METRICS FOR INDICATORS

GRID-POPULATION DENSITY MAP

Dasymetric mapping is used as a tool to disaggregate population data at census level in regular grid population density map at 100 m of spatial resolution.

The proposed method [29] requires, as input, a built-up map weighting depending on the building use. The building use information was extracted from the Copernicus Urban Atlas (UA), available for 2012 and recently updated to 2018. The UA classes are aggregated according to the type of building use, based on the associations shown in Table S1.

Table S1. Building use classes

Building use	UA classes	Correction factor
Residential	1111;11210; 11220; 11230; 11240; 13400	1
Rural	21000; 220000; 23000; 24000; 32000; 330000	0.7
Industrial, Commercial and Leisure	12100; 14100; 14200	0.1
Roads, Railways, Port and Airport	12210; 12220; 12230; 12300; 12400	0.01
Other	all remaining classes	

The criteria established to define the weights of redistribution are two-fold:

Population is proportional to building volumes (valid for residential areas);
Population allocation in a specific cell depends on building use as well as volumes, in non-residential area.

A site-specific correction factor (column 3rd, Table S1) was estimated by comparing mean population density per volume unit in non-residential area with mean population density per volume unit in residential areas.

To evaluate the building volume for Bari case study, the footprint area of buildings is estimated from the available settlement layer maps, whereas the heights are extracted from LiDAR data.

For Bari city, LiDAR data were acquired by the Italian Ministry of the Environment (new Ministry of Ecological Transition), within the “Extraordinary Remote Sensing Plan” and are based on surveys held in 2008.. LIDAR is pre-processed by filtering only areas occupied by buildings according to the binary mask generated from the settlement layers.

The following formula reflects the dasymetric computation method implemented in QGIS environment:

$$P_{grid} = \sum_{j=1}^{m} P_{j,\ census} \frac{\sum_{i=1}^{n} BF_{sub\_elemGRID_i} * Hmean_{sub\_elem\mathrm{GRID}_i} * Corr_{factor}}{\sum_{l=1}^{k} BF_{sub\_elemCENSUS_l} * Hmean_{sub\_elemCENSUS_l} * Corr_{factor}} \quad \text{(S1)}$$

where

$BF_{sub_{elemCENSUS_l}}$ is the built-up footprint area in a generic sub-element l of a census zone having different building use;
k is the number of census zone sub-elements with different building use, derived from the intersection of vector layers census zones and building use;
$BF_{sub\_elemGRID_i}$ is the built-up footprint area in a generic sub-element i of a census zone, with different building use, included in the output cell considered;
n is the number of census zones sub-elements, with different building uses, within a grid cell;
$P_{j,census}$ is the population of a generic census zone;
m is the number of census zones in a cell;
P_{grid} is the final population allocated to a cell of a regular grid;
$Hmean_{sub\_elemGRID_i}$ is a mean value of building heights of sub-elements in a cell;
$Hmean_{sub\_elemCENSUS_l}$ is a mean value of building heights in census zones*;*
$Corr_{factor}$ are correction factors based on building uses.

The choice of evaluating heights as an average in the LiDAR set (dated 2008) is a criterion that is useful to overcome the issue of missing information for buildings constructed after 2008. Such an approximation is justified by the existence of municipal regulations that prevent the construction of new buildings with height values differing from those prevailing in the urban context.

SDG 11.1.1 INDICATOR

For the implementation of the indicator SDG 11.1.1 "Proportion of urban population living in slums, informal settlements or inadequate housing" several calculation methods were developed depending on the meaning of "inadequate":

sub-indicator (1) the "proportion of households with non-durable housing;"
sub-indicator (2) the "proportion of households living in housing residing on or near hazardous areas;"
sub-indicator (3) "proportion of households with insufficient living space".

A house is considered as "durable" if it was built in a non-hazardous location and if it has a permanent and adequate structure able to protect its inhabitants from climatic extremes such as heavy rain, heat, cold and humidity [82].

In the absence of local information layers to be used as ground truth and very high-resolution EO data, in this work, all buildings were considered, without distinguishing the slums from the houses.

The analysis concerned the total population, as well as the regular migrant component. Furthermore, the population grid was used as input to calculate the cumulative number of people potentially living in "inadequate housing". This value can be used to compare results obtained at the intra-urban spatial disaggregation level with outcomes achieved at an urban scale.

Sub-indicator 1): "Proportion of households with not durable housing"

The sub-indicator 1)"proportion of households with not durable housing", related to structural quality criteria, under the hypothesis that people are equally distributed in all the cell settlements, according to [82] was computed as:

$$\mathrm{IHH\_1} = 100\left[\frac{\textit{Number of people living in inadequate housing households}}{\textit{City population}}\right] \tag{S2}$$

where the number of people leaving in inadequate housing households (N_IHH_1grid) per each output cell was provided as:

$$\mathrm{N\_IHH\_1}_{\mathrm{grid}} = P_{grid}\left[\frac{\textit{Footprint area of inadequate housing households}}{\textit{Footprinf area of settlement map}}\right] \tag{S3}$$

with P_{grid} representing the total regular population in the output cell considered.

For Bari city, the ancillary building use layer, available for Bari municipality only, updated to 2017, has provided useful information on number and position of inadequate housing with structural deficiencies (Figure S1).

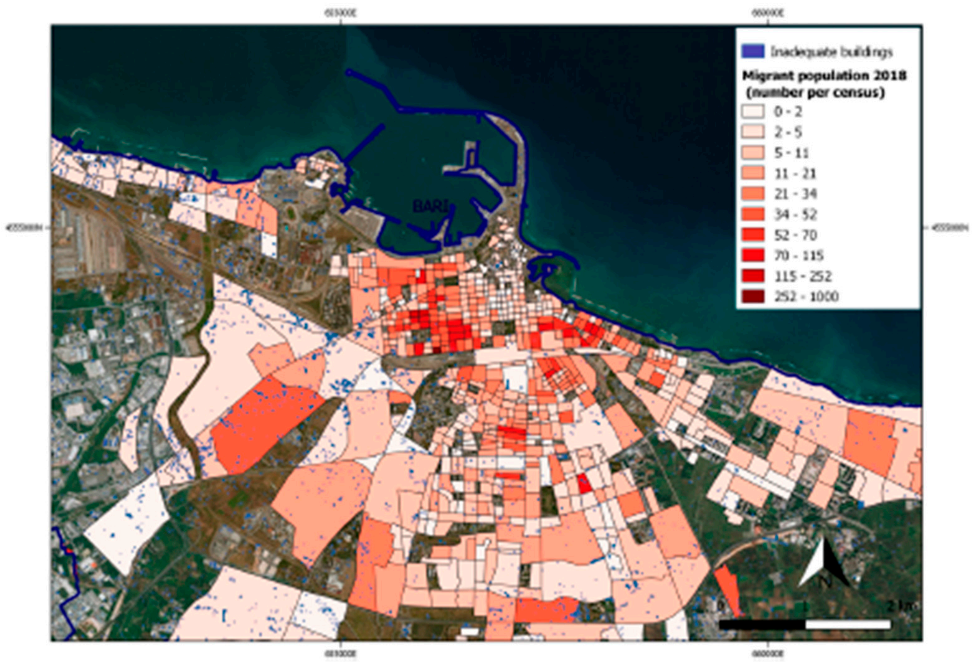

Figure S1. Map showing the number of inadequate buildings in Bari.

In Figure S1, the updated version of sub-indicator 1) SDG 11.1.1. with respect to the total population in 2020. The classes in the legend define the percentage of people in each cell who potentially reside in buildings with structural deficiencies.

SUB-INDICATOR 2): "PROPORTION OF HOUSEHOLDS LIVING IN HOUSING RESIDING ON OR NEAR HAZARDOUS AREAS"

The sub-indicator 2)"proportion of households living in housing residing on or near hazardous areas", related to location criteria, was computed as:

$$\text{IHH\_2} = 100 \left[\frac{\textit{Number of people living in housing households on or close to hazardous areas}}{\textit{City population}}\right] \quad \text{(S4)}$$

where the number of people leaving in housing households on or close to hazardous areas (N_IHH_2cell) per each output cell was provided as:

$$\text{N\_IHH\_2}_{grid} = P_{grid} \left[\frac{\textit{Footprint area of housing households on or close to hazardous areas}}{\textit{Footprinf area of settlement map } 2018}\right] \quad \text{(S5)}$$

The map of areas subjected to flood hazard, in Bari, was updated in November 2019 from the "Autorità di bacino distrettuale dell'Appennino Meridionale". As shown in Figure S2, Bari was affected by high and medium level of hazard.

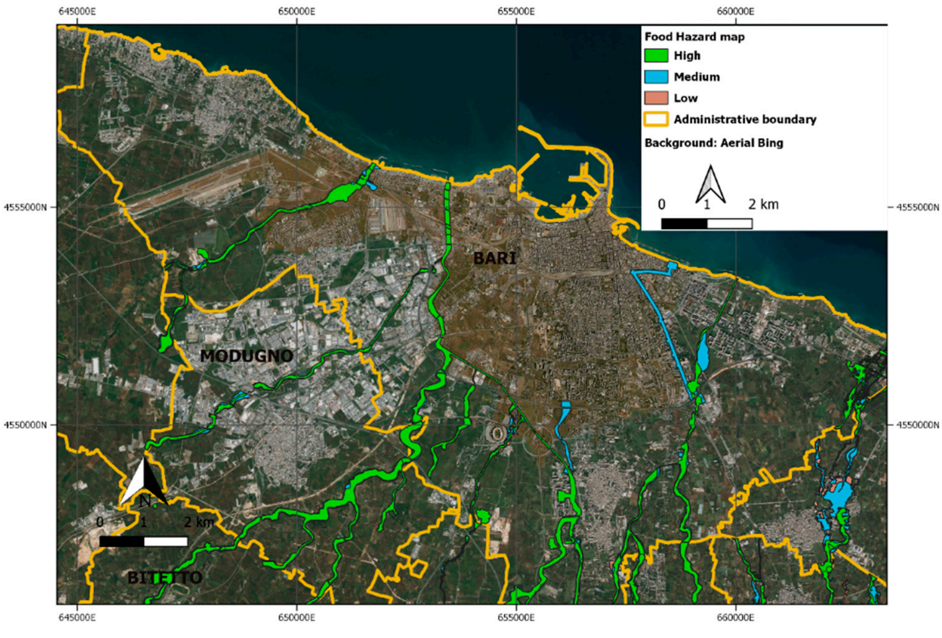

Figure S2. Map of flood hazard in Bari up to date to November 2019.

SUB-INDICATOR 3): "PROPORTION OF HOUSEHOLDS WITH NOT SUFFICIENT LIVING SPACE"

A sub-indicator was introduced as an additional criterion to define inadequate housing. To quantify the proportion of households with insufficient living space, building crowding degree maps were produced. The method to generate such maps consisted of calculating the housing per capita volume as a ratio between building volume and the number of resident people estimated in a cell.

As depicted in Figure S3, LiDAR height data were combined with building layers to obtain a representative 3-dimensional model of buildings of the city. Thus, the volume was computed by multiplying the footprint areas with the mean value of heights for each building. For Bari city, the "civilario comunale" dataset (2017) was adopted as the latest update of the building layer. The settlement map from EO data was, instead, used as additional input to model the urban area in newly built neighbourhoods. The volume was, then, divided by the number of people in each cell to obtain the volume per capita.

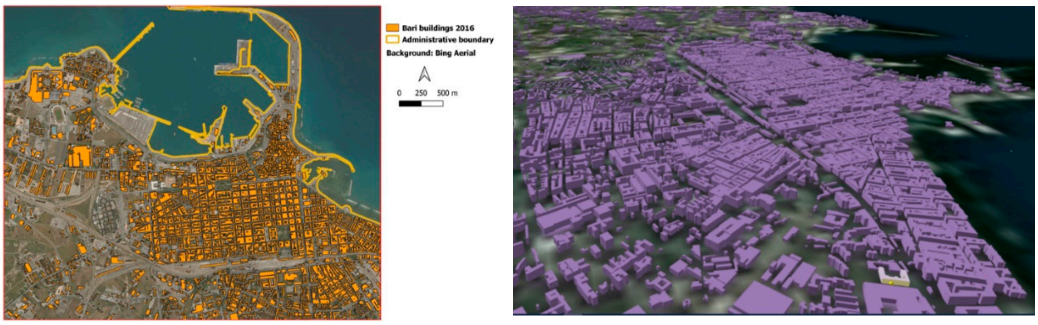

Figure S3. Closeup of Building use layer. Source: Bari municipality (on the left); 3D model from LIDAR data (on the right).

As an inherent limitation of the methodology, the useful volume per inhabitant appeared to be overestimated, as it included floor thicknesses, walls and technical rooms of the buildings. The volume could also have been overestimated mainly in the central areas of the city, where buildings included many commercial spaces. The final classification of housing volume per capita was clustered into 3 categories of increasing degree of crowding: low, medium and high. This was carried out based on the results obtained. In addition, for a more detailed analysis of critical crowding values, a per capita volume threshold of 60 m^3 was selected. As the useful height of a floor was approximately 3 m and the useful per capita volume was slightly overestimated, this threshold corresponded to less than 20 available square meters per capita. This threshold value conformed to the current legislation in Italy, according to which the limit criterion of habitability was about 14 square meters per inhabitant.

SDG 11.2.1 INDICATOR

The methodology for calculating the indicator has been reported in the metadata of indicator [83]. This document suggests quantifying the proportion of the population that does not have convenient access to public transport by those who must walk more than 500 m to reach the nearest stop in the city. In this work, the fine-grid population density map was adopted as an input to evaluate indicators at both intra-urban and urban scales. As main inputs, an inventory of public transport stops in the city and a network street graph were required.

The processing chain was developed by using PyQGIS libraries [36] designed for the analysis of network street graphs. The main steps of the implemented procedure are:

- The population grid is filtered by extracting those elements that do not contain one or more bus stops within.
- Each cell of the grid population density map is represented by its centroid.
- The centroids are projected onto the nearest point on the network street map which are denoted as starting points.
- Bus stops are also projected onto the nearest point on the grid which will be referred to as endpoints (Figure S4 provides a graphical representation of this step).
- For each starting point, an algorithm “graph tracker” searches for the nearest ending point, calculating the distance to travel necessary to reach it on the network.
- Those cells obtaining a distance greater than 500 m between starting and ending points are selected and highlighted.

The evaluation of indicators at the intra-urban scale consists of spatial overlapping of both total and migrant population density map with a spatial distribution map of the previously mentioned cells. The sum of the total population (including migrant component) living in these cells is an essential input to calculate the indicator at the urban scale.

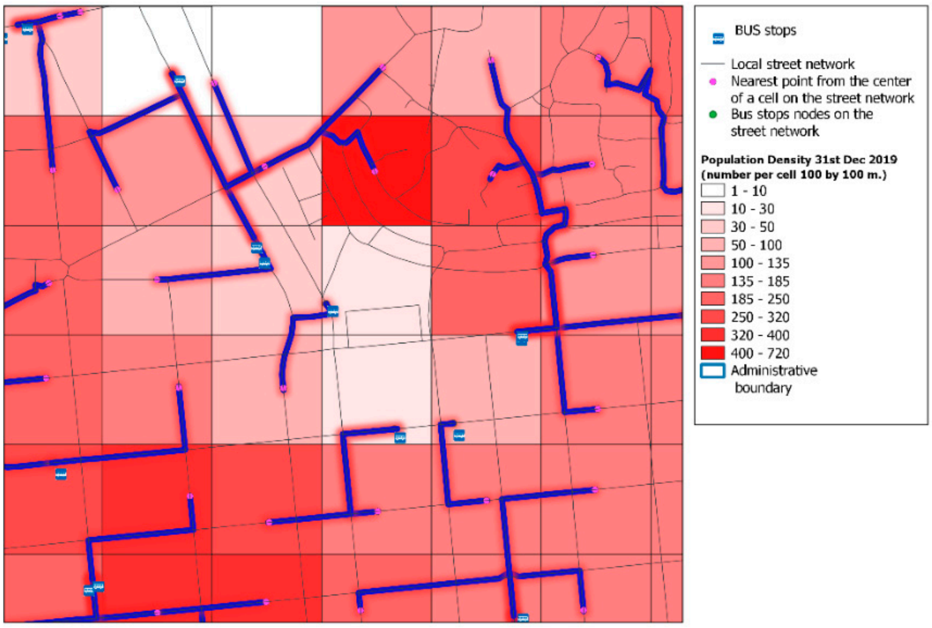

Figure S4. Graphical representation of SDG 11.2.1. computation step 4. The walkable paths from starting to ending points are shown in blue.

SDG 11.3.1 INDICATOR

The SDG 11.3.1. indicator was estimated according to its metadata description [84]. The related formula is based on the ratio between the Rate of Land Consumption (LCR) and the Population Growth rate (PGR) as follows

$$\text{LCRPGR} = \left[\frac{Land\ Consumption\ Rate}{Population\ Growth\ Rate}\right] \tag{S6}$$

LCR and PGR were computed cell by cell. The only inputs required are the population data and settlement maps in two years. The former maps were obtained by applying the dasymetric method to population census data. The latter map can be obtained by downloading the European Settlement Map or, alternatively, from a custom land cover classification based on satellite imagery such as Sentinel-2 data.

This indicator is also known as "land use efficiency" as it allows determination of where land consumption is justified by huge population growth and where, instead, it is due to external reasons such as industrial, commercial and tertiary expansion.

Population Growth Rate (PGR) component of Indicator SDG 11.3.1 can be calculated for both total and regular migrant populations for evaluating population fluxes over the time, by using the formula in metadata [84]

$$\text{PGR} = \frac{\ln\left(P_{grid,t+n}/P_{grid,t}\right)}{n} \tag{S7}$$

where:

$P_{grid,t+n}$ is the regular migrant population living in urban areas, in the output cell considered, at the final year (*t+n*)

$P_{grid,t}$ is the regular migrant population living in urban areas, in the output cell considered, at the initial reference year (*t*)

n = Number of years between initial and final dates considered.

SDG 11.6.2 INDICATOR

According to the reference metadata [103], SDG indicator 11.6.2. "Annual mean levels of fine particulate matter (e.g., PM2.5 and PM10) in cities (population-weighted)" was implemented through spatially overlaying a population grid map with maps of the annual mean levels of atmospheric pollution from particulate matter. The latter data, for Bari case study, had a lower spatial resolution (4 km × 4 km) than the fine-grid population density map (100 m × 100 m). Thus, as suggested in the metadata [103], the indicator was aggregated at the larger scale (at city level) using the formula

$$PWEL_{city} = \frac{\sum_{i=1}^{n} C_{\,4\,km\,\times\,4\,km} * \sum_{j=1}^{m} P_{GRID\_j}}{P_{city}} \tag{S8}$$

where

$PWEL_{city}$ is the Population Weighted Exposure Level estimated at city level;
$C_{4\,km\,\times\,4\,km}$ is the particulate matter concentration in a 4 km × 4 km cell;
P_{GRID_j} is population density value per cell 100 m × 100 m;
m is the number of cells of fine-grid population map included in a cell of atmospheric pollution map (4 km × 4 km);
n is the number of cells of atmospheric pollution map covering Bari territory;
P_{city} is the total population of Bari.

UNCERTAINTY ANALYSIS

When assessing the uncertainties associated with the indicators, we assumed that they essentially depend on the uncertainty of the population density map produced by the dasymetric method. Such a map is the essential variable for indicator estimation. The MAE, root mean square error (RMSE) and mean absolute percentage error (MAPE) were estimated at the output grid cell scale (100 m × 100 m) (Table S2).

A validation data set was created using the number of resident people, in the registry offices for each address. This data set was partly obtained automatically through geocoding tools in QGIS. However, some addresses were processed manually, due to the lack of a standardized toponymy data format. A further difficulty arose in matching house numbers (punctual data) to the corresponding buildings on the map, as the footprint area of the buildings could extend into more than one cell. The cells with the best match were selected for photo interpretation (see Figure S5).

Figure S5. Validation samples: single cell (at TOP); group of cells (AT bottom).

Validation samples sometimes considered a group of cells rather than just one cell (Figure S5). In The uncertainty was estimated by comparing the number of residents registered at the addresses in the validation data sample (P_{grid}) with the population data assigned to the cell by the dasymetric method ($\widehat{P_{grid}}$). These cells have to be spatially well distributed and selected in order to ensure good spatial coverage with all indicator maps.

Table S2. Uncertainty estimations for the previous dasymetric mapping methodand the new improved method.

Uncertainty Estimation metrics
$MAE = \frac{1}{N}\sum_{n}^{N}\left\|P_{n,grid} - \widehat{P_{n,grid}}\right\|$
$RMSE = \sqrt{\frac{1}{N}\sum_{n}^{N}\left(P_{n,grid} - \widehat{P_{n,grid}}\right)^2}$
$MAPE = \frac{100}{N}\sum_{n}^{N}\left\|\frac{P_{n,grid} - \widehat{P_{n,grid}}}{P_{n,grid}}\right\|$

The collection of reference data for validation purposes is hampered by uncertainty and difficulties. One of these difficulties is that not all statistical offices provide population and toponymy data in standard formats. Automatic tools are available in support of the geocoding of addresses, whose performance depends on the quality of the input data. When the data are available in the right format, the validation methodology can be easily reproduced.

Other ancillary data used for calculating the indicators, were official products, issued by institutional authorities following long processes of verification and validation and after quality checking of the data. Therefore, we assumed that the usage of such data introduced negligible uncertainties.