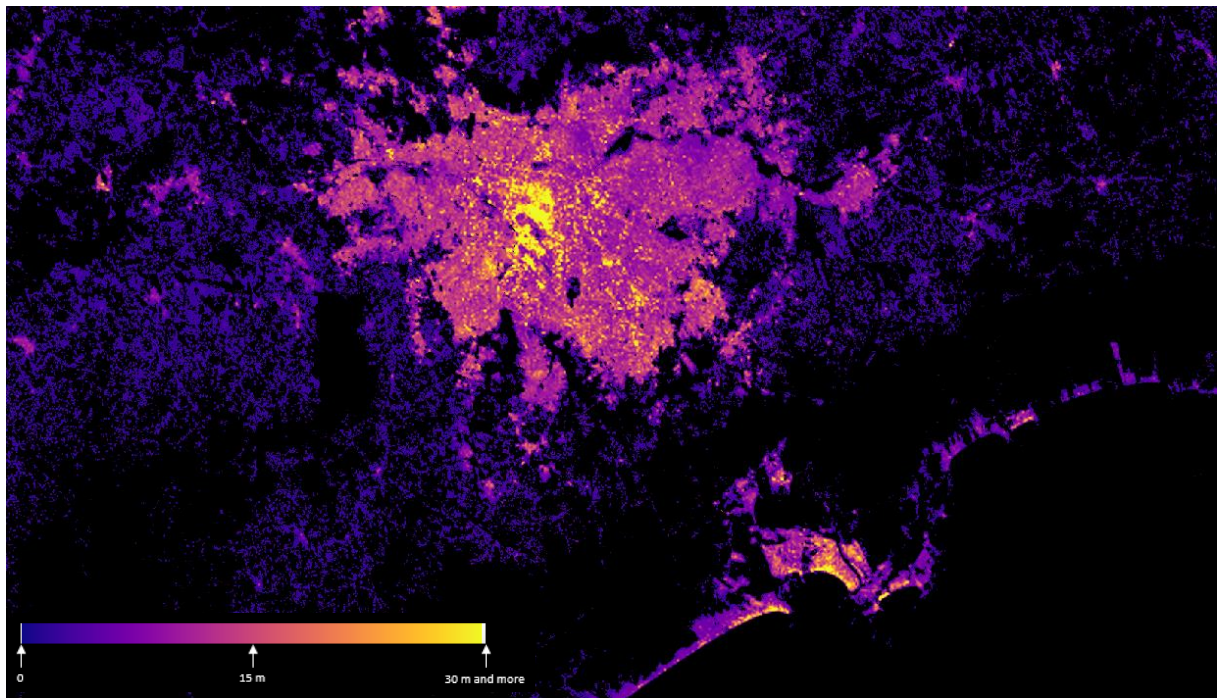


Figure 15 - Average building height (ANBH 100m) estimates in Sao Paulo – Santos (Brazil).

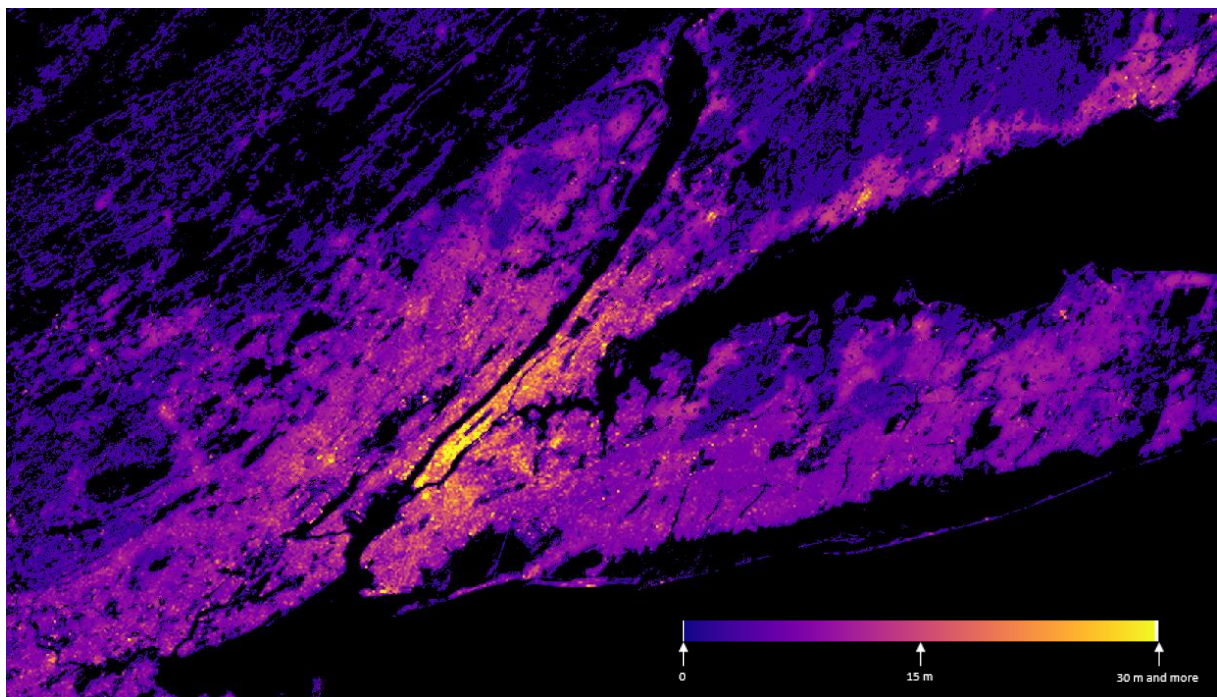


Figure 16 - Average building height (ANBH 100m) estimates in New York (United States).

2.2.3 Expected errors

The estimation of the GHS-BUILT-H error is currently ongoing, and will be delivered in a peer-reviewed publication, possibly in 2023-2024. A comparison with independent measurements not used in the model development and collected in 38 functional urban areas in the frame of the Copernicus Land Monitoring Service²⁸, Urban Atlas, Building Height 2012, set the expected errors in predicting the ANBH included in this release as 1.97m of Mean Absolute Error (MAE) and 3.55m of Root Mean Square Error (RMSE), with a standard deviation of 0.87 and 1.25 meters, respectively.

Table 14 – Errors of ANBH 100m in predicting the Copernicus Building Height generalized at the same spatial resolution

TEST CASE	Observed ANBH max	Observed ANBH average	Observed vs. Predicted MAE	Observed vs. Predicted RMSE	Number of Samples
IS001L1_REYKJAVIK_UA2012_DHM_v010	43.17	5.58	0.24	1.00	103182
ME001L1_PODGORICA_UA2012_DHM_v010	54.48	5.79	0.33	1.22	137558
XK001L1_PRISTINA_UA2012_DHM_v010	43.00	7.00	0.59	1.87	51457
RS001L1_BEOGRAD_UA2012_DHM_v010	168.91	6.85	0.69	2.18	177645
AL001L1_TIRANA_UA2012_DHM_v010	64.53	6.24	0.72	1.78	147009
NO001L2_OSLO_UA2012_DHM_v010	55.60	6.81	1.02	2.30	49706
SI001L1_LJUBLJANA_UA2012_DHM_v010	42.90	6.33	1.05	2.19	26719
BA001L1_SARAJEVO_UA2012_DHM_v010	82.18	6.55	1.37	2.74	33597
SE001L1_STOCKHOLM_UA2012_DHM_v010	62.81	7.51	1.39	2.97	131914
SK001L1_BRATISLAVA_UA2012_DHM_v010	77.00	8.52	1.39	3.29	36005
HR001L2_GRAD_ZAGREB_UA2012_DHM_v010	66.61	7.84	1.43	2.85	63172
IE001L1_DUBLIN_UA2012_DHM_v010	43.98	6.63	1.43	2.48	92095
FI001L2_HELSINKI_UA2012_DHM_v010	50.34	7.33	1.65	2.98	78704
CY001L1_LEFKOSIA_UA2012_DHM_v010	25.79	7.33	1.65	2.68	20169
BG001L2_SOFIA_UA2012_DHM_v010	119.71	9.59	1.67	3.54	44083
CH004L1_BERN_UA2012_DHM_v010	70.00	8.17	1.79	3.66	13714
DK001L2_KOBENHAVN_UA2012_DHM_v020	124.43	7.14	1.82	3.23	58052
UK001L2_LONDON_UA2012_DHM_v020	131.60	7.66	2.07	3.36	182840
LT001L1_VILNIUS_UA2012_DHM_v010	165.00	8.14	2.08	4.07	38955
MK001L1_SKOPJE_UA2012_DHM_v010	96.58	8.28	2.10	4.11	19196
HU001L2_BUDAPEST_UA2012_DHM_v010	60.19	8.86	2.13	3.37	51940
IT001L2_ROMA_UA2012_DHM_v010	85.57	10.36	2.24	4.09	127649
DE001L1_BERLIN_UA2012_DHM_v020	77.00	9.42	2.26	3.95	111079
AT001L2_WIEN_UA2012_DHM_v010	151.97	9.79	2.29	3.90	42863
EL001L1_ATHINA_UA2012_DHM_v020	68.60	9.96	2.32	3.53	61187
LV001L0_RIGA_UA2012_DHM_v010	122.13	9.61	2.37	4.79	29770
ES001L2_MADRID_UA2012_DHM_v020	264.00	12.24	2.39	4.70	87854
CZ001L1_PRAHA_UA2012_DHM_v010	57.00	9.76	2.41	4.05	48665
NL002L2_AMSTERDAM_UA2012_DHM_v020	120.00	9.08	2.44	4.31	39733
EE001L1_TALLINN_UA2012_DHM_v010	112.20	8.32	2.49	4.33	15452
LU001L1_LUXEMBOURG_UA2012_DHM_v010	51.71	9.46	2.64	4.12	5253
PT001L2_LISBOA_UA2012_DHM_v010	78.27	8.39	2.71	4.23	70512
PL001L2_WARSZAWA_UA2012_DHM_v010	113.91	9.01	2.82	4.31	55279
FR001L1_PARIS_UA2012_DHM_v010	174.22	9.71	2.85	4.57	134717
MT001L1_VALLETTA_UA2012_DHM_v010	39.16	8.27	2.97	4.10	7200
BE001L2_BRUXELLES_BRUSSEL_UA2012_DHM_v010	86.94	10.48	3.17	4.82	20449
RO001L1_BUCURESTI_UA2012_DHM_v010	209.00	8.67	3.84	5.73	27442
TR001L1_ANKARA_UA2012_DHM_v010	162.65	12.06	3.92	7.57	72799
SUM					2515615
Average			1.97	3.55	
Standard Deviation			0.87	1.25	

²⁸ <https://land.copernicus.eu/local/urban-atlas/building-height-2012>

2.2.4 Technical Details

Author: Pesaresi, Martino; Politis, Panagiotis

Product name: GHS-BUILT-H_GLOBE_R2023A

Spatial extent: Global

Temporal extent: 2018

Coordinate Systems: World Mollweide (ESRI:54009)

Spatial resolution available: 100m

Encoding: Values are expressed as decimals (Float32) reporting about the average height of the built surfaces in meters.

Data organisation ():* GeoTIFF file (100m) with overview images (OVR). Data tiles of 100×100 km size in GeoTIFF format (100 m). Tile schema in shapefile format

Table 15 outlines the technical characteristics of the datasets released in this data package.

Table 15 - Technical details of the datasets in GHS-BUILT-H_GLOBE_R2023A

GHS-BUILT-H_GLOBE_R2023A		
ID	Description	Resolution (Projection/Coordinate system)
GHS_BUILT_H_AGBH_E2018_GLOBE_R2023A_54009_100_V1_0	Average of the Gross Building Height AGBH 2018 100m Encoding: Float32 NoData: 255	100 m World Mollweide (ESRI:54009)

GHS-BUILT-H_ANBH_GLOBE_R2023A		
ID	Description	Resolution (Projection/Coordinate system)
GHS_BUILT_H_ANBH_E2018_GLOBE_R2023A_54009_100_V1_0	Average of the Net Building Height ANBH 2018 100m Encoding: Float32 NoData: 255	100 m World Mollweide (ESRI:54009)

2.2.5 How to cite

Dataset:

Pesaresi, Martino; Politis, Panagiotis (2023): GHS-BUILT-H R2023A - GHS building height, derived from AW3D30, SRTM30, and Sentinel2 composite (2018). European Commission, Joint Research Centre (JRC) [Dataset] doi: 10.2905/85005901-3A49-48DD-9D19-6261354F56FE PID: <http://data.europa.eu/89h/85005901-3a49-48dd-9d19-6261354f56fe>

Concept & Methodology:

Pesaresi, M., Corbane, C., Ren, C., and Edward, N. (2021). Generalized Vertical Components of built-up areas from global Digital Elevation Models by multi-scale linear regression modelling. PLOS ONE 16, e0244478. <https://doi.org/10.1371/journal.pone.0244478>

Essential methodological background:

Pesaresi M, Ehrlich D, Ferri S, Florczyk A, Carneiro Freire S, Halkia S, Julea A, Kemper T, Soille P, Syrris V. Operating procedure for the production of the Global Human Settlement Layer from Landsat data of the epochs 1975, 1990, 2000, and 2014. EUR 27741. Luxembourg (Luxembourg): Publications Office of the European Union; 2016. JRC97705

Bechtel, B., Pesaresi, M., Florczyk, A. and Mills, G., Beyond built-up – information on the internal makeup of urban areas, 2017, ISBN 978-1-138-05460-8, JRC107558

2.3 GHS-BUILT-V R2023A - GHS built-up volume spatial raster datasets derived from joint assessment of Sentinel-2, Landsat, and global DEM data, for 1975-2030 (5yrs interval)

This spatial raster dataset depicts the distribution of built-up volumes, expressed as number of cubic meters. The data reports about the total built-up volume and the built-up volume allocated to dominant non-residential (NRES) uses. Data are spatial-temporal interpolated from 1975 to 2030 in 5 year intervals.

The data is made by application of the formula: $BUVOLx = ANBHx * BUSURFx$, where:

the $ANBHx$ is the GHS-BUILT-H R2023A - GHS building height, derived from AW3D30, SRTM30, and Sentinel-2 composite (2018),

the $BUSURFx$ is the GHS-BUILT-S R2023A - GHS built-up surface spatial raster dataset, derived from Sentinel-2 composite and Landsat, multitemporal (1975-2030).

2.3.1 Input Data

GHS-BUILT-H R2023A - GHS building height, derived from AW3D30, SRTM30, and Sentinel-2 composite (2018)

GHS-BUILT-S R2023A - GHS built-up surface spatial raster dataset, derived from Sentinel-2 composite and Landsat, multitemporal (1975-2030).

2.3.2 Technical Details

Author: Pesaresi, Martino; Politis Panagiotis

Product name: GHS-BUILT-V_GLOBE_R2023A

Spatial extent: Global

Temporal extent: from 1975 to 2030, 5 year intervals

Coordinate Systems: World Mollweide (ESRI:54009), WGS84 (EPSG:4326)

Spatial resolution available: 100 m, 1 km, 3 ss, 30 ss

Encoding: integers (UInt32), unit: built cubic meters in the grid cell

Data organisation ():* Global GeoTIFF file (100m, 1km, 3 ss, 30 ss) with overview images (OVR). Data tiles of 100x100 km size in GeoTIFF format (100 m, 1 km, 3 ss, 30 ss). Tile schema in shapefile format

Disclaimer: the re-projection of the World Mollweide version of the GHS-BUILT-V_GLOBE_R2023A to coordinate systems requires specific technical knowledge. No responsibility is taken for workflows developed independently by users.

Table 16 - Technical details of the datasets in GHS-BUILT-V_GLOBE_R2023A

GHS-BUILT-V_GLOBE_R2023A		
ID	Description	Resolution (projection)
GHS_BUILT_V_E<epoch>_GLOBE_R2023A_<proj>_<res>_V1_0	BU volume <epoch> 1975-2030; <proj> 54009, 4326; <res> 100, 1000 Encoding: UInt32 Values range: 0-Inf NoData: 4294967295	100 m, 1 km World Mollweide (ESRI:54009)

GHS-BUILT-V_NRES_GLOBE_R2023A		
ID	Description	Resolution (projection)
GHS_BUILT_V_NRES_E<epoch>_GLOBE_R2023A_<proj>_<res>_V1_0	Non-residential BU volume <epoch> 1975-2030; <proj> 54009, 4326; <res> 100, 1000 Encoding: UInt32 Values range: 0-Inf NoData: 4294967295	100 m, 1 km World Mollweide (ESRI:54009)

2.3.3 Summary statistics

Table 17 - Summary statistics of predicted volume (cubic meters) of built-up total (BUTOT) and the built-up non-residential (BUNRES) component, per years of prediction

YEAR	BUTOT	BUNRES	NRES SHARE
1975	1,129,952,305,446	134,109,143,376	11.87%
1980	1,225,670,049,980	141,078,645,356	11.51%
1985	1,341,196,753,484	148,797,422,293	11.09%
1990	1,471,122,254,588	157,136,525,872	10.68%
1995	1,653,175,411,641	174,539,946,785	10.56%
2000	1,864,118,315,177	195,902,923,083	10.51%
2005	2,014,382,538,998	210,263,443,082	10.44%
2010	2,192,988,285,999	228,366,725,208	10.41%
2015	2,380,114,472,309	248,515,023,305	10.44%
2020	2,531,668,628,948	264,364,383,272	10.44%
2025	2,614,195,282,484	274,606,925,785	10.50%
2030	2,667,539,817,459	281,491,357,563	10.55%

2.3.4 How to cite

Dataset:

Pesaresi, Martino; Politis, Panagiotis (2023): GHS-BUILT-V R2023A - GHS built-up volume grids derived from joint assessment of Sentinel2, Landsat, and global DEM data, multitemporal (1975-2030). European Commission, Joint Research Centre (JRC) [Dataset] doi: 10.2905/AB2F107A-03CD-47A3-85E5-139D8EC63283 PID: <http://data.europa.eu/89h/ab2f107a-03cd-47a3-85e5-139d8ec63283>

Concept & Methodology:

European Commission, GHSL Data Package 2023, Publications Office of the European Union, Luxembourg, 2023, ISBN 978-92-68-02341-9, doi:10.2760/098587, JRC133256

Essential methodological background:

Pesaresi, M., Corbane, C., Ren, C., and Edward, N. (2021). Generalized Vertical Components of built-up areas from global Digital Elevation Models by multi-scale linear regression modelling. PLOS ONE 16, e0244478. <https://doi.org/10.1371/journal.pone.0244478>

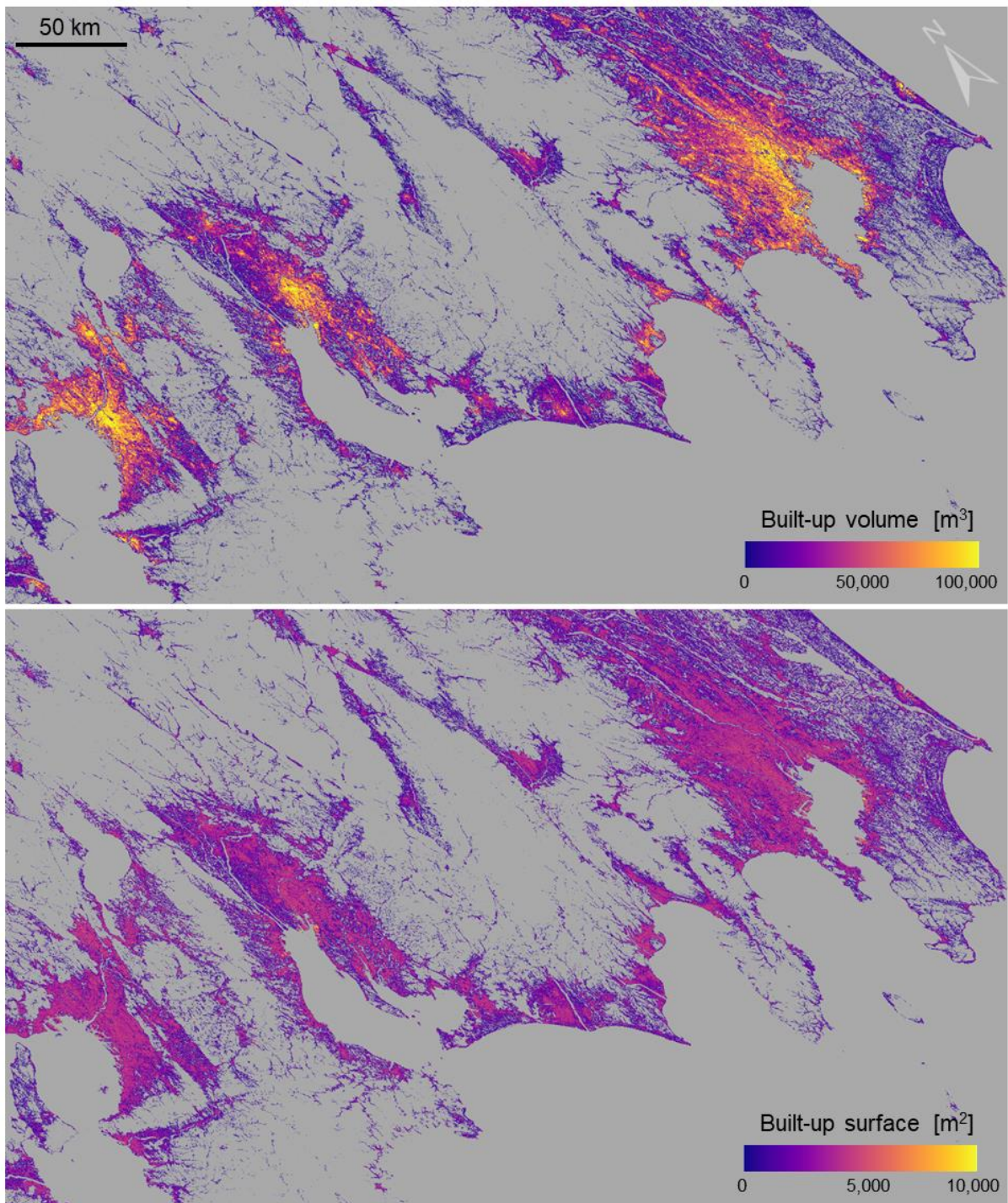


Figure 17 - Osaka-Nagoya-Tokyo (Japan): comparison between GHS-BUILT-V R2023A (above) and GHS-BUILT-S R2023A (below), year 2020.

2.4 GHS-BUILT-C R2023A - GHS Settlement Characteristics, derived from Sentinel-2 composite (2018) and other GHS R2023A data

The GHS-BUILT-C spatial raster datasets delineate the boundaries of the human settlements at 10m resolution, and describe their inner characteristics in terms of the morphology of the built environment and the functional use.

The Morphological Settlement Zone (MSZ) delineates the spatial domain of all the human settlements at the neighbourhood scale of approx. 100m, based on the spatial generalization of the built-up surface fraction (BUFRAC) function. The objective is to fill the open spaces that are surrounded by large patches of built space. MSZ, open spaces, and built spaces basic class abstractions are derived by mathematical morphology and spatial filtering (opening, closing, regional maxima) from the BUFRAC function. They are further classified accordingly to the information regarding vegetation intensity, water surfaces (GHS_LAND_GLOBE_R2022A), road surfaces (OSM highways), functional use (GHS-BUILT-C_FUN_GLOBE_R2023A), and building height (GHS-BUILT-H_GLOBE_R2023A).

Morphological Settlement Zone delineation

First, the spatial domain it is split in two sub-domains, “open spaces” vs. “built spaces”. The “Built spaces” set is derived from the BUFRAC continuous function, filtered for detecting salient raster samples that may summarize the function itself, also called “built-up markers” (BUMARKER). The BUMARKER set it is defined by the union of the morphological regional maxima (Vincent, 1993) of the BUFRAC function, with the raster samples dominated by the built-up surface class, so that $BUFRACx > 0.5$. The “open space” set is defined as the logical complement of the “built space” set.

Second, the BUMARKER set it is subdivided in the “COMPACT” vs. the “SPARSE” sets based on morphological filtering. The COMPACT set is defined by the opening of the closing of the BUMARKER, with a structuring element of a disk with 5 pixels (corresponding to 50 meters) radius. The SPARSE set is made by the BUMARKER in the logical complement of the COMPACT set.

Third, the Morphological Settlement Zone (MSZ) is defined as the Union of the hole-filled COMPACT set using a 4-connectivity rule and the dilation of the SPARSE set, using a minimal structure element of 2×2 (20×20 m) pixels.

Fourth, the classification is applied to the samples belonging to the MSZ domain accordingly to the information regarding vegetation intensity from S2 imageries, water surfaces (GHS_LAND_GLOBE_R2022A), road surfaces (OSM highways), functional use (GHS-BUILT-C_FUN_GLOBE_R2023A), and building height (GHS-BUILT-H_GLOBE_R2023A). The building height information it is downscaled to the 10m-resolution using the connected components of the BUMARKERS as spatial units.

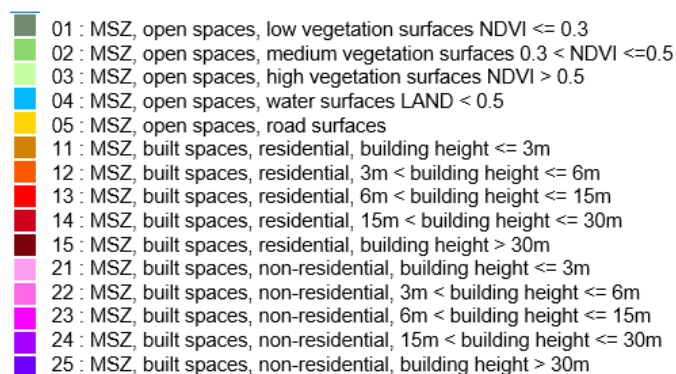


Figure 18 - Morphological Settlement Zone (MSZ) Legend

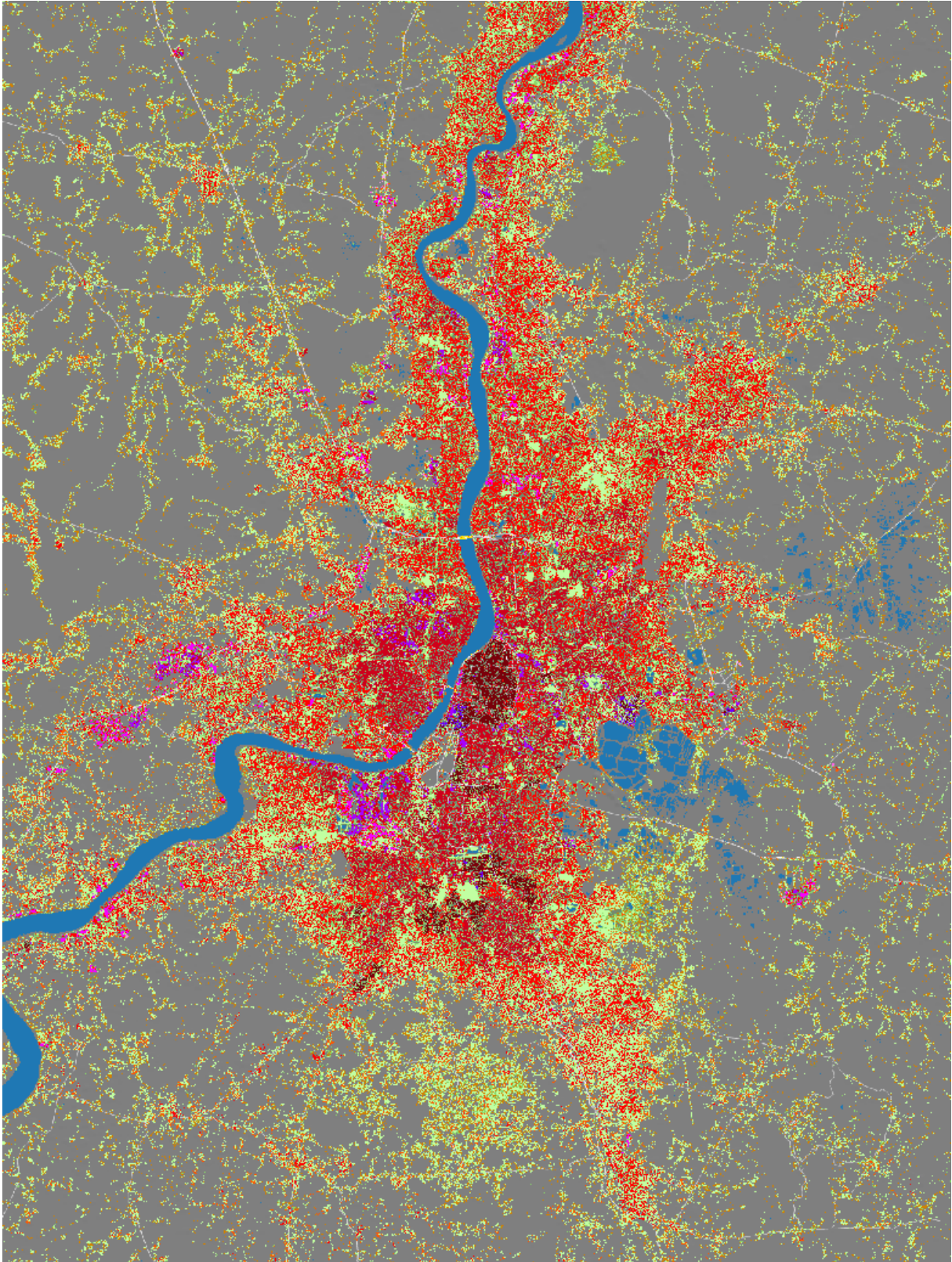


Figure 19 - Settlement Characteristics in Kolkata (India)

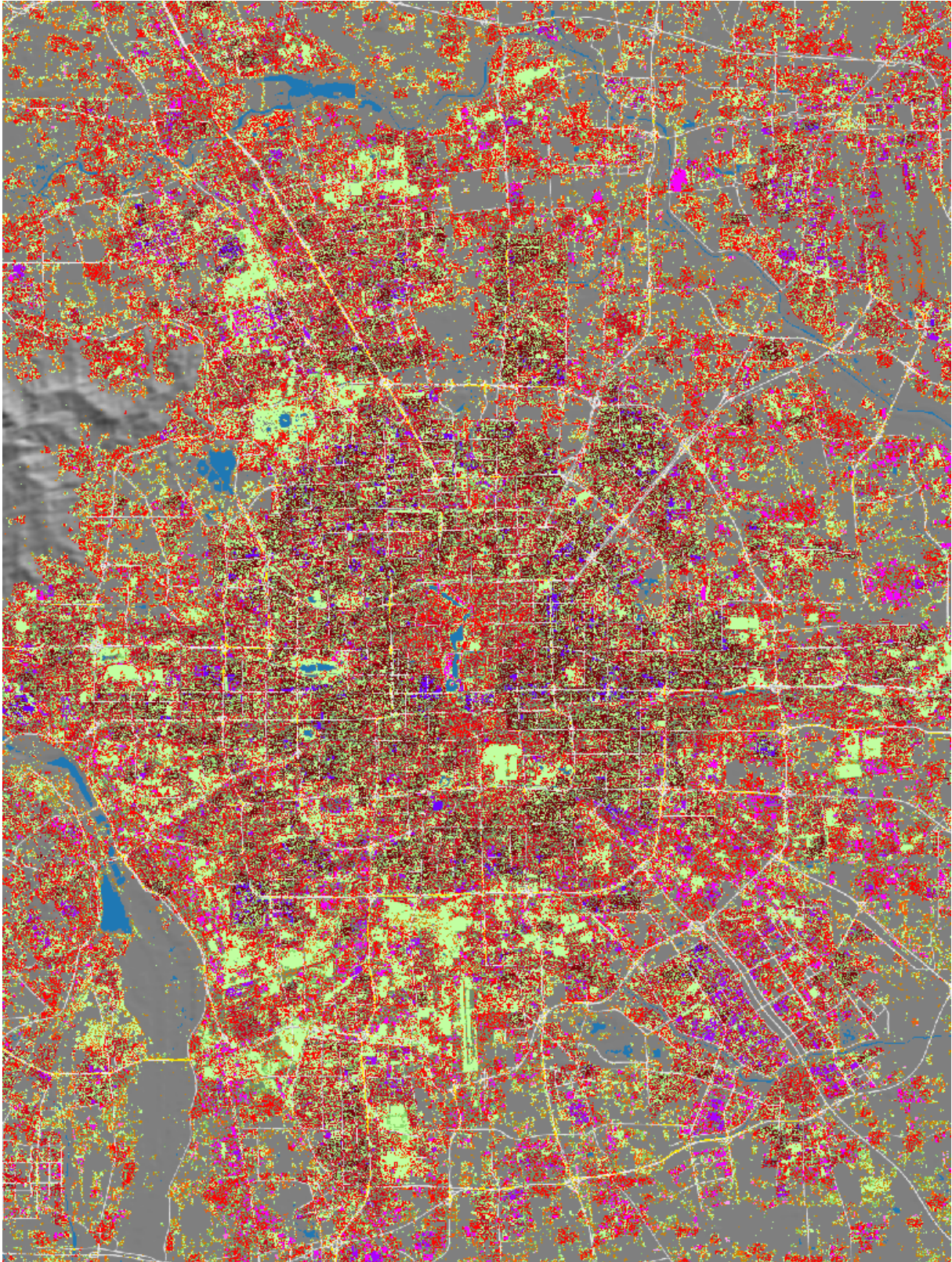


Figure 20 - Settlement Characteristics in Beijing (China)

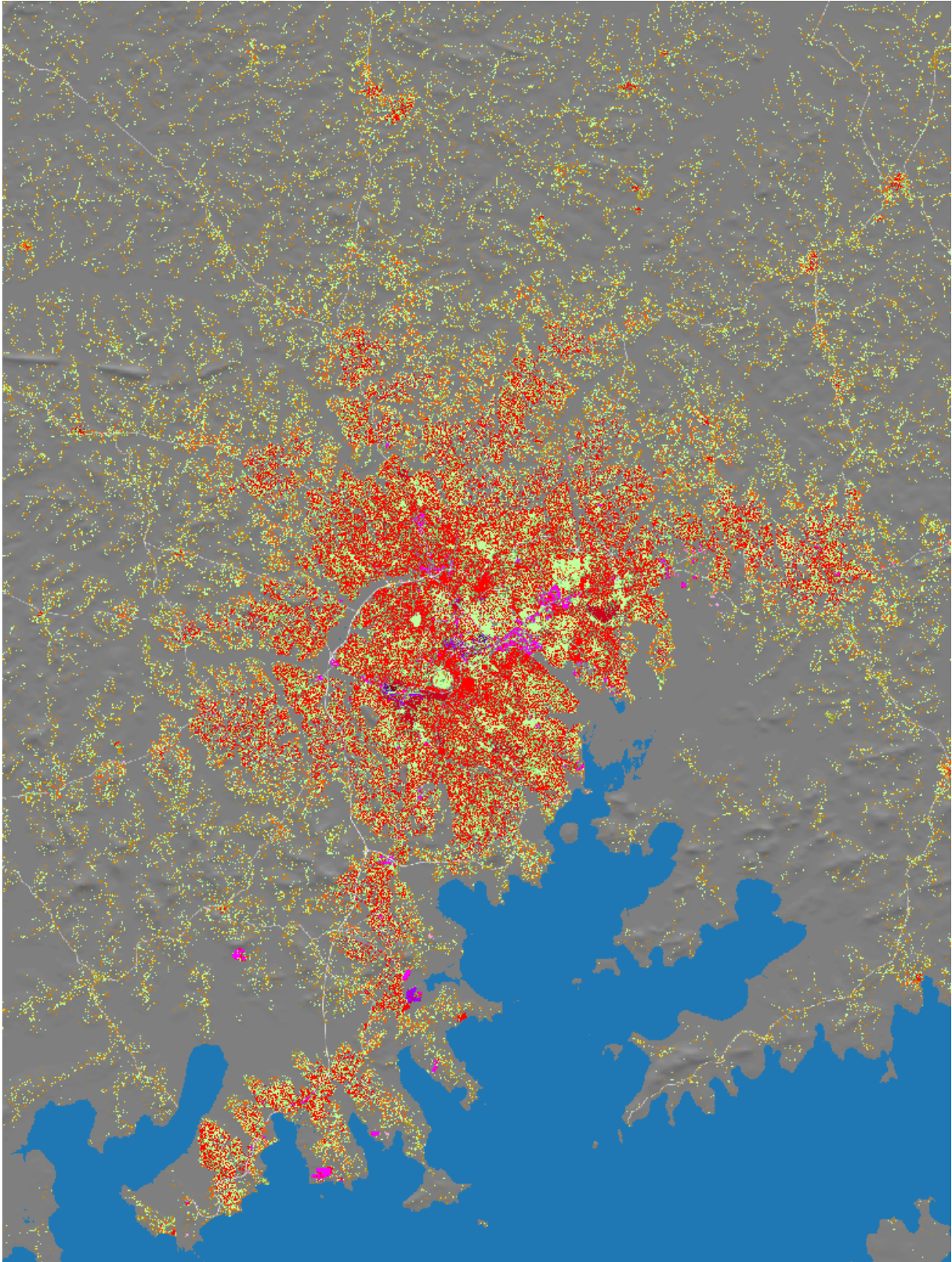


Figure 21 - Settlement Characteristics in Kampala (Uganda)

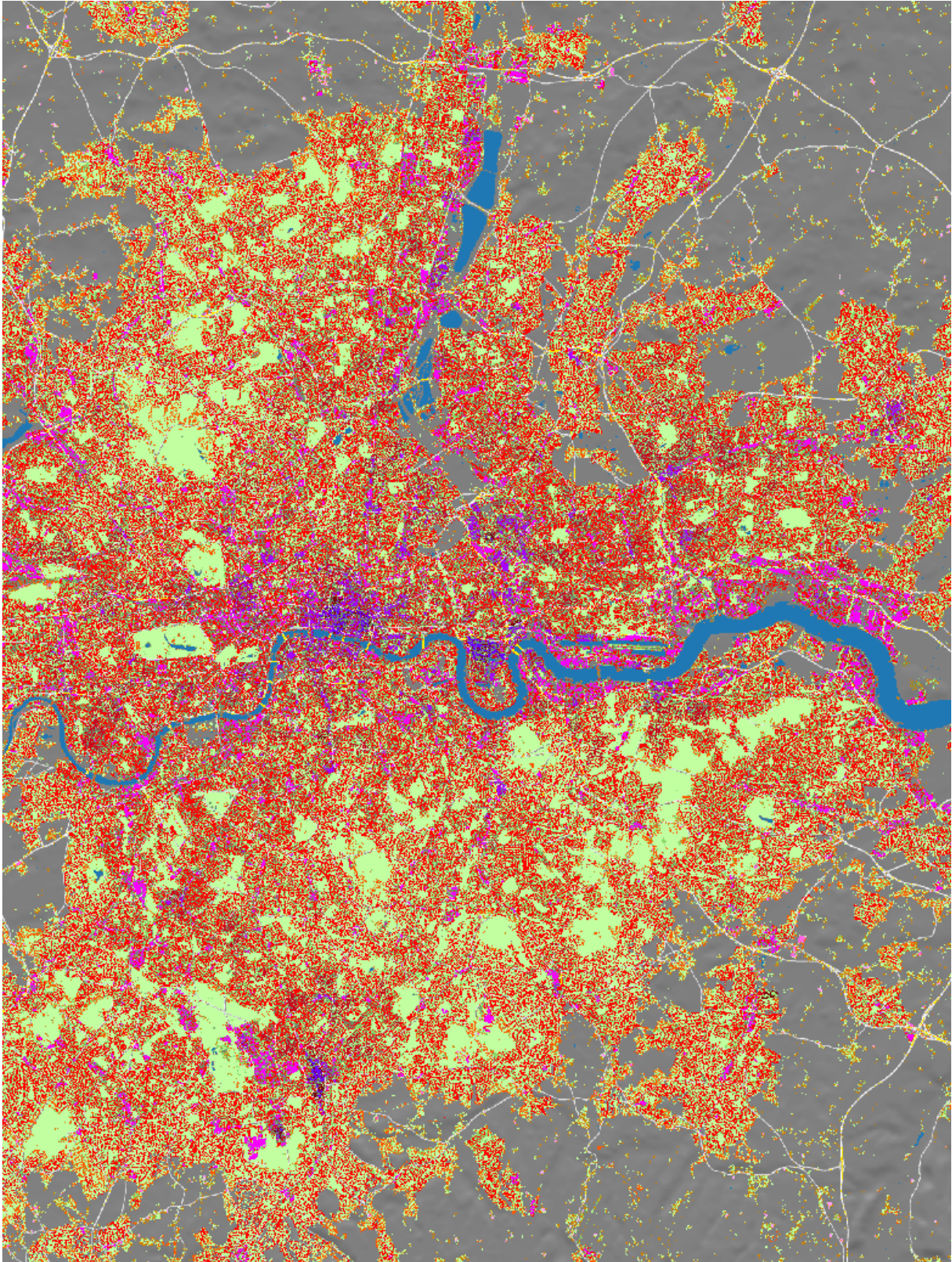


Figure 22 – Settlement Characteristics in London (United Kingdom)



Figure 23 – Settlement Characteristics in Kansas City (United States)

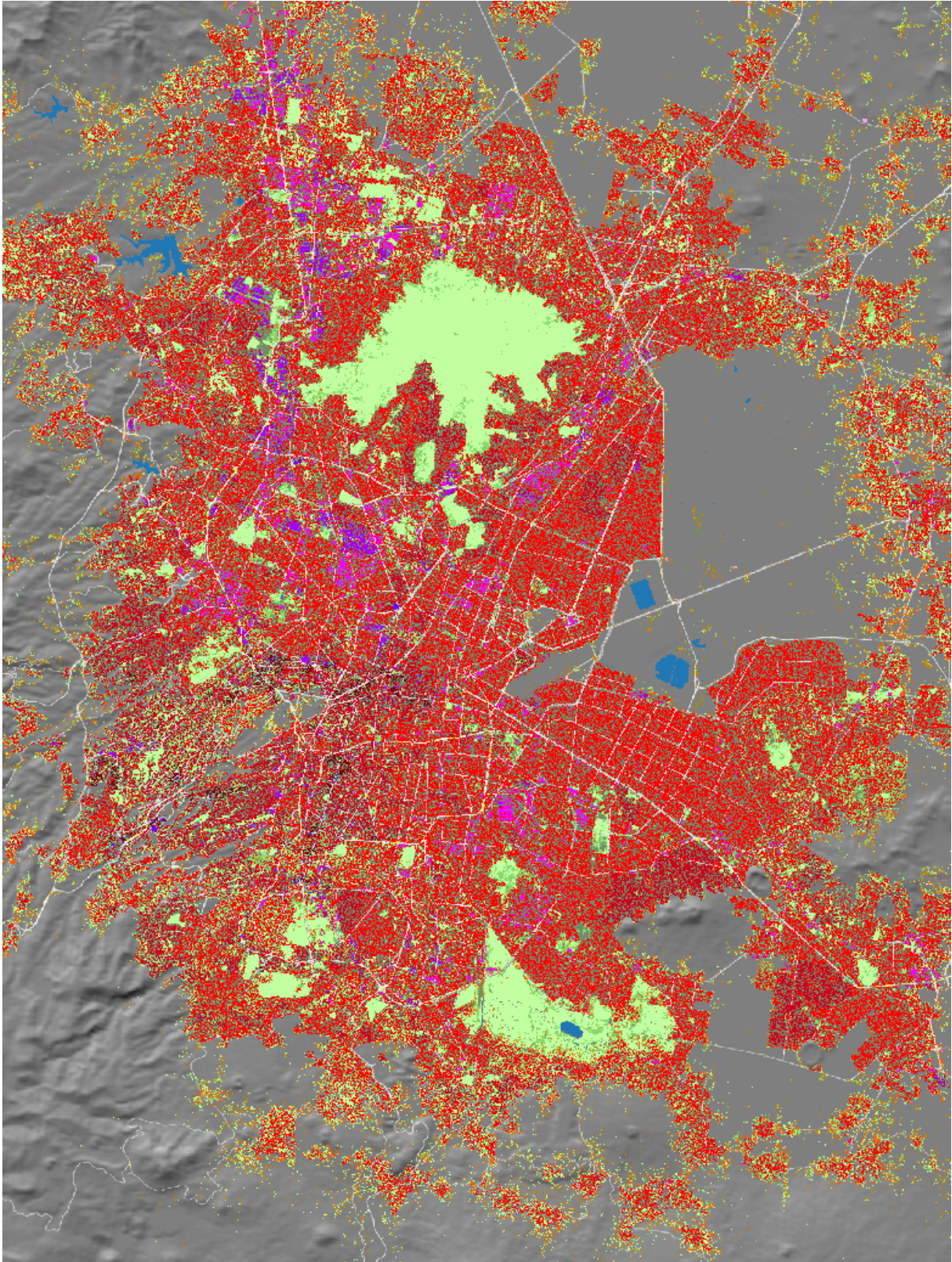


Figure 24 – Settlement Characteristics in Mexico City (Mexico)

2.4.1 Input data

Morphological filtering of the BUFRAC 10m-resolution

GHS_BUILT_S_E2018_GLOBE_R2023A_54009_10_V1_0., maximal vegetation intensity from S2 image data, water surfaces (GHS_LAND_GLOBE_R2022A), road surfaces (OSM highways), functional use (GHS-BUILT-C_FUN_GLOBE_R2023A), and building height (GHS-BUILT-H_GLOBE_R2023A).

2.4.2 Technical Details

Author: Pesaresi, Martino; Politis Panagiotis

Product name: GHS-BUILT-C_GLOBE_R2023A

Spatial extent: Global

Temporal extent: 2018

Coordinate Systems: World Mollweide (ESRI:54009)

Spatial resolution available: 10m

Encoding: Integer (Byte)

Data organisation: Global VRT file (10 m) with overview images (OVR). Data tiles of 100x100 km size in GeoTIFF format (10 m). Tile schema in shapefile format

Table 18 - Technical details of the datasets in GHS-BUILT-C_GLOBE_R2023A

GHS-BUILT-C_MSZ_GLOBE_R2023A		
ID	Description	Resolution (Projection/Coordinate system)
GHS_BUILT_C_MSZ_E2018_GLOBE_R2023A_54009_10_V1_0	Morphological Settlement Zone (MSZ) : classification by internal surface (soil sealed) and functional (BU RES/NRES) characteristics - 10m Encoding: Byte Values range: 1-25 (see Figure 18) NoData: 255	10 m World Mollweide (ESRI:54009)

GHS-BUILT-C_FUN_GLOBE_R2023A		
ID	Description	Resolution (Projection/Coordinate system)
GHS_BUILT_C_FUN_E2018_GLOBE_R2023A_54009_10_V1_0	Residential (RES) vs. non-residential (NRES) functional classification of the built spatial domain defined as BUFRAC > 0 Encoding: Byte Values range: 0 (non-BU), 1 (RES), 2 (NRES)NoData: 255	10 m World Mollweide (ESRI:54009)

2.4.3 How to cite

Dataset:

Pesaresi, Martino; Politis, Panagiotis (2023): GHS-BUILT-C R2023A - GHS Settlement Characteristics, derived from Sentinel2 composite (2018) and other GHS R2023A data. European Commission, Joint Research Centre (JRC) [Dataset] doi: 10.2905/3C60DDF6-0586-4190-854B-F6AA0EDC2A30 PID: <http://data.europa.eu/89h/3c60ddf6-0586-4190-854b-f6aa0edc2a30>

Concept & Methodology:

European Commission, GHSL Data Package 2023, Publications Office of the European Union, Luxembourg, 2023, ISBN 978-92-68-02341-9, doi:10.2760/098587, JRC133256

2.5 GHS-POP R2023A - GHS population spatial raster dataset multi-temporal (1975-2030)

This GHS-POP spatial raster product (GHS-POP_GLOBE_R2023) depicts the distribution of human population (Figure 25), expressed as the number of people per cell. Residential population estimates at 5 years interval between 1975 and 2030 are derived from the raw global census data harmonized by CIESIN for the Gridded Population of the World, version 4.11 (GPWv4.11) at polygon level, and disaggregated from census or administrative units to grid cells, informed by the distribution, classification and volume of built-up as mapped in the GHS-L global layers per corresponding epoch. The disaggregation methodology is described in a peer reviewed paper (Freire et al., 2016). This is an updated and improved release of the product (GHS_POP_GLOBE_R2022A) distributed within the GHS-L Data Package 2022 (GHS P2022).

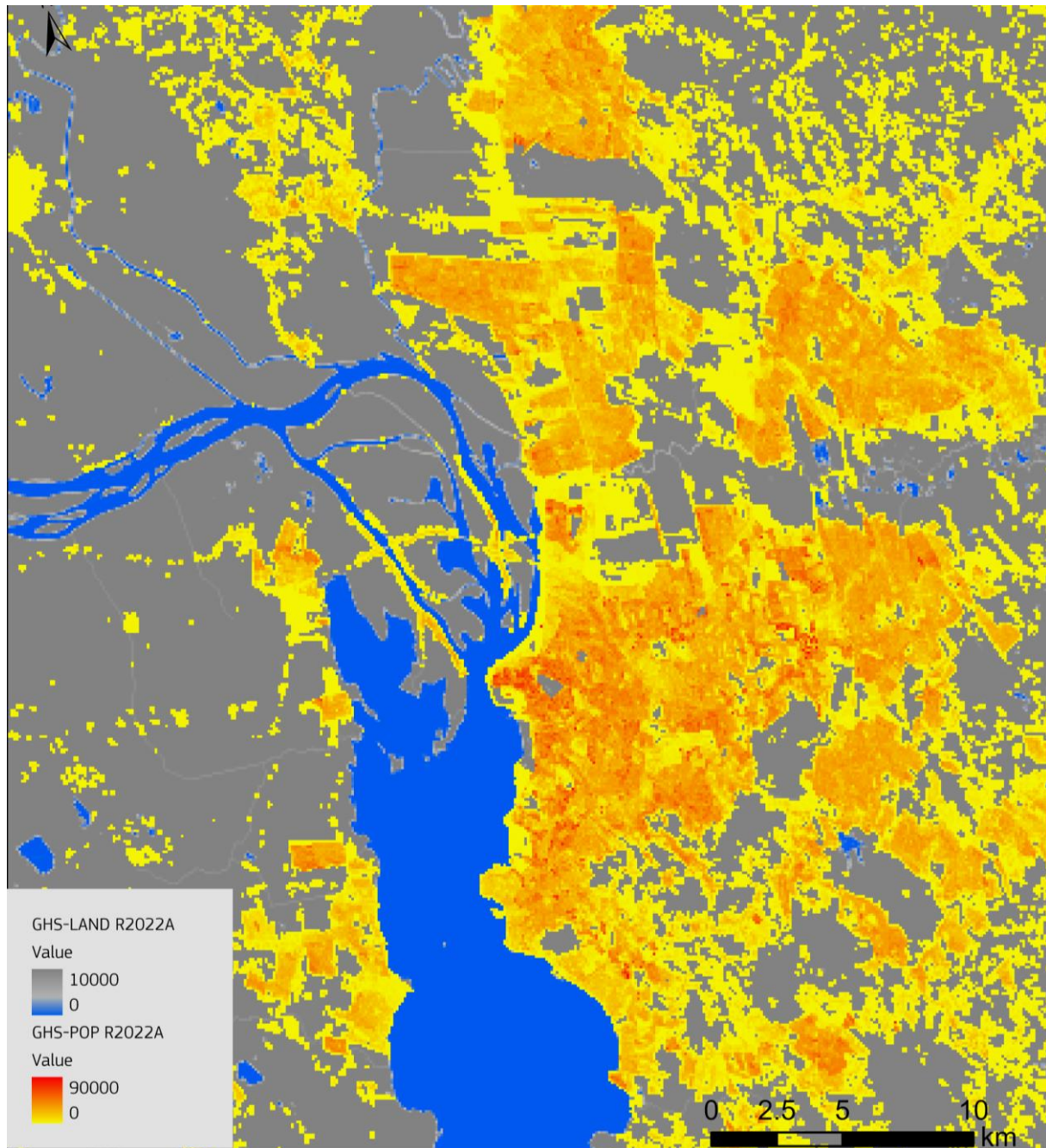


Figure 25 - GHS Population spatial raster dataset (GHS-POP) GHS_POP_E2020_GLOBE_R2023A_54009_100_V1_0 in Porto Alegre (Brazil).

2.5.1 Improvements compared to the previous release

The new GHSL population distribution spatial raster datasets release aimed at incorporating improvements originating from input datasets, namely population estimates and built-up presence. While the disaggregation relied essentially on the same clear and simple approach, there were significant differences to the input data that had a positive effect on the final quality and accuracy of population spatial raster datasets, along with new approach for temporal estimation of population and systematic revision of coastlines and unpopulated areas. Here, we describe the main differences between the currently released products (GHS-POP_GLOBE_R2023A) and the previous (GHS-POP_MT_GLOBE_R2019A and GHS-POP_MT_GLOBE_R2022A). Figure 26 summarizes the main steps and outputs resulting from the workflow implemented for production of GHS-POP R2023.

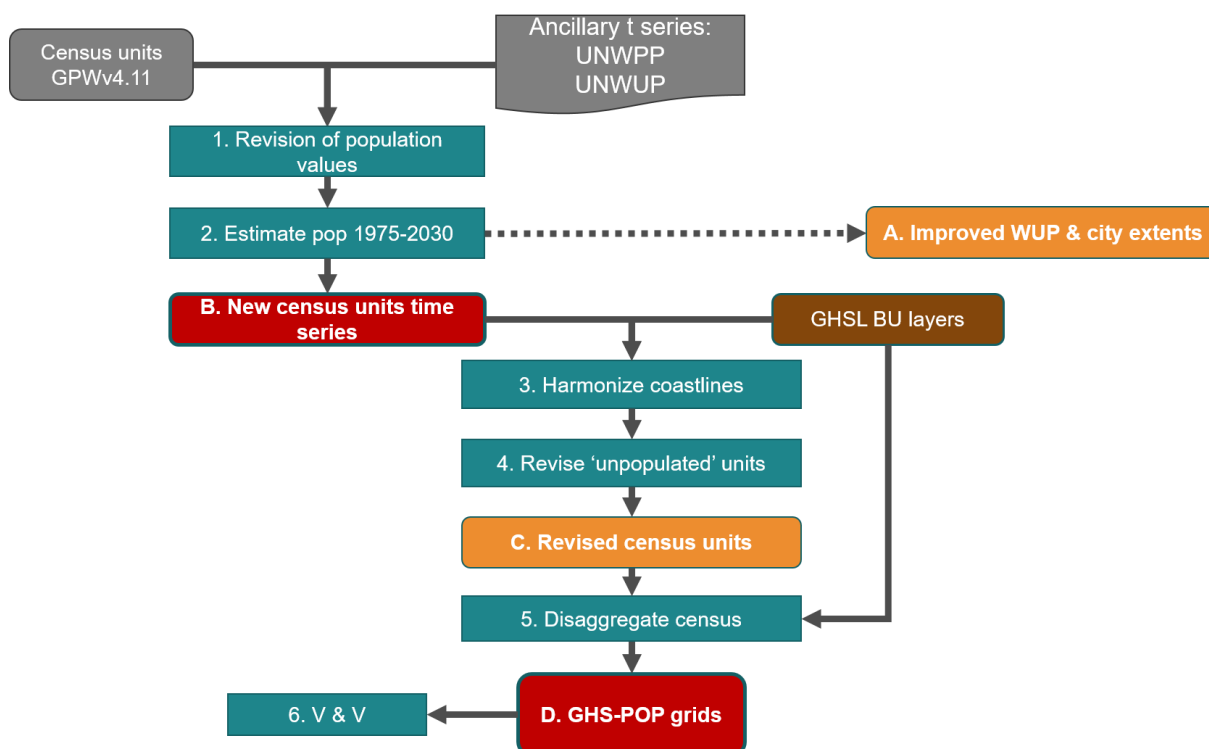


Figure 26 - Generalized workflow for producing GHS-POP R2022, with main steps (1-6) and intermediate and main outputs (A-D).

For the new GHS-POP (GHS-POP_GLOBE_R2023A), the new Sentinel/Landsat based GHS-BUILT-V (GHS-BUILT-V_GLOBE_R2023A, version 1.0) was used as target for disaggregation of population estimates. Total built-up volume (GHS-BUILT-V_GLOBE_R2023A) and non-residential built-up volume (GHS-BUILT-V_NRES_GLOBE_R2023A) were combined by subtracting the non-residential volume from the total volume for all 5-year time steps between 1975 and 2030. Cells declared as “NoData” in built-up layers were treated as zero for population disaggregation.

The base source for population estimates (both census unit counts and geometries) was the raw dataset (census population at the census year and growth rates) of the Gridded Population of the World, version 4.11 (GPWv4.11), from CIESIN/SEDAC (<https://sedac.ciesin.columbia.edu/data/collection/gpw-v4/whatsnewrev11>).

The population estimates at polygon level for each mapped epoch (5-year interval between 1975 and 2030) are obtained by applying for each unit the population growth rate computed by CIESIN within the census available dates and rapidly converging to the upper administrative level growth rate using a slow convergence to the national growth rate (WPP 2022) at 100 years from census epochs. The estimates are then rescaled to match (a) the total population time series at ‘city’ level from the extended database feeding the UN World Urbanisation Prospects 2018 (United Nations, Department of Economic and Social Affairs, Population Division, 2018), and (b) the total population time series at country level provided by the UN World Population Prospects 2022 (United Nations, Department of Economic and Social Affairs, Population Division, 2022). As the UN World Urbanisation Prospects 2018 provides the point location but not the boundaries for each ‘city’, the model performs an estimation of such boundaries starting from the coordinate pair for each settlement, after their

location is revised. This revision was conducted using Geocoding and Reverse Geocoding, as well as visual inspection, to ensure these coordinates correspond to the centre of the urban agglomeration. The model proceeds by aggregating administrative units (i.e. the census geometry provided by CIESIN) iteratively to match the total population of the city in the available census year. The units within the estimated boundaries are subject to the first rescaling procedure (a) at 'city' level (i.e. each UN 'city' determines the time series of the aggregated population of all units within each estimated boundary); while the other units are subject to the second procedure (b) at country level, to ensure the alignment with each country population time series estimated in UN WPP 2022 (medium variant). The set of estimated city boundaries matching UNWUP 2018 are released within this GHS P2023 data package in the GHS-SDATA product.

The previous releases of the GHS-POP (R2019 and R2022) already included some procedures aimed at further harmonising and critically revising the input population census data (GPW) provided by CIESIN. For the current release, those set of controls, checks and improvements were improved and expanded:

1. Revision of population values vs. an independent dataset (where available: EU)
2. Harmonisation of coastlines
3. Revision of unpopulated units

Control 1. aimed at mitigating large discrepancies between resident population counts in GPW and those of other authoritative sources. In this process, Denmark and Poland were flagged for inconsistencies between the population counts and distribution reported in GPW and those reported by ESTAT. Large discrepancies have been modified.

Coastlines are notoriously dynamic and their poor or outdated geospatial definition in census data can degrade the disaggregation of population along these critical areas. Therefore in this GHS-POP release, GPW coastlines were systematically modified to mitigate inconsistencies between the spatial extent of census data (or GADM) and built-up areas, since GHSL does not impose a coastline in mapping of these areas. This harmonisation has been carried out by extending all census units along coastlines (including those of inland water bodies) out using a 3 km buffer.

Units deemed as "unpopulated" in the GPW census data were critically assessed for presence of residential population, based on ancillary data (GHS-BUILT-S_GLOBE_R2023A) and very high-resolution imagery. Inconsistencies between census data and contradicting evidence were detected and reconciled accordingly, after confirmation.

Census units declared as "uninhabited" in GPW data but containing significant built-up surface in 2020 were selected for visual inspection with very high-resolution (VHR) imagery from web mapping services (Google maps and Bing). Those units where presence of residential built-up was confirmed by VHR imagery were selected for intervention. An automated method was applied to split and merge these polygons, based on geographical proximity, with those ones adjacent and containing resident population. This procedure was implemented while minimizing changes to source geometry, preserving the regional distribution of population, and the overall counts (Freire et al., 2018). This procedure modified 269 units in 31 countries.

GHS-POP product is produced in World Mollweide at 100 m, and then aggregated at 1 km. These two datasets are then warped to WGS 1984 coordinate system, at spatial resolutions of 3 arcsec and 30 arcsec respectively, by applying a thorough volume-preserving procedure (Maffenini et al., 2023).

2.5.2 Input Data

The new product GHS-BUILT-V_GLOBE_R2023A (version 1.0) was used to generate the target layers for disaggregation of population estimates by combining the GHS-BUILT-V_GLOBE_R2023A and GHS-BUILT-V_NRES_GLOBE_R2023A. GHS-LAND_GLOBE_R2022A was used as land ancillary in case of absence of built-up in polygons. The base source of population estimates for the different epochs was the raw census data with geometry of the Gridded Population of the World, version 4.11 (GPWv4.11), from CIESIN/SEDAC, with some modifications as described above, along with the UN World Population Prospects 2022 and the UN World Urbanization Prospects 2018. The ESTAT LAU2 population time series was used to control the population counts at LAU2 level in EU.

2.5.3 Technical Details

Author: Marcello Schiavina, Sergio Freire, Joint Research Centre (JRC) European Commission; *Kytt MacManus* Columbia University, Center for International Earth Science Information Network - CIESIN.

Product name: GHS_POP_GLOBE_R2023A

Spatial extent: Global

Temporal extent: from 1975 to 2030, 5 years interval

Coordinate Systems: World Mollweide (ESRI: 54009) and WGS 1984 (EPSG: 4326)

Spatial resolutions available: 100 m, 1 km, 3 ss, 30 ss

Encoding: Population data float64 [0, ∞); population counts (ESRI: 54009; EPSG: 4326) and density (ESRI: 54009) NoData: -200

Data organisation: The spatial raster datasets are provided as GeoTIFF file as single global layer with pyramids or tiled.

Table 15 outlines the technical characteristics of the datasets released in this data package.

Table 19 - Technical details of the datasets in GHS_POP_GLOBE_R2023A

GHS_POP_GLOBE_R2023A		
ID	Description	Resolution (Projection/Coordinate system)
GHS_POP_E<epoch>_GLOBE_R2023A_<proj>_<res>_V1_0	Population density <epoch> 1975-2030; <proj> 54009, 4326; <res> 100m, 1000; 3ss 30ss Values are expressed as decimals Encoding:: Float64 Values range: 0-Inf NoData [-200]	100 m, 1 km World Mollweide (ESRI:54009) 3ss, 30ss WGS84 (EPSG:4326)

2.5.4 Summary statistics

Table 20 - Summary statistics of total population as obtained from the 1-km World Mollweide grid - total population adjusted to the UN WPP 2022 (United Nations, Department of Economic and Social Affairs, Population Division, 2022).

	1975	1980	1985	1990
Total Population	4,069,437,259	4,444,007,748	4,861,730,652	5,316,175,909
	1995	2000	2005	2010
	5,743,219,510	6,148,899,024	6,558,176,175	6,985,603,172
	2015	2020	2025	2030
	7,426,597,609	7,840,952,947	8,191,988,536	8,546,141,407

2.5.5 How to cite

Dataset:

Schiavina, Marcello; Freire, Sergio; Alessandra Carioli; MacManus, Kytt (2023): GHS-POP R2023A - GHS population grid multitemporal (1975-2030). European Commission, Joint Research Centre (JRC) [Dataset] doi: 10.2905/2FF68A52-5B5B-4A22-8F40-C41DA8332CFE PID: <http://data.europa.eu/89h/2ff68a52-5b5b-4a22-8f40-c41da8332cfe>

Concept & Methodology:

Freire, Sergio; MacManus, Kytt; Pesaresi, Martino; Doxey-Whitfield, Erin; Mills, Jane (2016): Development of new open and free multi-temporal global population spatial raster datasets at 250 m resolution. Geospatial Data in a Changing World; Association of Geographic Information Laboratories in Europe (AGILE). AGILE 2016.

2.6 GHS-SMOD R2023A - GHS settlement layers, application of the Degree of Urbanisation methodology (stage I) to GHS-POP R2023A and GHS-BUILT-S R2023A, multitemporal (1975-2030)

The GHS Settlement Model layers (GHS-SMOD) GHS-SMOD_GLOBE_R2023A delineate and classify settlement typologies (Figure 27) via a logic of cell clusters population size, population and built-up area densities as defined by the stage I of the Degree of Urbanisation (European Commission & Statistical Office of the European Union, 2021) and recommended by the UN STAT COM. The GHS-SMOD is derived from the GHS-POP (GHS-POP_GLOBE_R2023A, version 1.0) and GHS-BUILT-S (GHS-BUILT-S_GLOBE_R2023A, version 1.0) released within this GHSL Data Package 2023 (GHS P2023).

The GHS Settlement Model layers GHS-SMOD_GLOBE_R2023A is composed by four datasets: the GHS-SMOD spatial raster dataset, the urban centre entities vector and the dense urban cluster. The first is a raster grid representing the settlement classification per grid cell and the other delineates the boundaries of settlement entities (i.e. urban centres and dense urban clusters, with main attributes, in vector files).

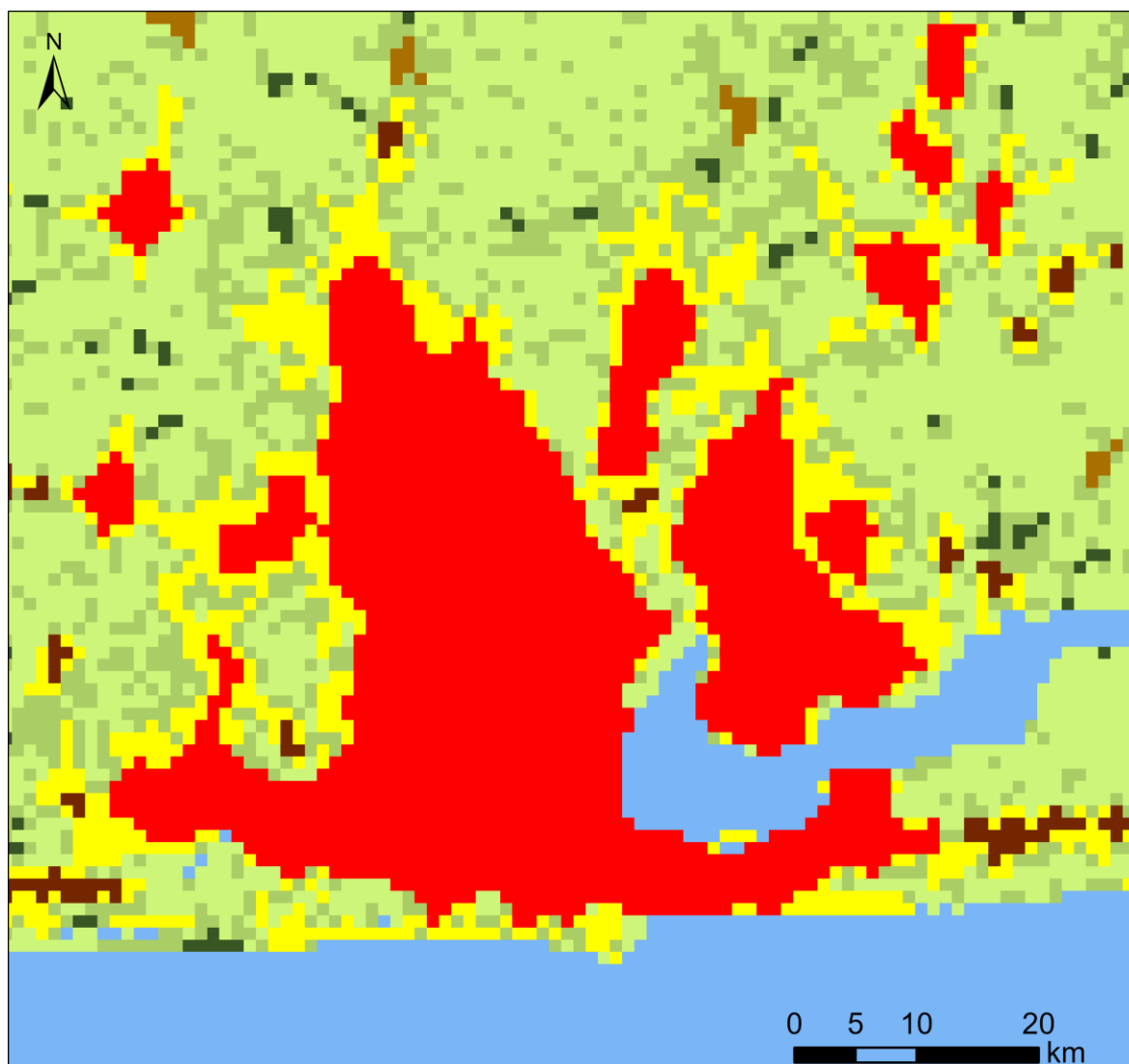


Figure 27 - GHS Settlement Model spatial raster dataset (GHS-SMOD) GHS-SMOD_E2020_GLOBE_R2023A_54009_1K_V1_0 displayed in the area of Lagos (Nigeria) –Legend in Table 21.

2.6.1 Improvements compared to the previous release

The GHS-SMOD spatial raster dataset is an improvement of the GHS-SMOD R2022A based on the specifications of the stage I of the Degree of Urbanisation methodology. The GHS-SMOD is provided at the detailed level (Second Level - L2) and the new classification benefits of the new population and built-up surface layers (GHS-POP_GLOBE_R2023A and GHS-BUILT-S_GLOBE_R2023A).

2.6.2 GHS-SMOD classification rules

The “*Settlement model*” GHS-SMOD generates output spatial raster datasets and spatial entities by classifying 1 km² grid cells, on the basis of population density, size and contiguity, with a classification schema organized in two separate hierarchical levels.

The input for the GHSL SMOD is a 1 km² population spatial raster dataset (GHS-POP_GLOBE_R2023A), the built-up surface (GHS-BUILT-S_GLOBE_R2023A) and the land layer (GHS-LAND_GLOBE_R2022A). Each grid cell has the same shape and size, thereby avoiding distortions caused by using units varying in shape and size. This is a considerable advantage when compared to methods based on the population size and density of local administrative units.

At the first hierarchical level, the GHSL SMOD classifies the 1 km² grid cells by identifying the following spatial entities: a) “Urban Centre”, b) “Urban Cluster” and classifying all the other cells as “Rural Grid Cells”.

The criteria for the definition of the spatial entities at the first hierarchical level are:

- **“Urban Centre” (also “High Density Cluster” - HDC)** - An urban centre consists of contiguous grid cells (4-connectivity cluster) with a density of at least 1,500 inhabitants per km² of permanent land, and has at least 50,000 inhabitants in the cluster with smoothed boundaries (3-by-3 conditional majority filtering²⁹) and <15 km² holes filled³⁰;
- **“Urban Cluster” (also “Moderate Density Cluster” - MDC)** - An urban cluster (or moderate density clusters) consists of contiguous grid cells (8-connectivity cluster) with a density of at least 300 inhabitants per km² of permanent land and has a population of at least 5,000 in the cluster. (The urban centres are subsets of the corresponding urban clusters).

The **“Rural grid cells” (also “Mostly Low Density Cells” - LDC)** are all the other cells that do not belong to an Urban Cluster. Most of these will have a density below 300 inhabitants per km² (grid cell); some may have a higher density, but they are not part of cluster with sufficient population to be classified as an Urban Cluster.

The settlement grid at level 1 represents these definitions on a layer grid. Each pixel is classified as follow:

- **Class 3: “Urban Centre grid cell”**, if the cell belongs to an Urban Centre;
- **Class 2: “Urban Cluster grid cell”**, if the cell belongs to an Urban Cluster and not to an Urban Centre;
- **Class 1: “Rural grid cell”**, if the cell does not belong to an Urban Cluster.

The second hierarchical level of the GHSL SMOD is a refinement of the DEGURBA set up to identify smaller settlements. It follows the same approach based on population density, population size and contiguity with a **nested classification** into the first hierarchical level. At the second hierarchical level, the GHSL SMOD classifies the 1 km² grid cells by identifying the following spatial entities: a) “Urban Centres” as at the first level; b) “Dense Urban Cluster” and c) “Semi-dense Urban Cluster” as parts of the “Urban Cluster”, classifying all the

²⁹ Water is excluded and majority is computed among populated or land (land >= 50%) pixels. Cases of draw with even number of pixels are taken as positive realisation.

³⁰ In a few countries with relatively low-density urban development and a strong separation of land use functions, the Degree of Urbanisation generates multiple urban centres for a single city. Creating urban centres and dense urban clusters using both cells with a density of at least 1,500 inhabitants and cells that have an optimal built-up density on permanent land resolves this issue. Such highly built-up cells typically contain office parks, shopping malls or factories and the optimal threshold is dynamically identified according to an input built-up layer as the average built-up density in clusters with a density of at least 1,500 inhabitants with a minimum population of 5,000 people.

other cells of “Urban Clusters” as “Suburban or peri-urban grid cells”; and identifying d) “Rural Cluster” within the “Rural grid cells”. All the other cells belonging to the “Rural grid cells” are classified as “Low Density grid cells” or “Very Low Density grid cells” according to their cell population (Figure 28). Here are reported the definition of the spatial entities at the second hierarchical:

- **“Urban Centre” (also “Dense, Large Settlement”)** - An urban centre consists of contiguous grid cells (4-connectivity cluster) with a density of at least 1,500 inhabitants per km² of permanent land, and has at least 50,000 inhabitants in the cluster with smoothed boundaries (3-by-3 conditional majority filtering³¹) and <15 km² holes filled³⁰;
- **“Dense Urban Cluster” (also “Dense, Medium Cluster”)** - A Dense Urban Cluster consists of contiguous cells (4-connectivity cluster) with a density of at least 1,500 inhabitants per km² of permanent land and has at least 5,000 and less than 50,000 inhabitants in the cluster;
- **“Semi-dense Urban Cluster” (also “Semi-dense, Medium Cluster”)** - A Semi-dense Urban Cluster consists of contiguous grid cells (8-connectivity cluster) with a density of at least 300 inhabitants per km² of permanent land, has at least 5,000 inhabitants in the cluster and is at least 3-km away from other Urban Clusters³²;
- **“Rural cluster” (also “Semi-dense, Small Cluster”)** - A Rural Cluster consists of contiguous cells (8-connectivity cluster) with a density of at least 300 inhabitants per km² of permanent land and has at least 500 and less than 5,000 inhabitants in the cluster.

The **“Suburban or peri-urban grid cells” (also Semi-dens grid cells)** are all the other cells that belong to an Urban Cluster but are not part of a Urban Centre, Dense Urban Cluster or a Semi-dense Urban Cluster.

The **“Low Density Rural grid cells” (also “Low Density grid cells”)** are Rural grid cells with a density of at least 50 inhabitants per km² of permanent land and are not part of a Rural Cluster.

The **“Very low density rural grid cells” (also “Very Low Density grid cells”)** are cells with a density of less than 50 inhabitants per km² of permanent land.

The GHSL SMOD classifies as **“Water grid cells”** all the cells with more than 0.5 share covered by permanent surface water that are not populated nor built.

The settlement grid at level 2 represents these definitions on a layer grid. Each pixel is classified as follow:

- **Class 30: “Urban Centre grid cell”**, if the cell belongs to an Urban Centre spatial entity;
- **Class 23: “Dense Urban Cluster grid cell”**, if the cell belongs to a Dense Urban Cluster spatial entity;
- **Class 22: “Semi-dense Urban Cluster grid cell”**, if the cell belongs to a Semi-dense Urban Cluster spatial entity;
- **Class 21: “Suburban or per-urban grid cell”**, if the cell belongs to an Urban Cluster cells at first hierarchical level but is not part of a Dense or Semi-dense Urban Cluster;
- **Class 13: “Rural cluster grid cell”**, if the cell belongs to a Rural Cluster spatial entity;
- **Class 12: “Low Density Rural grid cell”**, if the cell is classified as Rural grid cells at first hierarchical level, has more than 50 inhabitant and is not part of a Rural Cluster;
- **Class 11: “Very low density rural grid cell”**, if the cell is classified as Rural grid cells at first hierarchical level, has less than 50 inhabitant and is not part of a Rural Cluster;
- **Class 10: “Water grid cell”**, if the cell has 0.5 share covered by permanent surface water and is not populated nor built.

³¹ Water is excluded and majority is computed among populated or land (land >= 50%) pixels. Cases of draw with even number of pixels are taken as positive realisation.

³² Measured as outside a buffer of three grid cells of 1 km² around dense urban clusters and urban centres.

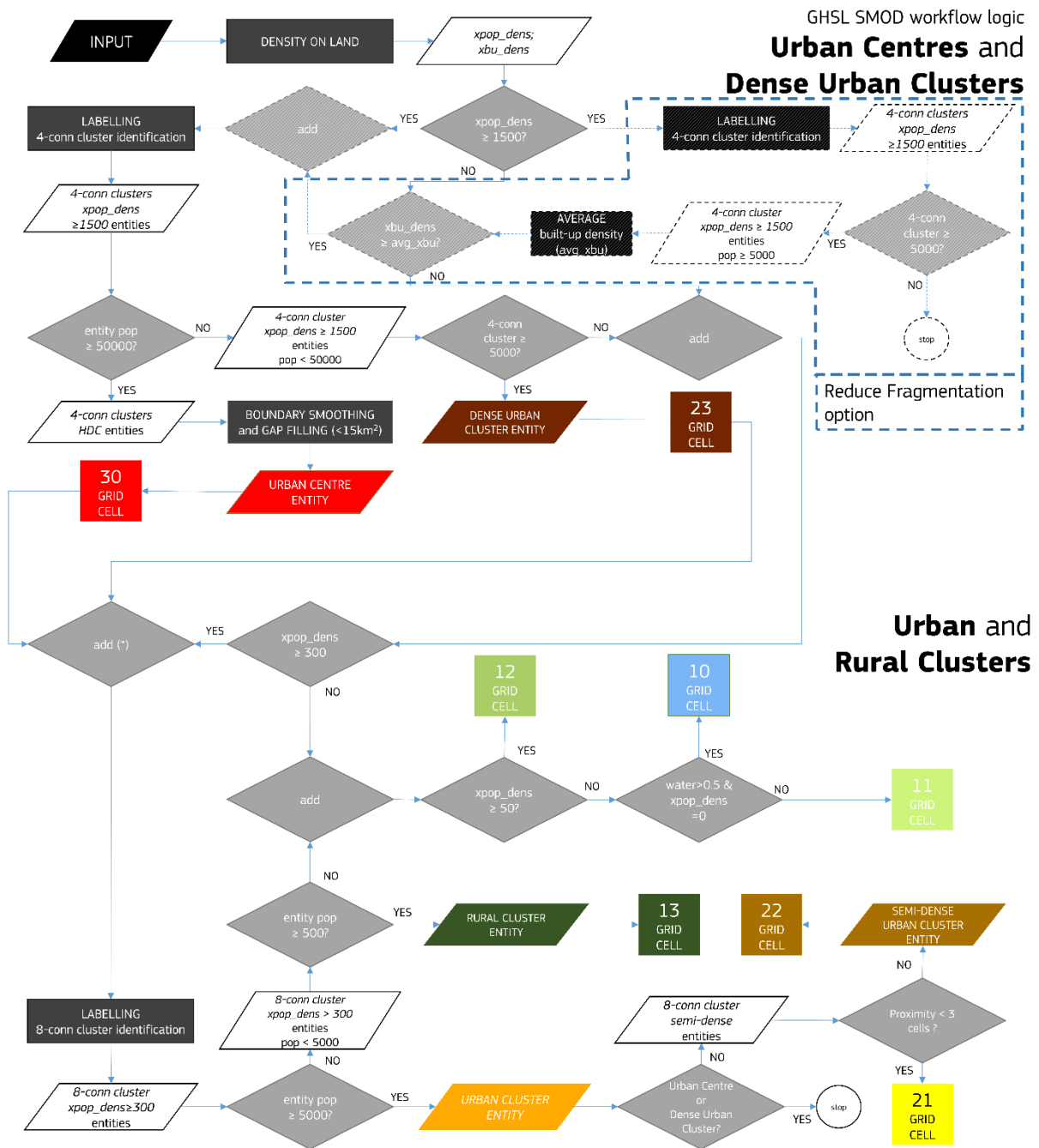


Figure 28 - Schematic overview of GHSL SMOD entities workflow logic. “xpop” represents the population abundance per grid cell; “xpop_dens” represents the population density on permanent land; “xbu” represents the built-up density per grid cell; “xbu_dens” represents the built-up density on permanent land. “DENSITY ON LAND” process fill built-up cells on water with max between 0.5 and built-up surface value and population on water with global average built-up per capita.

“GENERALISATION” process performs a median filtering (3x3) for smoothing boundaries and fills gaps below 15 km².

(*) this procedure of enforcement logic allows the delineation of Urban Clusters Entities which contains by definition the Urban Centres and all 2X classes. Each entity has a corresponding vector boundary.

2.6.3 GHS-SMOD L2 spatial raster dataset and L1 aggregation

Settlement typologies are identified in the GHS-SMOD grid at L2 with a two digit code (30 – 23 – 22 – 21 – 13 – 12 – 11 – 10), linking to grid level and municipal level description terms (both the municipal and grid level terms are accompanied by a technical term). **Classes 30 – 23 – 22 – 21 if aggregated form the “urban domain”, 13 – 12 – 11 – 10 form the “rural domain”**. Table 23 shows the L2 grid cells population (expressed as people per square kilometre: people/km²) and built-up area (expressed as square kilometres: km²) expected characteristics in terms of min-max population and built-up density bounds. Table 22 presents the logic to define settlement typologies.

L1 classifies three settlement typologies as displayed in Table 24. Settlement typologies are identified at L1 with a single digit code (3 – 2 – 1), and grid level and municipal level terms (both the municipal and grid level are accompanied by a technical term), HDC for type 3, MDC for type 2, and LDC for type 1). Classes 3 – 2 if aggregated form the “urban domain”, 1 forms the “rural domain”.

Table 25 presents the logic to define settlement typologies as described in section 2.6.2. Table 26 shows the L1 grid cells population and built-up area characteristics in terms of min-max population and built-up density bounds.

Table 21 - Settlement Model L2 nomenclature

Code	RGB	Grid level term	Spatial entity (polygon) Technical term	Other cells Technical term	Municipal level term Technical term
30	255 0 0	URBAN CENTRE GRID CELL	URBAN CENTRE (UC) <i>DENSE, LARGE CLUSTER</i>		CITY <i>LARGE SETTLEMENT</i>
23	115 38 0	DENSE URBAN CLUSTER GRID CELL	DENSE URBAN CLUSTER (DUC) <i>DENSE, MEDIUM CLUSTER</i>		DENSE TOWN <i>DENSE, MEDIUM SETTLEMENT</i>
22	168 112 0	SEMI-DENSE URBAN CLUSTER GRID CELL	SEMI-DENSE URBAN CLUSTER (SDUC) <i>SEMI-DENSE, MEDIUM CLUSTER</i>		SEMI-DENSE TOWN <i>SEMI-DENSE, MEDIUM SETTLEMENT</i>
21	255 255 0	SUBURBAN OR PERI-URBAN GRID CELL		SUBURBAN OR PERI-URBAN GRID CELLS <i>SEMI-DENSE GRID CELLS</i>	SUBURBAN OR PERI-URBAN AREA <i>SEMI-DENSE AREA</i>
13	55 86 35	RURAL CLUSTER GRID CELL	RURAL CLUSTER (RC) <i>SEMI-DENSE, SMALL CLUSTER</i>		VILLAGE <i>SMALL SETTLEMENT</i>
12	171 205 102	LOW DENSITY RURAL GRID CELL		LOW DENSITY RURAL GRID CELLS <i>LOW DENSITY GRID CELLS</i>	DISPERSED RURAL AREA <i>LOW DENSITY AREA</i>
11	205 245 122	VERY LOW DENSITY RURAL GRID CELL		VERY LOW DENSITY RURAL GRID CELLS <i>VERY LOW DENSITY GRID CELLS</i>	MOSTLY UNINHABITED AREA <i>VERY LOW DENSITY AREA</i>
10	122 182 245	WATER GRID CELL	-	-	-

Table 22 – Settlement Model L2 synthetic explanation of logical definition and grid cell sets

Code	Logical Definition at 1 km ² grid cell	Grid cell sets used in the logical definition (shares defined on land surface)			
		P _{dens} : Local Population Density lower bound ">" (people/km ²)	P _{min} : Cluster Population lower bound ">" (people)	B _{dens} : Local share of Built-up Area lower bound ">" (km ²)	T _{con} : Topological constraints
30	$((P_{dens} \vee B_{dens}) \wedge T_{con}) \wedge P_{min} \vee [iterative_median_filter(3-by-3)] \vee [gap_fill(<15km^2)]^{33}$	1,500	50,000	Average in HDC	4-connectivity clusters
23	$((P_{dens} \vee B_{dens}) \wedge T_{con}) \wedge P_{min} \wedge \neg 30$	1,500	5,000	Average in HDC	4-connectivity clusters
22	$((P_{dens} \wedge T_{con_1}) \wedge P_{min}) \wedge \neg (30 \vee 23) \wedge T_{con_2}$	300	5,000	none	1: 8-connectivity clusters; 2: farther than 3km (beyond 3 cells buffer) from 23 or 30
21	$((((P_{dens} \wedge (30 \vee 23)) \wedge T_{con_1}) \wedge P_{min}) \wedge \neg (30 \vee 23)) \wedge T_{con_2}$	300	5,000	none	1: 8-connectivity clusters; 2: within 3km (within 3 cells buffer) from 23 or 30
13	$((P_{dens} \wedge T_{con}) \wedge P_{min}) \wedge \neg (30 \vee 2X)$	300	500	none	8-connectivity clusters
12	$P_{dens} \wedge \neg (30 \vee 2X \vee 13)$	50	none	none	none
11	$T_{con} \wedge \neg (30 \vee 2X \vee 13 \vee 12)$	none	none	none	On Land (Land \geq 50% \vee BU ³⁴ >0% \vee Pop>0)
10	T _{con}	none	none	none	Not on Land

³³ The seeds for the related spatial entity is obtained before morphological operations

³⁴ Retaining only contiguous BU at least partially on land.

Table 23 – Settlement Model L2 grid cells population and built-up area characteristics (densities on permanent land)

Code	Population		Built-up area	
	Minimum density expected (people/km ²)	Maximum density expected (people/km ²)	Minimum density expected (share)	Maximum density expected (share)
30	0	∞	0	1
23	0	50,000	0	1
22	300	5,000	0	1
21	300	5,000	0	1
13	300	5,000	0	1
12	50	500	0	1
11	0	50	0	1
10	0	0	0	0

Table 24 – Settlement Model L1 nomenclature

Code	RGB	Grid level term	Spatial entity (polygon)	Other cells	Municipal level term
			<i>Technical term</i>	<i>Technical term</i>	
3	255 0 0	URBAN CENTRE GRID CELL	URBAN CENTRE <i>HIGH DENSITY CLUSTER (HDC)</i>		CITIES <i>DENSELY POPULATED AREA</i>
2	255 170 0	URBAN CLUSTER GRID CELL	URBAN CLUSTER <i>MODERATE DENSITY CLUSTER (MDC)</i>		TOWNS & SEMI-DENSE AREA <i>INTERMEDIATE DENSITY AREA</i>
1	115 178 115	RURAL GRID CELL		RURAL GRID CELLS <i>LOW DENSITY GRID CELL (LDC)</i>	RURAL AREAS <i>THINLY POPULATED AREA</i>

Table 25 - Settlement Model L1 synthetic explanation of logical definition and grid cell sets

Code	Logical Definition at 1 km ² grid cell	Grid cell sets used in the logical definition (shares defined on land surface)			
		P_{dens}: Local Population Density lower bound ">" (people/km ²)	P_{min}: Cluster Population lower bound ">" (people)	B_{dens}: Local share of Built-up Area lower bound ">" (km ²)	T_{con}: Topological constrains
3	$((P_{dens} \vee B_{dens}) \wedge T_{con}) \wedge P_{min} \vee$ $\vee [\text{iterative_median_filter}(3\text{-by-}3)] \vee$ $\vee [\text{gap_fill}(<15\text{km}^2)]^{35}$	1,500	50,000	Average in HDC	4- connectivity clusters
2	$P_{dens} \wedge P_{min} \wedge T_{con} \wedge \neg 3$	300	5,000	none	8- connectivity clusters
1	$((P_{dens} \wedge 3) \wedge T_{con}) \wedge P_{min} \wedge$ $\wedge \neg 3^S$	none	none	none	none

Table 26 - Settlement Model L1 grid cells population and built-up area characteristics (densities on permanent land)

Code	Population		Built-up area	
	Minimum density expected (people/km ²)	Maximum density expected (people/km ²)	Minimum density expected (share)	Maximum density expected (share)
3	0	∞	0	1
2	0	50,000	0	1
1	0	5,000	0	1

2.6.4 Input Data

The input data are the multi-temporal GHS-BUILT-S and the GHS-POP grids of the GHSL Data Package 2023 (GHS P2023) and GHS-LAND R2022.

2.6.5 Technical Details

Author: Marcello Schiavina, Michele Melchiorri, Martino Pesaresi, Joint Research Centre (JRC) European Commission.

Product name: GHS_SMOD_GLOBE_R2023A

Spatial extent: Global

Temporal extent: from 1975 to 2030, 5 years interval

Coordinate System: World Mollweide (EPSG: 54009)

Spatial resolution available: 1 km

Table 27 outlines the technical characteristics of the datasets released in this data package.

³⁵ The seeds for the related spatial entity is obtained before morphological operations

2.6.5.1 GHS-SMOD raster spatial raster dataset

Encoding: integer16 [30 – 23 – 22 – 21 – 13 – 12 – 11 – 10], No Data: -200

Data organisation: TIF with CLR colormap (L2_colcod.tif.clr) file as single global layer or tiled.

2.6.5.2 GHS-SMOD urban centre entities

Data organisation: Shapefile (SHP) database with vector layer of Urban Centre entities boundaries (polygons).

Attributes:

- ID_UC_G0: Unique Identifiers of the urban centre entity;
- POP_2020: sum of GHS-POP within the spatial entity extent for 2020;
- BU_2020: sum of GHS-BU within the spatial entity extent for 2020

2.6.5.3 GHS-SMOD dense urban cluster entities

Data organisation: Shapefile (SHP) database with vector layer of Urban Centre entities boundaries (polygons).

Attributes:

- ID_DUC_G0: Unique Identifiers of the urban centre entity;
- POP_2020: sum of GHS-POP within the spatial entity extent for 2020;
- BU_2020: sum of GHS-BU within the spatial entity extent for 2020

Table 27 - Technical details of the datasets in GHS_SMOD_GLOBE_R2023A

GHS_SMOD_GLOBE_R2023A		
ID	Description	Resolution (Projection)
GHS_SMOD_E<epoch>_GLOBE_R2023A_54009_1000_V1_0	Settlement typology codes for <epoch> 1975-2030 (5 years interval) Encoding Int16 Values range: 10-30 NoData [-200]	1 km (World Mollweide)
GHS_SMOD_E2020_GLOBE_R2023A_54009_1000_UC_V1_0	2020 urban centre entities boundaries File format: shapefile	1 km (World Mollweide)
GHS_SMOD_E2020_GLOBE_R2023A_54009_1000_DUC_V1_0	2020 dense urban cluster entities boundaries File format: shapefile	1 km (World Mollweide)

2.6.6 Summary statistics

Table 28 - Summary statistics of total area in square kilometres of each settlement typology at global level as obtained from the 1-km GHS-POP spatial raster datasets L2.

	1975	1980	1985	1990	1995	2000
30	264,887	294,970	328,788	367,059	414,435	457,024
23	191,844	202,810	219,188	238,010	254,244	265,937
22	196,094	211,769	228,401	244,640	249,371	254,957
21	727,432	879,951	1,050,324	1,203,066	1,279,891	1,335,515
13	570,345	599,889	635,441	672,594	686,441	697,086
12	4,698,566	5,032,542	5,232,909	5,341,280	5,414,303	5,454,772
11	139,300,069	138,735,600	138,267,647	137,901,171	137,671,463	137,506,844
	2005	2010	2015	2020	2025	2030
30	503,107	548,967	593,886	633,857	667,551	698,177
23	280,459	293,788	304,714	309,778	318,533	325,171
22	263,086	273,842	288,414	316,341	341,160	356,937
21	1,440,673	1,551,829	1,690,679	1,892,187	2,020,884	2,139,233
13	709,528	724,956	744,085	767,118	790,520	803,741
12	5,639,490	5,819,383	6,001,958	6,164,559	6,164,294	6,272,225
11	137,138,771	136,764,537	136,362,002	135,906,160	135,689,080	135,398,861

Table 29 - Summary statistics of total built-up area in square kilometres for each settlement typology at global level as obtained from the 1-km GHS-POP spatial raster datasets L2.

	1975	1980	1985	1990	1995	2000
30	46,666	51,569	57,157	63,899	74,595	87,242
23	20,031	21,337	23,517	26,164	29,624	33,694
22	6,915	7,758	8,772	9,980	10,960	12,341
21	22,905	27,258	33,635	41,671	49,183	56,963
13	14,903	16,845	19,382	22,390	24,533	27,128
12	36,749	42,003	48,077	54,122	58,532	64,115
11	25,410	27,518	29,544	31,607	32,685	34,193
	2005	2010	2015	2020	2025	2030
30	96,501	107,979	120,223	129,055	133,895	137,385
23	36,403	39,706	43,218	45,286	46,397	46,891
22	13,255	14,408	15,815	17,425	18,896	19,407
21	64,854	73,945	83,895	96,623	105,834	111,305
13	28,993	31,337	33,918	36,366	38,107	38,610
12	69,965	77,202	85,840	97,505	104,740	110,371
11	35,815	37,672	39,908	42,325	43,768	45,309

Table 30 - Summary statistics of total population in each settlement typology at global level as obtained from the 1-km GHS-POP spatial raster datasets L2.

	1975	1980	1985	1990	1995	2000
30	1,322,180,453	1,489,843,838	1,677,467,789	1,898,657,841	2,176,116,565	2,473,886,715
23	757,448,435	776,005,401	809,491,118	860,576,779	917,108,779	958,355,398
22	173,328,355	185,217,567	197,928,476	211,712,024	216,776,457	221,849,424
21	572,052,573	683,115,168	812,230,703	936,974,506	1,000,756,215	1,046,179,168
13	436,556,958	449,906,779	470,452,660	494,642,844	506,685,689	515,815,045
12	608,655,444	657,434,486	691,078,445	710,580,568	722,173,878	730,227,412
11	199,215,041	202,484,509	203,081,460	203,031,347	203,601,927	202,585,862
	2005	2010	2015	2020	2025	2030
30	2,728,358,495	2,996,835,491	3,272,487,867	3,508,281,456	3,725,940,836	3,957,118,842
23	994,804,965	1,032,103,677	1,057,987,485	1,048,977,584	1,057,403,358	1,068,440,865
22	227,673,534	235,012,203	243,821,086	259,224,665	275,918,905	285,812,626
21	1,124,377,294	1,204,747,336	1,300,941,116	1,440,322,764	1,535,484,553	1,616,730,838
13	522,360,002	529,816,063	536,361,178	539,974,247	549,420,148	553,002,427
12	755,383,981	783,360,020	814,812,100	850,972,724	857,968,070	877,882,081
11	205,217,904	203,728,383	200,186,778	193,199,508	189,852,666	187,153,727

Table 31 - Summary statistics of total area in square kilometres of each settlement typology at global level as obtained from the 1-km GHS-POP spatial raster datasets L1.

	1975	1980	1985	1990	1995	2000
3	264,887	294,970	328,788	367,059	414,435	457,024
2	1,115,370	1,294,530	1,497,913	1,685,716	1,783,506	1,856,409
1	648,095,743	647,886,500	647,649,299	647,423,225	647,278,059	647,162,567
	2005	2010	2015	2020	2025	2030
3	503,107	548,967	593,886	633,857	667,551	698,177
2	1,984,218	2,119,459	2,283,807	2,518,306	2,680,577	2,821,341
1	646,988,675	646,807,574	646,598,307	646,323,837	646,127,872	645,956,482

Table 32 - Summary statistics of total built-up area in square kilometres for each settlement typology at global level as obtained from the 1-km GHS-POP spatial raster datasets L1.

	1975	1980	1985	1990	1995	2000
3	46,666	51,569	57,157	63,899	74,595	87,242
2	49,851	56,353	65,924	77,815	89,768	102,998
1	77,062	86,366	97,002	108,119	115,750	125,437
	2005	2010	2015	2020	2025	2030
3	96,501	107,979	120,223	129,055	133,895	137,385
2	114,512	128,059	142,927	159,335	171,126	177,603
1	134,773	146,210	159,665	176,196	186,616	194,290

Table 33 - Summary statistics of total population in each settlement typology at global level as obtained from the 1-km GHS-POP spatial raster datasets L1.

	1975	1980	1985	1990	1995	2000
3	1,322,180,453	1,489,843,838	1,677,467,789	1,898,657,841	2,176,116,565	2,473,886,715
2	1,502,829,363	1,644,338,136	1,819,650,297	2,009,263,310	2,134,641,452	2,226,383,989
1	1,244,427,443	1,309,825,774	1,364,612,565	1,408,254,759	1,432,461,494	1,448,628,320
	2005	2010	2015	2020	2025	2030
3	2,728,358,495	2,996,835,491	3,272,487,867	3,508,281,456	3,725,940,836	3,957,118,842
2	2,346,855,793	2,471,863,216	2,602,749,687	2,748,525,013	2,868,806,816	2,970,984,329
1	1,482,961,887	1,516,904,466	1,551,360,055	1,584,146,479	1,597,240,884	1,618,038,235

2.6.7 How to cite

Dataset:

Schiavina, Marcello; Melchiorri, Michele; Pesaresi, Martino (2023): GHS-SMOD R2023A - GHS settlement layers, application of the Degree of Urbanisation methodology (stage I) to GHS-POP R2023A and GHS-BUILT-S R2023A, multitemporal (1975-2030). European Commission, Joint Research Centre (JRC) [Dataset] doi: 10.2905/A0DF7A6F-49DE-46EA-9BDE-563437A6E2BA PID: <http://data.europa.eu/89h/a0df7a6f-49de-46ea-9bde-563437a6e2ba>

Concept & Methodology:

European Commission, and Statistical Office of the European Union, 2021. Applying the Degree of Urbanisation — A methodological manual to define cities, towns and rural areas for international comparisons — 2021 edition Publications Office of the European Union, 2021, ISBN 978-92-76-20306-3 doi: 10.2785/706535

2.7 GHS-DUC R2023A - GHS Degree of Urbanisation Classification, application of the Degree of Urbanisation methodology (stage II) to GADM 3.6 layer, multitemporal (1975-2030)

The GHS Degree of Urbanisation Classification (GHS-DUC) GHS-DUC_GLOBE_R2023A classifies all GADM 4.1³⁶ administrative units (from level 0 to level 5) by applying the stage II of the Degree of Urbanisation (European Commission & Statistical Office of the European Union, 2021) as recommended by the UN STAT COM. In total, 386,741 GADM units are classified. This is done according to a logic of majority of population (GHS-POP_GLOBE_R2023A) in unit overlaid to the settlement classification spatial raster dataset (GHS-SMOD_GLOBE_R2023A).

In GHS-DUC each GADM polygon (for all available GADM levels) is coded by Degree of Urbanisation Level 1 and Level 2, and has statistics on number of residents and built-up area surface. The GHS-DUC is derived from the GHS-POP (GHS-POP_GLOBE_R2023A, version 1.0) and GHS-SMOD (GHS-SMOD_GLOBE_R2023A, version 1.0) to compute population counts per epoch.

The GHS Degree of Urbanisation Classification GHS-DUC_GLOBE_R2023A is composed by:

- one summary Excel file collecting results at the finest level available per country for each epoch,
- 72 classification files of all GADM 4.1 units for each level (0-5) and each epoch (1975-2030, 5 years interval) released in CSV format.

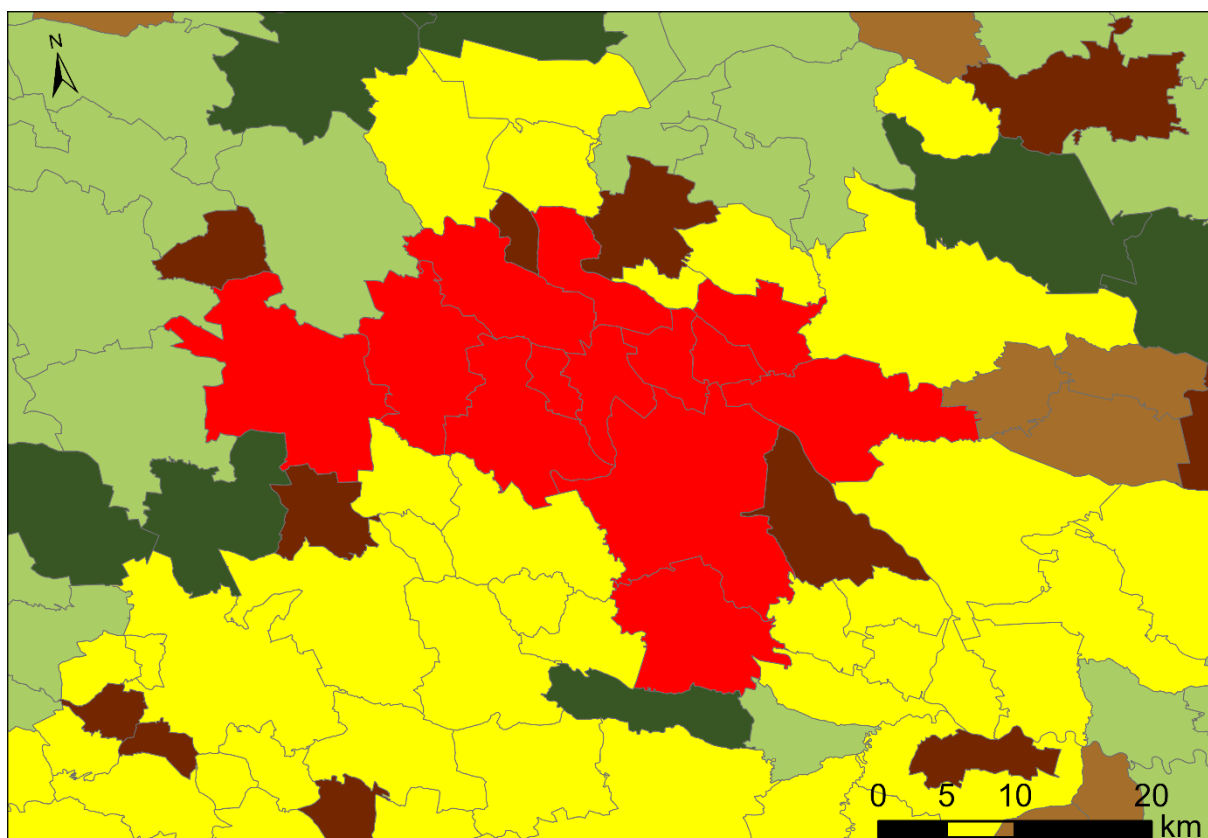


Figure 29 - GHS Degree of Urbanisation Classification (GHS-DUC) GHS-DUC_GLOBE_R2023A_V1_0_GADM41_2020_level4 joined to the GADM 4.1 level 4 layer, displayed in the area of Katowice (Poland) showing the classification of local units by Degree of Urbanisation Level 2—Legend in Table 34. The boundaries shown on this map do not imply official endorsement or acceptance by the European Union.

³⁶ <https://gadm.org/index.html>

2.7.1 Improvements compared to previous release

This classification of administrative units and territories relies on the updated settlement classifications and population spatial raster datasets of GHS P2023 and includes all epochs between 1975 and 2030 at 5-year interval.

2.7.2 GHSL Territorial Units Classification

The Degree of Urbanisation classifies local units based on population majority applied to the grid level classification. Each local unit is assigned exclusively one DEGURBA class at Level 1 and one at Level 2 (hierarchy based). Local units can be administrative units - such as municipalities - or statistical units - such as census enumeration or reporting areas.

2.7.2.1 Territorial units classification Level 1

Once all grid cells covered by GADM have been classified as urban centres, urban clusters and rural grid cells using the GHS-DUG Tool, the next step concerns overlaying these results onto local units, as follows (Figure 31):

- **Cities (or densely populated areas):** local units that have at least 50% of their population in urban centres, **code 3**.
- **Towns and semi-dense areas (or intermediate density areas):** local units that have less than 50% of their population in urban centres and no more than 50% of their population in rural grid cells, **code 2**.
- **Rural areas (or thinly populated areas):** local units that have more than 50% of their population in rural grid cells, **code 1**.

Urban areas consist of cities plus towns and semi-dense areas.

In some countries, not all the small spatial units contain inhabitants. To classify the spatial units without any population, the same rules should be applied to their area as are applied to their population. For example, a small unpopulated spatial unit that has more than 50 % of its area in rural grid cells is classified as a rural area.

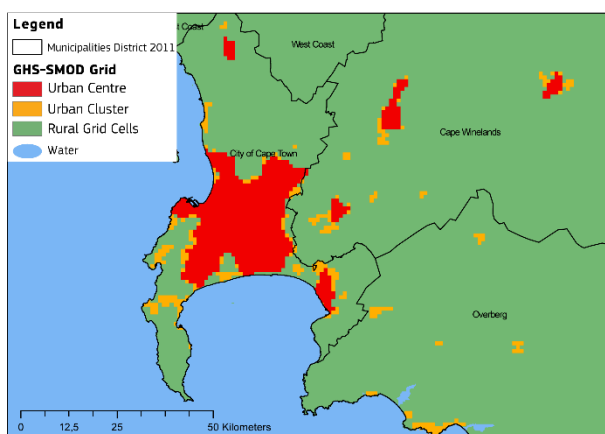


Figure 30 - Urban centre, urban cluster and rural grid cells around Cape Town, South Africa

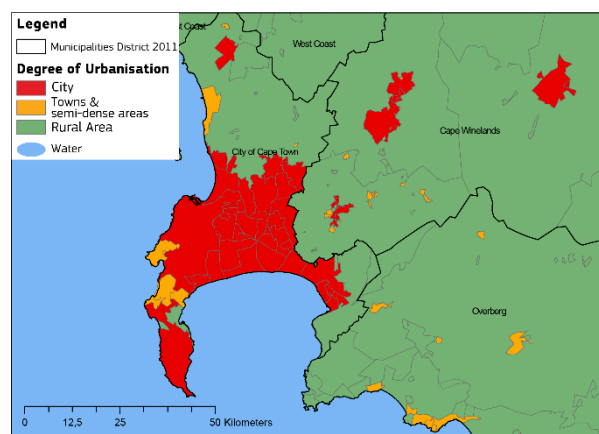


Figure 31 - City, towns & semi-dense areas and rural areas around Cape Town, South Africa (classification of Main Places units, note that Cape Peninsula is part of Cape Town Main Place)

2.7.2.2 Territorial units classification Level 2

Local units are classified as cities in identical manner to the Degree of Urbanisation level 1 (Figure 33):

- A city consists of local units that have at least 50% of their population in an urban centre, **code 30**.

Local units classified as “towns and semi-dense areas” can be divided into three classes:

- Dense Towns have a larger share of their population in dense urban clusters than in semi-dense urban clusters (i.e. are dense) and a larger share in dense plus semi-dense urban clusters than in suburban or peri-urban cells (i.e. are towns), **code 23**.
- Semi-dense Towns have a larger population share in semi-dense urban clusters than in dense urban clusters (i.e. are semi-dense) and a larger share in dense plus semi-dense urban clusters than in suburban or peri-urban cells (i.e. are towns), **code 22**.
- Suburban or peri-urban areas have a larger population share in suburban or peri-urban cells than in dense plus semi-dense urban clusters, **code 21**.

Dense and semi-dense towns can be combined into towns. This reduces the number of classes and may be especially useful if the population share in semi-dense towns is low.

Local units classified as “rural areas” can be divided into three classes:

- Villages have the largest share of their rural grid cell population living in a rural cluster, **code 13**.
- Dispersed rural areas have the largest share of their rural grid cell population living in low density rural grid cells, **code 12**.
- Mostly uninhabited areas have the largest share of their rural grid cell population living in very low density rural grid cells, **code 11**.

As for Level 1, to classify the spatial units without any population, the same rules that are applied to population are applied to area.

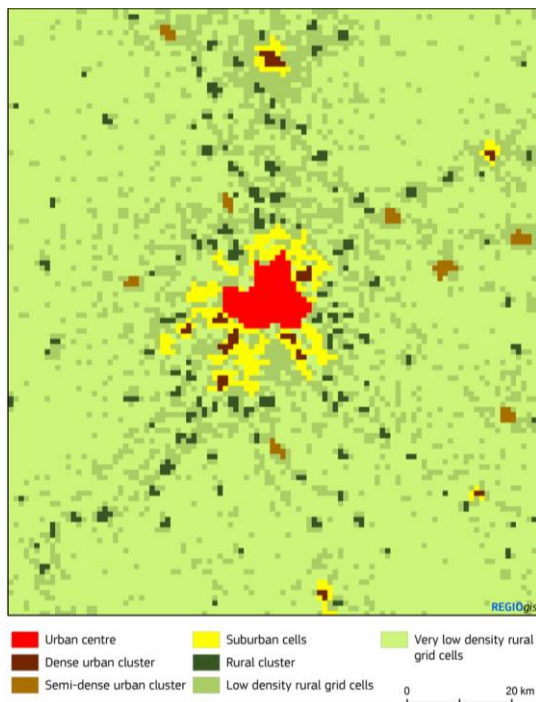


Figure 32 - Degree of urbanisation level 2 grid classification around Toulouse, France

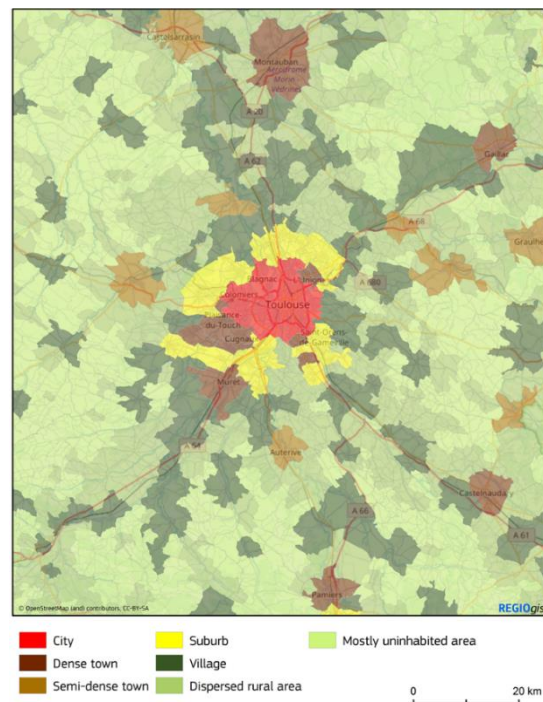


Figure 33 - Degree of urbanisation level 2 local unit classification around Toulouse, France

2.7.2.3 Classification workflow

The classification has been performed combining three inputs of different nature for each epoch and GADM level:

— two raster layers:

- the settlement classification grid at 1 km for the processed year (GHS-SMOD);
- the population grid at 100m resolution for the same epoch (GHS-POP);

— one vector layer of territorial units from GADM4.1³⁷ at the processed level.

The procedure begins with the rasterization of the vector layer. As suggested, the unit classification works better with the smallest administrative units available, therefore these are rasterized using a resolution of 50 m, snapped to the population grid, to reduce the number of units that will not have a representation in the raster layer. The settlement classification grid (at 1 km resolution) is oversampled using nearest neighbour algorithm to align with the 50-m territorial units' raster. The population grid is also oversampled and the values are then adjusted by dividing all original cells by the oversampling ratio (e.g. from 100 m to 50 m the ratio is 4, as 4 grid cells of 50 m compose each 100 m cell) assuming a uniform distribution of population within each cell.

Once the pre-processing of the layers is completed, the algorithm computes for each unit the share of population in each class of the settlement classification grid (both at Level 1 and 2), through zonal statistics, and assigns the class of the unit accordingly (i.e. following the classification rules described in sections 2.7.2.1 and 2.7.2.2). When a unit is unpopulated it runs zonal statistics of areas per settlement classification.

Even if the working resolution is set at 50 m, it could happen that some small polygons could not be rasterised due to geospatial data processing constraints. In such cases the algorithm evaluates the class of these polygons by running separately the zonal statistics (i.e. one polygon at a time) and performing the rasterization procedure with "all touching cells" option. To avoid double counting of population, no population is assigned to such polygons, but the classification still considers population per class in the rasterised cells.

2.8 A consistent nomenclature for the Degree of Urbanisation

Two sets of terms have been developed to describe each of the classes of the Degree of Urbanisation (Table 34, Table 35). The first set uses simple and short terms such as city, town, suburb and village. The second set uses a more neutral and technical language. The second set can be helpful to avoid overlap with the terms used in the national definition.

Table 34 - Territorial Units classification L2 nomenclature

Code	RGB	Municipal level term <i>Technical term</i>
30	255 0 0	CITY <i>LARGE SETTLEMENT</i>
23	115 38 0	DENSE TOWN <i>DENSE, MEDIUM SETTLEMENT</i>
22	168 112 0	SEMI-DENSE TOWN <i>SEMI-DENSE, MEDIUM SETTLEMENT</i>
21	255 255 0	SUBURBS OR PERI-URBAN AREA <i>SEMI-DENSE AREA</i>
13	55 86 35	VILLAGE <i>SMALL SETTLEMENT</i>
12	171 205 102	DISPERSED RURAL AREA <i>LOW DENSITY AREA</i>
11	205 245 122	MOSTLY UNINHABITED AREA <i>VERY LOW DENSITY AREA</i>

³⁷ https://gadm.org/download_world.html

Table 35 - Territorial Units classification L1 nomenclature

Code	RGB	Municipal level term
		<i>Technical term</i>
3	255 0 0	CITY <i>DENSELY POPULATED AREA</i>
2	255 170 0	TOWNS & SEMI-DENSE AREA <i>INTERMEDIATE DENSITY AREA</i>
1	115 178 115	RURAL AREA <i>THINLY POPULATED AREA</i>

2.8.1 How to use the statistics tables

The classification of territorial units by Degree of Urbanisation has two principal objectives. Primarily to relate available statistics (e.g. Demographic and Health Surveys, statistics on labour, housing, etc.) to a DEGURBA classification (e.g. urban/rural). Second, to account urban and rural populations for administrative areas. Both applications would harmonise nationally collected statistics to a common urban and rural classification of territorial units, useful for international statistical comparison as recommended by the United Nations Statistical Commission.

To relate available national statistics to the corresponding GHS-DUC level, it is important to verify in the mapping table Table 36 the relation between the territorial unit for which the statistic is available and the corresponding GADM level. Once the territorial designation in the statistic matches a GADM level, the statistic can be coded by Degree of Urbanisation joining or relating the field identifying the administrative unit in the statistics table, to the GADM level classification of the units by Degree of Urbanisation with the GHS-DUC field 'DEGURBA_L1' or 'DEGURBA_L2'. This operation can be conducted using any of the GHS-DUC tables GHS-DUC_GLOBE_R2023A_v1_0_GADM41_<year>_levelX, where <year> correspond to the epoch, and X to the GADM Level in the specific table. To account urban and rural populations for administrative areas by Degree of Urbanisation the user can refer to the product GHS-DUC_GLOBE_R2023A_v1_0.xlsx. The table lists for all GADM countries and territories, the population per unit by Degree of Urbanisation class and the corresponding share for the finest GADM level. The table also includes statistics aggregated at global level and per epoch.

The epoch refers to the underlying GHS-POP and GHS-SMOD epoch used, keeping the GADM geometry fixed (version 4.1).

2.8.2 Input Data

The input data are the multi-temporal GHS-SMOD and GHS-POP spatial raster datasets of the GHSL Data Package 2023 (GHS P2023). Territorial units are the Global Administrative Map 4.1³⁸

³⁸ <https://gadm.org/data.html>

2.8.3 Technical Details

Author: Marcello Schiavina, Michele Melchiorri, Sergio Freire, Joint Research Centre (JRC) European Commission.

Product name: GHS_DUC_GLOBE_R2023A

Spatial extent: Global

Temporal extent: from 1975 to 2030, 5 years interval

2.8.3.1 GHS-DUC Summary Statistics Table

Data organisation: XLSX with Global statistics of Population per DEGURBA class for each epoch, and sheets per epoch showing Territory or Country statistics of classification at the finest GADM level available.

Territory or Country statistics sheet attributes:

- GADM code: Numerical ID of territory in GADM
- GADM ISO: ISO code of territory in GADM
- GADM NAME: Territory name in GADM
- Selected GADM Level: Finest available GADM level for territory
- GADM level type: Description of the selected level according to GADM attribute "ENGTYPE" for the level (When GADM entry is missing description "N/A" is reported)
- Total Units: Total Territory units at selected GADM level
- Total Area km2: Total Area of the territory in km2
- Average Area km2: Average unit size of the territory at selected GADM level
- Share of Urban Population: Share of population in administrative units classified as Urban (Cities, Towns and Suburbs)
- DEGURBA L1 Population
 - Rural Area: Population of units classified as Rural Areas in Degree of Urbanisation level 1
 - Town & Semi-Dense area: Population of units classified as Town & Suburbs in Degree of Urbanisation level 1
 - City: Population of units classified as Cities in Degree of Urbanisation level 1
- DEGURBA L2 Population
 - Mostly uninhabited area: Population of units classified as Mostly uninhabited Areas in Degree of Urbanisation level 2
 - Rural dispersed area: Population of units classified as Rural dispersed Areas in Degree of Urbanisation level 2
 - Village: Population of units classified as Villages in Degree of Urbanisation level 2
 - Suburban or peri-urban area: Population of units classified as Suburbs or peri-urban areas in Degree of Urbanisation level 2
 - Semi-dense Town: Population of units classified as Semi-dense Towns in Degree of Urbanisation level 2
 - Dense Town: Population of units classified as Dense Towns in Degree of Urbanisation level 2
 - City: Population of units classified as Cities in Degree of Urbanisation level 2
- Total Pop: Total Territory population
- DEGURBA L1 Units
 - Rural Area: Number of units classified as Rural Areas in Degree of Urbanisation level 1

- Town & Semi-Dense area: Number of units classified as Town & Suburbs in Degree of Urbanisation level 1
- City: Number of units classified as Cities in Degree of Urbanisation level 1
- DEGURBA L2 Units
 - Mostly uninhabited area: Number of units classified as Mostly uninhabited Areas in Degree of Urbanisation level 2
 - Rural dispersed area: Number of units classified as Rural dispersed Areas in Degree of Urbanisation level 2
 - Village: Number of units classified as Villages in Degree of Urbanisation level 2
 - Suburban or peri-urban area: Number of units classified as Suburbs or peri-urban areas in Degree of Urbanisation level 2
 - Semi-dense Town: Number of units classified as Semi-dense Towns in Degree of Urbanisation level 2
 - Dense Town: Number of units classified as Dense Towns in Degree of Urbanisation level 2
 - City: Number of units classified as Cities in Degree of Urbanisation level 2

2.8.3.2 GHS-DUC Admin Classification layers

Data organisation: CSV files to be joined to the original GADM4.1 layer at the respective level.

Attributes:

- GID_<level>: GADM 4.1 ID at current level [join filed with GADM layer at respective level]
- GID_0: GADM 4.1 ID at country or territory level0
- Tot_Pop: Total population
- UCentre_Pop: Urban Centre population
- UCluster_Pop: Urban Cluster population
- Rural_Pop: Rural Population
- UCentre_share: Share of Urban Centre Population
- UCluster_share: Share of Urban Cluster population
- Urban_share: Share of Urban Population (Urban Centre + Urban Cluster)
- Rural_share: Share of Rural Population
- DEGURBA_L1: Classification according to Degree of Urbanisation level 1
- DUC_Pop: Dense Urban Cluster Population
- SDUC_Pop: Semi-dense Urban Cluster Population
- SUrb_Pop: Suburban and peri-urban grid cells Population
- RC_Pop: Rural Cluster Population
- LDR_Pop: Low Density Rural grid cells Population
- VLDR_Pop: Very Low Density Rural grid cells Population
- DUC_share: Share of Dense Urban Cluster Population
- SDUC_share: Share of Semi-dense Urban Cluster Population
- SUrb_share: Share of Suburban and peri-urban grid cells Population
- RC_share: Share of Rural Cluster Population
- LDR_share: Share of Low Density Rural grid cells Population

- VLDR_share: Share of Very Low Density Rural grid cells Population
- DEGURBA_L2: Classification according to Degree of Urbanisation level 2

Classified GADM level types per country or territory: see Table 36

Table 37 outlines the technical characteristics of the datasets released in this data package.

Table 36 – GADM level type per country or territory (level 0 omitted as representing the full country or territory)

GADM ISO	GADM NAME	Level 1	Level 2	Level 3	Level 4	Level 5
ABW	Aruba	-	-	-	-	-
AFG	Afghanistan	Province	District	-	-	-
AGO	Angola	Province	Municipality City Council	Commune	-	-
AIA	Anguilla	District	-	-	-	-
ALA	Aland	Sub-Region	Municipality	-	-	-
ALB	Albania	County	NA	NA	-	-
AND	Andorra	Parish	-	-	-	-
ARE	United Arab Emirates	Emirate	Municipal Region	Municipality	-	-
ARG	Argentina	Province	Part	-	-	-
ARM	Armenia	Province	-	-	-	-
ASM	American Samoa	District	County	Village	-	-
ATA	Antarctica	-	-	-	-	-
ATF	French Southern Territories	District	-	-	-	-
ATG	Antigua and Barbuda	Dependency	-	-	-	-
AUS	Australia	Territory	Territory	-	-	-
AUT	Austria	State	District	Municipality	Cadastral community	-
AZE	Azerbaijan	Region	District	-	-	-
BDI	Burundi	Province	Commune	Colline	Sous Colline	-
BEL	Belgium	Region	Capital Region	Arrondissement	Commune	-
BEN	Benin	Department	Commune	Borough	-	-
BES	Bonaire, Sint Eustatius and Saba	Municipality	-	-	-	-
BFA	Burkina Faso	Region	Province	Department	-	-
BGD	Bangladesh	Division	Distict	Upazilla	Union	-
BGR	Bulgaria	Province	Municipality	-	-	-
BHR	Bahrain	Governorate	-	-	-	-
BHS	Bahamas	District	-	-	-	-
BIH	Bosnia and Herzegovina	District	Canton	Commune	-	-
BLM	Saint-Barthelemy	Parish	Quarter	-	-	-
BLR	Belarus	Region	District	-	-	-
BLZ	Belize	District	-	-	-	-
BMU	Bermuda	Parish	-	-	-	-
BOL	Bolivia	Department	Province	Distrito	-	-
BRA	Brazil	State	Municipality	-	-	-
BRB	Barbados	Parish	-	-	-	-
BRN	Brunei	District	Mukim	-	-	-
BTN	Bhutan	District	Village block	-	-	-
BVT	Bouvet Island	-	-	-	-	-
BWA	Botswana	District	Sub-district	-	-	-
CAF	Central African Republic	Prefecture	Sub-prefecture	-	-	-
CAN	Canada	Province	Census Division	Town	-	-
CCK	Cocos Islands	-	-	-	-	-
CHE	Switzerland	Canton	District	Municipality	-	-
CHL	Chile	Region	Province	Municipality	-	-
CHN	China	Province	Prefecture City	County City	-	-
CIV	Côte d'Ivoire	Autonomous district	Autonomous district	Department	Sub-prefecture	-
CMR	Cameroon	Region	Department	Arrondissement	-	-
COD	Democratic Republic of the Congo	Province	Territory	-	-	-
COG	Republic of the Congo	Region	District	-	-	-
COK	Cook Islands	Island Council	-	-	-	-

COL	Colombia	Commissiary	Corregimiento Departamental	-	-	-
COM	Comoros	Autonomous Island	-	-	-	-
CPV	Cabo Verde	County	-	-	-	-
CRI	Costa Rica	Province	Canton	District	-	-
CUB	Cuba	Province	Municipality	-	-	-
CUW	Curaçao	-	-	-	-	-
CXR	Christmas Island	-	-	-	-	-
CYM	Cayman Islands	District	-	-	-	-
CYP	Cyprus	District	-	-	-	-
CZE	Czechia	Region	District	-	-	-
DEU	Germany	State	District	Municipality	Town	-
DJI	Djibouti	Region	NA	-	-	-
DMA	Dominica	Parish	-	-	-	-
DNK	Denmark	Region	Municipality	-	-	-
DOM	Dominican Republic	Province	Municipality	-	-	-
DZA	Algeria	Province	Chef-Lieu-Wilaya	-	-	-
ECU	Ecuador	Province	Canton	Cantonal Head	-	-
EGY	Egypt	Governorate	Subdivision	-	-	-
ERI	Eritrea	Region	District	-	-	-
ESH	Western Sahara	Province	-	-	-	-
ESP	Spain	Autonomous Community	Province	Comarca	Municipality	-
EST	Estonia	County	Parish	Town	-	-
ETH	Ethiopia	City	Zone	District	-	-
FIN	Finland	Province	Region	Sub-Region	Municipality	-
FJI	Fiji	Division	Province	-	-	-
FLK	Falkland Islands	-	-	-	-	-
FRA	France	Region	Department	Districts	Canton	Commune
FRO	Faroe Islands	Region	Commune	-	-	-
FSM	Micronesia	State	Municipality	-	-	-
GAB	Gabon	Province	Department	-	-	-
GBR	United Kingdom	Constituent Country	Unitary Authority	Unitary authority	NA	-
GEO	Georgia	Autonomous Republic	District	-	-	-
GGY	Guernsey	Parish	-	-	-	-
GHA	Ghana	Region	Municipality	-	-	-
GIB	Gibraltar	-	-	-	-	-
GIN	Guinea	Region	Prefecture	Sub-prefecture	-	-
GLP	Guadeloupe	District	Commune	-	-	-
GMB	Gambia	Independent City	District	-	-	-
GNB	Guinea-Bissau	Region	Sector	-	-	-
GNQ	Equatorial Guinea	Province	Districts Municipals	-	-	-
GRC	Greece	Decentralized administration	Region	Municipality	-	-
GRD	Grenada	Dependency	-	-	-	-
GRL	Greenland	Commune	-	-	-	-
GTM	Guatemala	Department	Municipality	-	-	-
GUF	French Guiana	Arrondissement	Commune	-	-	-
GUM	Guam	Municipality	-	-	-	-
GUY	Guyana	Region	Not Classified	-	-	-
HMD	Heard Island and McDonald Island	-	-	-	-	-
HND	Honduras	Department	Municipality	-	-	-
HRV	Croatia	County	Commune	-	-	-
HTI	Haiti	Department	District	Commune	Sub-commune	-
HUN	Hungary	County	Subregion	-	-	-
IDN	Indonesia	Province	Regency	Sub-district	Village	-
IMN	Isle of Man	Parish District	-	-	-	-
IND	India	Union Territory	District	Taluk	-	-
IOT	British Indian Ocean Territory	-	-	-	-	-
IRL	Ireland	County	Municipal District	-	-	-
IRN	Iran	Province	County	-	-	-
IRQ	Iraq	Province	District	-	-	-
ISL	Iceland	Region	Municipality	-	-	-
ISR	Israel	District	-	-	-	-
ITA	Italy	Region	Province	Commune	-	-
JAM	Jamaica	Parish	-	-	-	-
JEY	Jersey	Parish	-	-	-	-
JOR	Jordan	Province	Sub-Province	-	-	-

JPN	Japan	Prefecture	Town	-	-	-
KAZ	Kazakhstan	Region	District	-	-	-
KEN	Kenya	County	Constituency	Ward	-	-
KGZ	Kyrgyzstan	Province	District	-	-	-
KHM	Cambodia	Province	District	Commune	-	-
KIR	Kiribati	-	-	-	-	-
KNA	Saint Kitts and Nevis	Parish	-	-	-	-
KOR	South Korea	Metropolitan City	District	Neighborhood	-	-
KWT	Kuwait	Province	-	-	-	-
LAO	Laos	Province	District	-	-	-
LBN	Lebanon	Governorate	District	Municipality	-	-
LBR	Liberia	County	District	Clan	-	-
LBY	Libya	District	-	-	-	-
LCA	Saint Lucia	Quarter	-	-	-	-
LIE	Liechtenstein	Commune	-	-	-	-
LKA	Sri Lanka	District	Division	-	-	-
LSO	Lesotho	District	-	-	-	-
LTU	Lithuania	County	District Municipality	-	-	-
LUX	Luxembourg	District	Canton	Commune	Commune (same as level 3)	-
LVA	Latvia	Province	District	-	-	-
MAF	Saint-Martin	-	-	-	-	-
MAR	Morocco	Region	Province	District	Rural Commune	-
MCO	Monaco	-	-	-	-	-
MDA	Moldova	District	-	-	-	-
MDG	Madagascar	NA	NA	NA	NA	-
MDV	Maldives	-	-	-	-	-
MEX	Mexico	State	Municipality	-	-	-
MHL	Marshall Islands	Atol	-	-	-	-
MKD	North Macedonia	Municipality	-	-	-	-
MLI	Mali	District	Circle	Arrondissement	Commune	-
MLT	Malta	Region	Local council	-	-	-
MMR	Myanmar	Division	District	Village Township	-	-
MNE	Montenegro	Municipality	-	-	-	-
MNG	Mongolia	Province	Sum	-	-	-
MNP	Northern Mariana Islands	Municipality	-	-	-	-
MOZ	Mozambique	Province	District	Locality	-	-
MRT	Mauritania	Region	Department	-	-	-
MSR	Montserrat	Parish	-	-	-	-
MTQ	Martinique	Arrondissement	Commune	-	-	-
MUS	Mauritius	Region	-	-	-	-
MWI	Malawi	District	Town	Unknown	-	-
MYS	Malaysia	State	District	-	-	-
MYT	Mayotte	Commune	-	-	-	-
NAM	Namibia	Region	Constituency	-	-	-
NCL	New Caledonia	Province	Commune	-	-	-
NER	Niger	Department	Arrondissement	Commune	-	-
NFK	Norfolk Island	-	-	-	-	-
NGA	Nigeria	State	Local Authority	-	-	-
NIC	Nicaragua	Autonomous Region	Municipality	-	-	-
NIU	Niue	-	-	-	-	-
NLD	Netherlands	Province	Municipality	-	-	-
NOR	Norway	County	Municipality	-	-	-
NPL	Nepal	Development Region	Administrative Zone	District	Village development committee	-
NRU	Nauru	District	-	-	-	-
NZL	New Zealand	Region	District	-	-	-
OMN	Oman	Region	Province	-	-	-
PAK	Pakistan	Province	Division	District	-	-
PAN	Panama	Province	District	Municipality	-	-
PCN	Pitcairn Islands	-	-	-	-	-
PER	Peru	Region	Province	District	-	-
PHL	Philippines	Province	Municipality	Village	-	-
PLW	Palau	State	-	-	-	-
PNG	Papua New Guinea	Autonomous Region	District	-	-	-
POL	Poland	Voivodeship	County	Municipality (urban)	-	-
PRI	Puerto Rico	Municipality	-	-	-	-
PRK	North Korea	Province	County	-	-	-

PRT	Portugal	District	Municipality	Parish	-	-
PRY	Paraguay	Department	District	-	-	-
PSE	Palestine	District	Governorate	-	-	-
PYF	French Polynesia	Administrative subdivisions	-	-	-	-
QAT	Qatar	Municipality	-	-	-	-
REU	Reunion	Arrondissement	Commune	-	-	-
ROU	Romania	County	Commune	-	-	-
RUS	Russia	Republic	District	NA	-	-
RWA	Rwanda	Province	District	Sector	Cell	NA
SAU	Saudi Arabia	Province	Governorate	-	-	-
SDN	Sudan	State	District	Unknown	-	-
SEN	Senegal	Region	Department	Arrondissement	Commune	-
SGP	Singapore	Region	-	-	-	-
SGS	South Georgia and the South Sand	-	-	-	-	-
SHN	Saint Helena, Ascension and Tris	Administrative Area	Administrative Area	-	-	-
SJM	Svalbard and Jan Mayen	Territory	-	-	-	-
SLB	Solomon Islands	Province	Ward	-	-	-
SLE	Sierra Leone	Province	District	Chiefdom	-	-
SLV	El Salvador	Department	Municipality	-	-	-
SMR	San Marino	Municipality	-	-	-	-
SOM	Somalia	Region	District	-	-	-
SPM	Saint Pierre and Miquelon	Commune	-	-	-	-
SRB	Serbia	District	Town Municipal	-	-	-
SSD	South Sudan	State	District	Unknown	-	-
STP	Sao Tome and Principe	Municipality	NA	-	-	-
SUR	Suriname	District	Ressort	-	-	-
SVK	Slovakia	Region	District	-	-	-
SVN	Slovenia	Statistical Region	Commune Municipality	-	-	-
SWE	Sweden	County	Municipality	-	-	-
SWZ	Swaziland	District	Constituency	-	-	-
SXM	Sint Maarten	-	-	-	-	-
SYC	Seychelles	District	-	-	-	-
SYR	Syria	Governorate	District	-	-	-
TCA	Turks and Caicos Islands	District	-	-	-	-
TCO	Chad	Region	Department	Sub-prefecture	-	-
TGO	Togo	Region	Prefecture	Commune	-	-
THA	Thailand	Province	District	Sub district	-	-
TJK	Tajikistan	Districts of Republican Subordin	District	NA	-	-
TKL	Tokelau	Atoll	-	-	-	-
TKM	Turkmenistan	Province	District	-	-	-
TLS	Timor-Leste	District	Subdistrict	Community	-	-
TON	Tonga	Island Group	NA	-	-	-
TTO	Trinidad and Tobago	Borough	-	-	-	-
TUN	Tunisia	Governorate	Delegation	-	-	-
TUR	Turkey	Province	District	-	-	-
TUV	Tuvalu	Town Council	-	-	-	-
TWN	Taiwan	Province	County	-	-	-
TZA	Tanzania	Region	District	Ward	-	-
UGA	Uganda	District	County	Sub-county	Parish	-
UKR	Ukraine	?	NA	-	-	-
UMI	United States Minor Outlying Isl	Island	-	-	-	-
URY	Uruguay	Department	Municipality	-	-	-
USA	United States	State	County	-	-	-
UZB	Uzbekistan	Region	District	-	-	-
VAT	Vatican City	-	-	-	-	-
VCT	Saint Vincent and the Grenadines	Parish	-	-	-	-
VEN	Venezuela	State	Municipality	-	-	-
VGB	British Virgin Islands	District	-	-	-	-

VIR	Virgin Islands, U.S.	District	NA	-	-	-
VNM	Vietnam	Province	District	Townlet	-	-
VUT	Vanuatu	Province	Area council	-	-	-
WLF	Wallis and Futuna	Kingdom	District	-	-	-
WSM	Samoa	District	Unknown	-	-	-
XAD	Akrotiri and Dhekelia	Sovereign Base Area	-	-	-	-
XCA	Caspian Sea	-	-	-	-	-
XCL	Clipperton Island	-	-	-	-	-
XKO	Kosovo	District	Town Municipal	-	-	-
XPI	Paracel Islands	-	-	-	-	-
XSP	Spratly Islands	-	-	-	-	-
YEM	Yemen	Governorate	District	-	-	-
ZAF	South Africa	Province	District Municipality	Local Municipality	Ward	-
ZMB	Zambia	Province	District	-	-	-
ZNC	Northern Cyprus	District	-	-	-	-
ZWE	Zimbabwe	City	District	Ward	-	-
GADM	GADM NAME	Level 1	Level 2	Level 3	Level 4	Level 5
ISO						
ABW	Aruba	-	-	-	-	-

Table 37 - Technical details of the datasets in GHS-DUC_GLOBE_R2023A

GHS-DUC_GLOBE_R2023A	
ID	Description
GHS_DUC_GLOBE_R2023A_V1_0	Global Degree of Urbanisation by epoch File format: excel table
GHS_DUC_GLOBE_R2023A_V1_0_GADM41_E<epoch>_<level>	Degree of Urbanisation of GADM36 <level> 0-5 units in epoch 1975-2030 (5 years interval) File format: comma separated values file

2.8.4 Summary statistics

Table 38 - Summary statistics of total population in each administrative classification typology at global level as obtained from the 1-km GHS-SMOD grids L1 and L2 and GHS-POP 100m.

GLOBAL DEGURBA									
1975				1980		1985		1990	
Urban Population		3,143,042,255	77.3%	3,285,183,486	77.7%	3,872,048,956	79.7%	4,316,451,896	81.3%
DEGURBAL1	City	1,246,059,564	30.6%	1,336,994,840	31.6%	1,580,988,792	32.5%	1,781,297,284	33.5%
	Town & Semi Dense areas	1,896,982,691	46.6%	1,948,188,647	46.1%	2,291,060,163	47.2%	2,535,154,612	47.7%
	Rural Area	923,640,995	22.7%	942,227,630	22.3%	986,052,339	20.3%	995,477,350	18.7%
DEGURBAL2	City	1,246,059,564	30.6%	1,336,892,378	31.6%	1,580,988,792	32.5%	1,781,297,284	33.5%
	Dense Town	1,509,973,478	37.1%	1,533,983,910	36.3%	1,697,349,301	34.9%	1,842,116,182	34.7%
	Semi-dense Town	171,998,686	4.2%	177,514,145	4.2%	224,653,297	4.6%	245,459,625	4.6%
	Suburban or peri-urban area	215,010,527	5.3%	236,793,053	5.6%	369,057,565	7.6%	447,578,805	8.4%
	Village	344,548,472	8.5%	350,204,125	8.3%	379,413,544	7.8%	406,860,792	7.7%
	Rural dispersed area	491,065,027	12.1%	503,966,953	11.9%	522,021,754	10.7%	507,708,356	9.6%
	Mostly uninhabited area	88,027,496	2.2%	88,056,552	2.1%	84,617,041	1.7%	80,908,201	1.5%

GLOBAL DEGURBA									
1995			2000			2005		2010	
Urban Population		4,757,846,636	82.9%	5,180,192,096	84.3%	5,581,450,145	85.2%	6,001,330,107	86.0%
DEGURBAL1	City	2,060,054,242	35.9%	2,378,548,710	38.7%	2,632,090,857	40.2%	2,895,658,402	41.5%
	Town & Semi Dense areas	2,697,792,395	47.0%	2,801,643,386	45.6%	2,949,359,288	45.0%	3,105,671,705	44.5%
	Rural Area	980,704,302	17.1%	963,581,962	15.7%	970,893,264	14.8%	977,580,943	14.0%
DEGURBAL2	City	2,059,959,024	35.9%	2,378,359,499	38.7%	2,631,677,748	40.2%	2,895,211,595	41.5%
	Dense Town	1,978,994,163	34.5%	2,075,487,548	33.8%	2,163,586,829	33.0%	2,273,591,116	32.6%
	Semi-dense Town	243,122,482	4.2%	239,870,557	3.9%	258,491,371	3.9%	263,094,410	3.8%
	Suburban or peri-urban area	475,770,968	8.3%	486,474,492	7.9%	527,694,197	8.1%	569,432,986	8.2%
	Village	403,148,717	7.0%	392,777,120	6.4%	389,366,339	5.9%	383,635,511	5.5%
	Rural dispersed area	499,151,232	8.7%	496,876,546	8.1%	510,633,018	7.8%	525,957,852	7.5%
	Mostly uninhabited area	78,404,353	1.4%	73,928,295	1.2%	70,893,907	1.1%	67,987,580	1.0%

GLOBAL DEGURBA									
		2015		2020		2025		2030	
Urban Population		6,428,652,978	86.7%	6,807,458,296	86.9%	7,147,867,059	87.4%	7,501,091,486	87.9%
DEGURBAL1	City	3,172,093,393	42.8%	3,440,951,755	43.9%	3,660,811,253	44.7%	3,912,595,311	45.8%
	Town & Semi Dense areas	3,256,559,585	43.9%	3,366,506,540	43.0%	3,487,055,806	42.6%	3,588,496,175	42.0%
	Rural Area	990,383,070	13.3%	1,025,002,826	13.1%	1,034,952,369	12.6%	1,035,318,574	12.1%
DEGURBAL2	City	3,172,704,393	42.8%	3,441,648,288	43.9%	3,661,521,425	44.7%	3,913,305,482	45.8%
	Dense Town	2,356,437,661	31.8%	2,251,785,772	28.7%	2,256,504,795	27.6%	2,229,233,461	26.1%
	Semi-dense Town	282,922,873	3.8%	331,336,937	4.2%	369,512,309	4.5%	411,444,992	4.8%
	Suburban or peri-urban area	617,810,853	8.3%	784,028,936	10.0%	861,691,993	10.5%	948,471,013	11.1%
	Village	379,097,586	5.1%	378,354,388	4.8%	388,411,076	4.7%	374,707,428	4.4%
	Rural dispersed area	547,219,954	7.4%	589,297,228	7.5%	592,733,161	7.2%	607,843,508	7.1%
	Mostly uninhabited area	64,065,530	0.9%	57,351,209	0.7%	53,808,132	0.7%	52,767,639	0.6%

2.8.5 How to cite

Dataset:

Schiavina, Marcello; Melchiorri, Michele; Freire, Sergio (2023): GHS-DUC R2023A - GHS Degree of Urbanisation Classification, application of the Degree of Urbanisation methodology (stage II) to GADM 4.1 layer, multitemporal (1975-2030). European Commission, Joint Research Centre (JRC) [Dataset] doi: 10.2905/DC0EB21D-472C-4F5A-8846-823C50836305 PID: <http://data.europa.eu/89h/dc0eb21d-472c-4f5a-8846-823c50836305>

Concept & Methodology:

European Commission, and Statistical Office of the European Union, 2021. Applying the Degree of Urbanisation — A methodological manual to define cities, towns and rural areas for international comparisons — 2021 edition Publications Office of the European Union, 2021, ISBN 978-92-76-20306-3 doi:10.2785/706535

2.9 GHS-BUILT-LAUSTAT R2023A - GHS built-up surface statistics in European LAU, multitemporal (1975-2020)

This product contains the summary statistics of GHS-BUILT-S multi-temporal (1975-2020) at Local Administrative Unit level (LAU) from the 2020 polygon layer provided by GISCO.

For each LAU the table contains the sum of built-up surface (GHS-BUILT-S) between 1975 and 2020 in 5 years interval, expressed in square kilometres.

2.9.1 Input data

The new product GHS-BUILT-S_GLOBE_R2023A (version 1.0) was used to compute the total built-up surface present at each epoch in EU LAU. The LAU geometry is obtained from GISCO³⁹.

2.9.2 Technical Details

Author: Marcello Schiavina, Michele Melchiorri, Joint Research Centre (JRC) European Commission

Product name: GHS-BUILT-LAUSTAT_EUROPE_R2023A

Spatial extent: Global

Temporal extent: 1975-2020 (5 years interval)

Data organisation: Data are provided as excel table with LAU codes ("GISCO ID"), country code ("Country") and built-up in square kilometres for each epoch

Table 15 outlines the technical characteristics of the datasets released in this data package.

Table 39 - Technical details of the datasets in GHS-BUILT-LAUSTAT_EUROPE_R2023A

GHS-BUILT-LAUSTAT_EUROPE_R2023A	
ID	Description
GHS_BUILT_LAUSTAT_MT_EUROPE_R2023A_V1_0	zonal sums of built-up surface MT by LAU

2.9.3 How to cite

Dataset:

Schiavina, Marcello; Melchiorri, Michele (2023): GHS-BUILT-LAUSTAT R2023A - GHS built-up surface statistics in European LAU, multitemporal (1975-2020). European Commission, Joint Research Centre (JRC) [Dataset] doi: 10.2905/C56D51B2-AA73-4DA8-8184-67D3D6816F16 PID: <http://data.europa.eu/89h/c56d51b2-aa73-4da8-8184-67d3d6816f16>

Concept & Methodology:

Schiavina, Marcello; Melchiorri, Michele; Corbane, Christina; Freire, Sergio; Batista e Silva, Filipe (2022): Built-up areas are expanding faster than population growth: regional patterns and trajectories in Europe, Journal of Land Use Science, DOI: 10.1080/1747423X.2022.2055184

³⁹ <https://ec.europa.eu/eurostat/web/gisco/geodata/reference-data/administrative-units-statistical-units/lau>

2.10 GHS-SDATA R2023A - GHSL data supporting the production of R2023A Data Package (GHS-BUILT, GHS-POP)

The GHS-SDATA product contains several intermediate data supporting the production of the R2023A with the function of baseline or quality control: consequently they have a downstream effect on the characteristics of the final information included in the R2023A. They are shared for the purpose of a better understanding of the GHSL data characteristics and facilitate the transparency of the GHSL production workflow.

GHS_SDATA_LDS_QUANT reports about the quantity of Landsat image data measurements used by the GHSL for assessing each specific epoch, aggregated at 100m-resolution.

GHS_SDATA_WUP2018_BOUNDARIES reports about the 'city' boundaries as have been estimated during the GHSL production from the UN World Urbanization Prospects 2018. WUP 2018 includes population time series for cities represented by single location points (coordinates). GHSL developed an automatic approach for inferring the city boundaries and extent in WUP database that is based on iterative aggregation of administrative units adjacent to the main unit (determined by WUP city coordinates), using density and compactness criteria to reach the WUP city population data in the available census year. The procedure leverages on the GHS-SmartDissolve tool (Schiavina et al., 2023).

2.10.1 Technical Details

Author: Pesaresi, Martino; Politis, Panagiotis; Schiavina, Marcello; Freire, Sergio; Maffenini, Luca

Product name: GHS-SDATA_GLOBE_R2023A

Spatial extent: Global

Table 40 - Technical details of the datasets in GHS-SDATA_GLOBE_R2023A

GHS-SDATA_LDS-QUANT_GLOBE_R2023A		
ID	Description	Resolution (projection)
GHS_SDATA_LDS_QUANT_MT_GLOBE_R2023A_54009_100_V1_0	Amount of Landsat image data observations supporting the multi-temporal assessment in the different epochs Encoding: Byte Number of Bands: 4 (b1 : 1975, b2 : 1990, b3 :2000, b4 : 2014) Values range: 0-254 NoData: 255	100 m World Mollweide (ESRI:54009)

GHS-SDATA_WUP2018-BOUNDARIES_GLOBE_R2023A		
ID	Description	Resolution (projection)
GHS_SDATA_WUP2018_BOUNDARIES_GLOBE_R2023A_V1_0	Estimated city boundaries matching UN World Urbanization Prospects 2018 File format: shapefile	World Mollweide (ESRI:54009)

2.10.2 How to cite

Dataset:

Pesaresi, Martino; Maffenini, Luca; Freire, Sergio; Politis, Panagiotis; Schiavina, Marcello (2023): GHS-SDATA R2023A - GHS supporting data. European Commission, Joint Research Centre (JRC) [Dataset] doi: 10.2905/7520C0F6-A54C-41E7-8F13-1EA3ABFAC320 PID: <http://data.europa.eu/89h/7520c0f6-a54c-41e7-8f13-1ea3abfac320>

Concept & Methodology:

European Commission, GHSL Data Package 2023, Publications Office of the European Union, Luxembourg, 2023, ISBN 978-92-68-02341-9, doi:10.2760/098587, JRC133256

3 Conclusions

The release of the GHSL P2023 data package provides an update of the GHSL P2022. This update was necessary, because new independent data showed an anomaly in the performance of the multi-temporal model that was not visible during the model development. According to the JRC internal tests, the anomaly was introducing a positive bias in predicted change rates of built-up surfaces and built-up volumes after the year 2000. The positive bias is especially remarkable in the rural domain.

The new release GHS P2023 fixes the anomaly in the multi-temporal modelling mechanism and recalculates the multi-temporal built-up surfaces, built-up volumes, population, and degree of urbanization spatial raster datasets (SMOD) accordingly. This is an important improvement for a number of thematic applications that rely on the GHSL time series. With the historic reference data it is possible for the first time to quantify the accuracy of the multi-temporal model. Moreover, some other improvements are applied in the POP downscaling mechanism. The 10m-resolution products directly derived from the Sentinel-2 image composite of the year 2018 remains substantially the same in the GHS P2023 as compared to the GHS P 2022, with some marginal improvements.

This new data package will be the basis for the operational data production under the Copernicus Emergency Management Service (CEMS, <https://emergency.copernicus.eu>) that will provide updates of the data package every two years starting with the first update for the reference year 2022 under the guidance of the GHSL team to assure an alignment of the new data with the time series delivered by this data package.

References

- Bechtel, B., Pesaresi, M., Florczyk, A. J., & Mills, G. (2018). Beyond built-up: The internal makeup of urban areas. *Urban Remote Sensing*.
- Buchhorn, M., Smets, B., Bertels, L., Roo, B. D., Lesiv, M., Tsendbazar, N.-E., Herold, M., & Fritz, S. (2020). *Copernicus Global Land Service: Land Cover 100m: collection 3: epoch 2019: Globe* [Data set]. Zenodo. <https://doi.org/10.5281/ZENODO.3939050>
- Corbane, C., Pesaresi, M., Kemper, T., Politis, P., Florczyk, A. J., Syrris, V., Melchiorri, M., Sabo, F., & Soille, P. (2019). Automated global delineation of human settlements from 40 years of Landsat satellite data archives. *Big Earth Data*, 3(2), 140–169. <https://doi.org/10.1080/20964471.2019.1625528>
- Corbane, C., Pesaresi, M., Politis, P., Syrris, V., Florczyk, A. J., Soille, P., Maffenini, L., Burger, A., Vasilev, V., Rodriguez, D., Sabo, F., Dijkstra, L., & Kemper, T. (2017). Big earth data analytics on Sentinel-1 and Landsat imagery in support to global human settlements mapping. *Big Earth Data*, 1(1–2), 118–144. <https://doi.org/10.1080/20964471.2017.1397899>
- Corbane, C., Politis, P., Kempeneers, P., Simonetti, D., Soille, P., Burger, A., Pesaresi, M., Sabo, F., Syrris, V., & Kemper, T. (2020). A global cloud free pixel- based image composite from Sentinel-2 data. *Data in Brief*, 31, 105737. <https://doi.org/10.1016/j.dib.2020.105737>
- Corbane, C., Syrris, V., Sabo, F., Politis, P., Melchiorri, M., Pesaresi, M., Soille, P., & Kemper, T. (2020). Convolutional neural networks for global human settlements mapping from Sentinel-2 satellite imagery. *Neural Computing and Applications*. <https://doi.org/10.1007/s00521-020-05449-7>
- Costa, L. da F. (2022). Further generalizations of the Jaccard index. *HAL Open Science Hal-03384438*. <https://hal.science/hal-03384438/>
- European Commission, & Statistical Office of the European Union. (2021). *Applying the Degree of Urbanisation - a methodological manual to define cities, towns and rural areas for international comparisons*. Publications Office of the European Union.
- Freire, S., MacManus, K., Pesaresi, M., Doxsey-Whitefield, E., & Mills, J. (2016). Development of new open and free multi-temporal global population grids at 250 m resolution. *Proc. of the 19th AGILE Conference on Geographic Information Science*, 250.

- Freire, S., Schiavina, M., Florczyk, A., MacManus, K., Pesaresi, M., Corbane, C., Bokovska, O., Mills, J., Pistoiesi, L., Squires, J., & Sliuzas, R. (2018). Enhanced data and methods for improving open and free global population grids: putting 'leaving no one behind' into practice. *International Journal of Digital Earth*, 11(12). <https://doi.org/10.1080/17538947.2018.1548656>
- Gueguen, L., Soille, P., & Pesaresi, M. (2012). A new built-up presence index based on density of corners. *Proc. Int. Symp. on Geoscience and Remote Sensing (IGARSS)*.
- Huang, X., Song, Y., Yang, J., Wang, W., Ren, H., Dong, M., Feng, Y., Yin, H., & Li, J. (2022). Toward accurate mapping of 30-m time-series global impervious surface area (GISA). *International Journal of Applied Earth Observation and Geoinformation*, 109, 102787.
- Maffenini, L., Schiavina, M., Freire, S., M. Melchiorri, & Kemper, T. (2023). *GHS-POPWARP User Guide*. Publications Office of the European Union. <https://doi.org/10.2760/24288>
- Marconcini, M., Metz-Marconcini, A., Esch, T., & Gorelick, N. (2021). Understanding current trends in global urbanisation-the world settlement footprint suite. *GI_Forum*, 9(1), 33–38.
- Melchiorri, M., Pesaresi, M., Florczyk, A. J., Corbane, C., & Kemper, T. (2019). Principles and Applications of the Global Human Settlement Layer as Baseline for the Land Use Efficiency Indicator—SDG 11.3.1. *ISPRS International Journal of Geo-Information*, 8(2), 96. <https://doi.org/10.3390/ijgi8020096>
- Ouzounis, G. K., Pesaresi, M., & Soille, P. (2012). Differential Area Profiles: decomposition properties and efficient computation. *Pattern Analysis and Machine Intelligence, IEEE Transactions On*, 34(8), 1533–1548. <https://doi.org/10.1109/TPAMI.2011.245>
- Pesaresi, M., & Benediktsson, J. A. (2001). A new approach for the morphological segmentation of high-resolution satellite imagery. *Geoscience and Remote Sensing, IEEE Transactions On*, 39(2), 309–320. <https://doi.org/10.1109/36.905239>
- Pesaresi, M., Corbane, C., Julea, A., Florczyk, A., Syrris, V., & Soille, P. (2016). Assessment of the Added-Value of Sentinel-2 for Detecting Built-up Areas. *Remote Sensing*, 8(4), 299. <https://doi.org/10.3390/rs8040299>
- Pesaresi, M., Corbane, C., Ren, C., & Edward, N. (2021). Generalized Vertical Components of built-up areas from global Digital Elevation Models by multi-scale linear regression modelling. *PLOS ONE*, 16(2), e0244478. <https://doi.org/10.1371/journal.pone.0244478>

- Pesaresi, M., Ehrlich, D., Ferri, S., Florczyk, A., Carneiro Freire Sergio, M., Halkia, S., Julea, A., Kemper, T., Soille, P., & Syrris, V. (2016). *Operating procedure for the production of the Global Human Settlement Layer from Landsat data of the epochs 1975, 1990, 2000, and 2014*. Publications Office of the European Union. <http://publications.jrc.ec.europa.eu/repository/handle/111111111/40182>
- Pesaresi, M., Gerhardinger, A., & Kayitakire, F. (2008). A Robust Built-Up Area Presence Index by Anisotropic Rotation-Invariant Textural Measure. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 1(3), 180–192. <https://doi.org/10.1109/JSTARS.2008.2002869>
- Pesaresi, M., Huadong, G., Blaes, X., Ehrlich, D., Ferri, S., Gueguen, L., Halkia, M., Kauffmann, M., Kemper, T., Lu, L., Marin-Herrera, M. A., Ouzounis, G. K., Scavazzon, M., Soille, P., Syrris, V., & Zanchetta, L. (2013). A Global Human Settlement Layer From Optical HR/VHR RS Data: Concept and First Results. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 6(5), 2102–2131. <https://doi.org/10.1109/JSTARS.2013.2271445>
- Pesaresi, M., Ouzounis, G. K., & Gueguen, L. (2012). A new compact representation of morphological profiles: Report on first massive VHR image processing at the JRC. *Algorithms and Technologies for Multispectral, Hyperspectral, and Ultraspectral Imagery XVIII*, 8390, 839025.
- Pesaresi, M., Syrris, V., & Julea, A. (2016). A New Method for Earth Observation Data Analytics Based on Symbolic Machine Learning. *Remote Sensing*, 8(5), 399. <https://doi.org/10.3390/rs8050399>
- Schiavina, M., Melchiorri, M., & Freire, S. (2023). A smart and flexible approach for aggregation of adjacent polygons to meet a minimum target area or attribute value. *Scientific Reports*, 13(1), 4367. <https://doi.org/10.1038/s41598-023-31253-z>
- Schneider, A., Friedl, M. A., & Potere, D. (2010). Mapping global urban areas using MODIS 500-m data: New methods and datasets based on ‘urban ecoregions.’ *Remote Sensing of Environment*, 114(8), 1733–1746. <https://doi.org/10.1016/j.rse.2010.03.003>
- See, L., Georgieva, I., Duerauer, M., Kemper, T., Corbane, C., Maffenini, L., Gallego, J., Pesaresi, M., Sirbu, F., Ahmed, R., & others. (2022). A crowdsourced global data set for validating built-up surface layers. *Scientific Data*, 9(1), 1–14.
- Theobald, D. M. (2014). Development and applications of a comprehensive land use classification and map for the US. *PloS One*, 9(4), e94628.

- Uhl, J. H., & Leyk, S. (2022). MTBF-33: A multi-temporal building footprint dataset for 33 counties in the United States (1900-2015). *ArXiv Preprint ArXiv:2203.11078*.
- United Nations, Department of Economic and Social Affairs, Population Division. (2018). *World Urbanization Prospects: The 2018 Revision (ST/ESA/SER.A/420)*. United Nations.
- United Nations, Department of Economic and Social Affairs, Population Division. (2019). *World Population Prospects 2019, Online Edition. Rev. 1*.
- United Nations, Department of Economic and Social Affairs, Population Division. (2022). *World Population Prospects 2022, Data Sources*. UN DESA/POP/2022/DC/NO. 9.
- Vincent, L. (1993). Morphological grayscale reconstruction in image analysis: applications and efficient algorithms. *Image Processing, IEEE Transactions On*, 2(2), 176–201.
<https://doi.org/10.1109/83.217222>

List of Figures

Figure 1 - Santiago de Chile: comparison of the built-up surfaces as assessed by the previous GHS_BUILT_LDSMT_GLOBE_R2018A for the epoch 2014 from Landsat image data with a Boolean 30m-resolution method (upper), vs the new GHS-BUILT-S_GLOBE_R2023A for the epoch 2018 from Sentinel-2 image data with a continuous 10m-resolution method (lower).	8
Figure 2 - Mumbai-Pune (India): residential (RES) and non-residential (NRES) components of the built-surfaces estimated for the GHSL 2020 epoch. RES and NRES are represented with blue and magenta, respectively.	9
Figure 3 - Shanghai-Changzhou (China): residential (RES) and non-residential (NRES) components of the built-surfaces estimated for the GHSL 2020 epoch. RES and NRES are represented with blue and magenta, respectively.	9
Figure 4 - Lagos-Porto Novo-Abeokuta (Nigeria): residential (RES) and non-residential (NRES) components of the built-surfaces estimated for the GHSL 2020 epoch. RES and NRES are represented with blue and magenta, respectively.	10
Figure 5 - Sao Paulo- Campinas - Sao Jose dos Campos (Brazil): residential (RES) and non-residential (NRES) components of the built-surfaces estimated for the GHSL 2020 epoch. RES and NRES are represented with blue and magenta, respectively.	10
Figure 6 - Detroit-Lansing-Flint (United States): residential (RES) and non-residential (NRES) components of the built-surfaces estimated for the GHSL 2020 epoch. RES and NRES are represented with blue and magenta, respectively.	11
Figure 7 - The Hague - Rotterdam- Antwerp (The Netherlands): residential (RES) and non-residential (NRES) components of the built-surfaces estimated for the GHSL 2020 epoch. RES and NRES are represented with blue and magenta, respectively.	11
Figure 8 - Multi-temporal accuracy estimations in URBAN and RURAL domains, and across both domains. J-Accuracy is the generalized version of the Jaccard similarity index to the continuous numerical domain (Costa, 2022)	18
Figure 9 – Temporal evolution of the predicted and observed (REF_SUM) normalized built-up surfaces in the considered test areas, URBAN 2020 stratum.	19
Figure 10- Temporal evolution of the predicted and observed (REF_SUM) normalized built-up surfaces in the considered test areas, RURAL 2020 stratum.	19
Figure 11 – Average building height (ANBH 100m) estimates in Guangzhou - Shenzhen (China).....	27
Figure 12 - Average building height (ANBH 100m) estimates in Delhi (India).	27
Figure 13 - Average building height (ANBH 100m) estimates in Pretoria – Johannesburg (South Africa).	28
Figure 14 - Average building height (ANBH 100m) estimates in Paris (France).	28
Figure 15 - Average building height (ANBH 100m) estimates in Sao Paulo – Santos (Brazil).....	29
Figure 16 - Average building height (ANBH 100m) estimates in New York (United States).....	29
Figure 17 - Osaka-Nagoya-Tokyo (Japan): comparison between GHS-BUILT-V R2023A (above) and GHS-BUILT-S R2023A (below), year 2020.	35
Figure 18 - Morphological Settlement Zone (MSZ) Legend.....	36
Figure 19 - Settlement Characteristics in Kolkata (India)	37
Figure 20 - Settlement Characteristics in Beijing (China)	38
Figure 21 - Settlement Characteristics in Kampala (Uganda).....	39
Figure 22 – Settlement Characteristics in London (United Kingdom).....	40
Figure 23 – Settlement Characteristics in Kansas City (United States)	41
Figure 24 – Settlement Characteristics in Mexico City (Mexico)	42
Figure 25 - GHS Population spatial raster dataset (GHS-POP) GHS_POP_E2020_GLOBE_R2023A_54009_100_V1_0 in Porto Alegre (Brazil).....	45

Figure 26 - Generalized workflow for producing GHS-POP R2022, with main steps (1-6) and intermediate and main outputs (A-D).....	46
Figure 27 - GHS Settlement Model spatial raster dataset (GHS-SMOD) GHS-SMOD_E2020_GLOBE_R2023A_54009_1K_V1_0 displayed in the area of Lagos (Nigeria) –Legend in Table 21.	49
Figure 28 - Schematic overview of GHSL SMOD entities workflow logic. “xpop” represents the population abundance per grid cell; “xpop_dens” represents the population density on permanent land; “xbu” represents the built-up density per grid cell; “xbu_dens” represents the built-up density on permanent land. “DENSITY ON LAND” process fill built-up cells on water with max between 0.5 and built-up surface value and population on water with global average built-up per capita. “GENERALISATION” process performs a median filtering (3x3) for smoothing boundaries and fills gaps below 15 km ² . (*) this procedure of enforcement logic allows the delineation of Urban Clusters Entities which contains by definition the Urban Centres and all 2X classes. Each entity has a corresponding vector boundary.	52
Figure 29 - GHS Degree of Urbanisation Classification (GHS-DUC) GHS-DUC_GLOBE_R2023A_V1_0_GADM41_2020_level4 joined to the GADM 4.1 level 4 layer, displayed in the area of Katowice (Poland) showing the classification of local units by Degree of Urbanisation Level 2–Legend in Table 34. The boundaries shown on this map do not imply official endorsement or acceptance by the European Union.	62
Figure 30 - Urban centre, urban cluster and rural grid cells around Cape Town, South Africa.....	63
Figure 31 - City, towns & semi-dense areas and rural areas around Cape Town, South Africa (classification of Main Places units, note that Cape Peninsula is part of Cape Town Main Place).....	63
Figure 32 - Degree of urbanisation level 2 grid classification around Toulouse, France.....	64
Figure 33 - Degree of urbanisation level 2 local unit classification around Toulouse, France.....	64

List of Tables

Table 1 – Total and JAHC samples per Region, sorted by decreasing Joint Agreement High Confidence share of the human interpretation of S2 data.	12
Table 2 – Reference set by voting schema, any confidence level: confusion matrix and accuracy or agreement metrics	13
Table 3 – Reference set by subsampling in the JAHC domain: confusion matrix and accuracy or agreement metrics	13
Table 4 – Agreement metrics by sub-region in the JAHC domain, ordered by decreasing overall accuracy. Precision and Recall are also called “Producer Accuracy” and “User Accuracy”, respectively.....	14
Table 5 - Accuracy performances in model detection as compared with human visual inspection of the same image data. Jaccard similarity (also called intersection-over-union), Overall Accuracy, Commission Error and Omission Error. (a) the BU vs. NBU and (b) the WATER vs. LAND abstraction semantics. (right) the new GHSL release R2023, (left) the previous GHSL release R2019 tested vs. the same reference data.....	15
Table 6 – Expected errors of the new GHS-BUILT-S R2023A release at 10m resolution stratified by class of the Copernicus Global Land cover at 100m resolution (Buchhorn et al., 2020).....	16
Table 7 – Expected error scores in prediction of the built-up surface fraction (BUFRAC) at the aggregated 100m and 1km resolution.....	16
Table 8 – The amount of total built-up surfaces, the NRES built-up surfaces assessed in the GHS-BUILT-S R2023A data and the NRES built-up surface share stratified by land use classes in United States (NLUD) and Europe (CLC), ordered by decreasing NRES surface share.....	17
Table 9 – number of valid samples used in the MT test.....	18
Table 10 - Summary of the characteristics of the new GHS-BUILT data vs. the previous releases.....	21
Table 11 - Summary of the Landsat Image data used in input.....	22
Table 12 - Technical details of the datasets in GHS-BUILT-S_GLOBE_R2023A.....	23
Table 13 - Summary statistics of predicted surface (square meters) of built-up total (BUTOT) and the built-up non-residential (BUNRES) component, per years of prediction.....	24
Table 14 – Errors of ANBH 100m in predicting the Copernicus Building Height generalized at the same spatial resolution.....	30
Table 15 - Technical details of the datasets in GHS-BUILT-H_GLOBE_R2023A	31
Table 16 - Technical details of the datasets in GHS-BUILT-V_GLOBE_R2023A	33
Table 17 - Summary statistics of predicted volume (cubic meters) of built-up total (BUTOT) and the built-up non-residential (BUNRES) component, per years of prediction.....	34
Table 18 - Technical details of the datasets in GHS-BUILT-C_GLOBE_R2023A.....	43
Table 19 - Technical details of the datasets in GHS_POP_GLOBE_R2023A.....	48
Table 20 - Summary statistics of total population as obtained from the 1-km World Mollweide grid - total population adjusted to the UN WPP 2022 (United Nations, Department of Economic and Social Affairs, Population Division, 2022).	48
Table 21 - Settlement Model L2 nomenclature.....	54
Table 22 - Settlement Model L2 synthetic explanation of logical definition and grid cell sets.....	55
Table 23 - Settlement Model L2 grid cells population and built-up area characteristics (densities on permanent land)	56
Table 24 - Settlement Model L1 nomenclature.....	56
Table 25 - Settlement Model L1 synthetic explanation of logical definition and grid cell sets.....	57
Table 26 - Settlement Model L1 grid cells population and built-up area characteristics (densities on permanent land)	57

Table 27 - Technical details of the datasets in GHS_SMOD_GLOBE_R2023A	58
Table 28 - Summary statistics of total area in square kilometres of each settlement typology at global level as obtained from the 1-km GHS-POP spatial raster datasets L2.....	59
Table 29 - Summary statistics of total built-up area in square kilometres for each settlement typology at global level as obtained from the 1-km GHS-POP spatial raster datasets L2.	59
Table 30 - Summary statistics of total population in each settlement typology at global level as obtained from the 1-km GHS-POP spatial raster datasets L2.	60
Table 31 - Summary statistics of total area in square kilometres of each settlement typology at global level as obtained from the 1-km GHS-POP spatial raster datasets L1.....	60
Table 32 - Summary statistics of total built-up area in square kilometres for each settlement typology at global level as obtained from the 1-km GHS-POP spatial raster datasets L1.	60
Table 33 - Summary statistics of total population in each settlement typology at global level as obtained from the 1-km GHS-POP spatial raster datasets L1.	60
Table 34 - Territorial Units classification L2 nomenclature.....	65
Table 35 - Territorial Units classification L1 nomenclature.....	66
Table 36 - <i>GADM level type per country or territory (level 0 omitted as representing the full country or territory)</i>	69
Table 37 - Technical details of the datasets in GHS-DUC_GLOBE_R2023A.....	73
Table 38 - Summary statistics of total population in each administrative classification typology at global level as obtained from the 1-km GHS-SMOD grids L1 and L2 and GHS-POP 100m.	74
Table 39 - Technical details of the datasets in GHS-BUILT-LAU2STAT_EUROPE_R2023A	77
Table 40 - Technical details of the datasets in GHS-SDATA_GLOBE_R2023A.....	78

GETTING IN TOUCH WITH THE EU

In person

All over the European Union there are hundreds of Europe Direct centres. You can find the address of the centre nearest you online (european-union.europa.eu/contact-eu/meet-us_en).

On the phone or in writing

Europe Direct is a service that answers your questions about the European Union. You can contact this service:

- by freephone: 00 800 6 7 8 9 10 11 (certain operators may charge for these calls),
- at the following standard number: +32 22999696,
- via the following form: european-union.europa.eu/contact-eu/write-us_en.

FINDING INFORMATION ABOUT THE EU

Online

Information about the European Union in all the official languages of the EU is available on the Europa website (european-union.europa.eu).

EU publications

You can view or order EU publications at op.europa.eu/en/publications. Multiple copies of free publications can be obtained by contacting Europe Direct or your local documentation centre (european-union.europa.eu/contact-eu/meet-us_en).

EU law and related documents

For access to legal information from the EU, including all EU law since 1951 in all the official language versions, go to EUR-Lex (eur-lex.europa.eu).

Open data from the EU

The portal data.europa.eu provides access to open datasets from the EU institutions, bodies and agencies. These can be downloaded and reused for free, for both commercial and non-commercial purposes. The portal also provides access to a wealth of datasets from European countries.

Science for policy

The Joint Research Centre (JRC) provides independent, evidence-based knowledge and science, supporting EU policies to positively impact society



EU Science Hub

joint-research-centre.ec.europa.eu



@EU_ScienceHub



EU Science Hub - Joint Research Centre



EU Science, Research and Innovation



EU Science Hub



@eu_science



Publications Office
of the European Union