ABSTRACT
With more than half of the world’s population living in towns and cities, urban areas get more and more into the focus of humanitarian relief organisations such as ICRC, Médecins sans Frontières (MSF), or SOS Children’s Villages. A key information required for almost any intervention is an estimation of the population numbers for the towns and cities where these organisations operate in. As census data are usually not available or outdated, population numbers have to be estimated by alternative methods such as remote sensing. To do that, built-up densities are estimated from high-resolution image data and population numbers are disaggregated proportional to the densities in a top-down approach. Alternatively, population counts per density unit can be aggregated following a bottom-up approach. Both approaches were tested applying normalised Digital Surface Models (nDSM) derived from stereo Pléiade images for Salzburg, Austria and Port-au-Prince, Haiti; the former for testing the quality and stability of the approach in a well-known setting, the latter for testing the approach in a critical environment. Key findings are that satellite-derived nDSMs provide sufficient accuracy for estimating population distributions, as long as reliable information is available for the separation of residential and non-residential urban areas.

Introduction
With more than half of the world’s population living in towns and cities, urban areas get more and more into the focus of humanitarian relief organisations such as ICRC, Médecins sans Frontières (MSF) or SOS Children’s Villages. A key information required for almost any intervention is an estimation of the population numbers for the towns and cities where these organisations operate in. As census data are often not available or outdated, population numbers have to be estimated by alternative methods such as remote-sensing.

In order to obtain a population distribution dataset to be used at a given level, two basic strategies can be applied using GIS and remote-sensing methods. The first strategy is to calculate a local population density for a regular grid or individual buildings, using local data on average occupancy per unit (grid cell/building) in order to come to total population numbers in an area of interest (bottom-up approach); the second strategy is to disaggregate total population numbers available at a higher level (e.g. district or state level) using a high-resolution remote-sensing or GIS layer as proxy for population density (top-down approach). This method is also known as dasymetric mapping (Eicher & Brewer, 2001).

One possible option for a top-down approach is to use a land use/land cover (LULC) classification from a published source, such as CORINE Land Cover data (Gallego, Batista, Rocha, & Mubareka, 2011), Urban Atlas (Batista & Poelman, 2016), or the imperviousness layer provided by Copernicus Land Monitoring Services (Steinnocher, Köstl, & Weichselbaum, 2011). The latter was used to produce a European-wide population grid for Eurostat in the framework of the GEOSTAT project (Eurostat, 2016).

The partition of the population as well as the geographical distribution of the economic value of built-up infrastructures in an urban environment is a fundamental element in the calculation of the risk related to natural disasters. For the Global Assessment Report on Disaster Risk Reduction, (GAR, 2013, 2015), a new approach – integrating population and country-specific residential-non-residential building typology, use and value – was developed in order to generate a global dataset with 5-km spatial resolution (1km for coastal areas) (De Bono & Chatenoux, 2015; De Bono & Mora, 2014). The methodology is based on a multi-layered top-down approach, where data of administrative units are disaggregated to a regular grid by means of ancillary data. Built-up features are characterised in terms of their use and their structure (residential, industrial, commercial, institutional, etc.) and accordingly the population is distributed.

In order to calculate the residential population distribution on a finer, i.e. local scale, very high-resolution satellite imagery (e.g. IKONOS, WorldView, Pléiades)
Increasing of the semantic depth of the classes

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- cusses the in the next chapter. Then, the scenarios for Salzburg Pléiades stereo data for both test sites is presented of di

Prince, Haiti. The former is used to test the impacts the other representing a reality setting in Port-au-

sites are analysed, one providing an optimum setting for urban area modelling based on 3D building models. Two test

above, the presented research focuses on population when using volume-based disaggregation procedures.

All approaches described above assume that a) the population is distributed evenly inside the source zones, b) is living in residential buildings and c) the number of residents per building is dependent on the size of the housing space (Taubenböck & Wurm, 2015).

Based on the findings of the studies described above, the presented research focuses on population modelling based on 3D building models. Two test sites are analysed, one providing an optimum setting in terms of data availability for Salzburg, Austria, and the other representing a reality setting in Port-au-

Prince, Haiti. The former is used to test the impacts of different data combinations and qualities, the latter applying the methods to limited data sets.

The derivation of 3D building models from Pléiades stereo data for both test sites is presented in the next chapter. Then, the scenarios for Salzburg and for Port-au-

Prince are described and a comparison of the results is presented. The last chapter discusses the findings of the study.

Derivation of nDSM

Within this study, height information for urban population estimation is derived from stereo models, which are often the only available data source to derive 3D information (digital surface models, DSM) in the areas where humanitarian relief effort is needed the most. An additional digital terrain model (DTM), derived from the DSM is a pre-requisite for the calculation of normalised nDSM representing the building heights, allowing more accurate population estimations compared to 2D urban area analysis. Stereo-model-derived DSMs have some disadvantages in comparison with surface models derived from airborne laser scanning, mainly a coarser resolution and quality problems if the image pairs are not matching perfectly. The main drawback regarding the derivation of DTMs compared to airborne laser scanning are the missing multiple returns which are hampering the clear identification of ground/non-ground areas, especially in vegetated areas and/or steep terrain. On the other hand, stereo-model derived DSMs from very high resolution (VHR) satellite data have in addition to the 3D information, the spectral value of the images as a source of information for improving the DTM extraction. Within this study, we adapted the approach by Luethje, Tieb, and Eisank (2017), which uses the spectral information of the VHR data to stratify the sampling of ground/non-ground points for the DTM extraction. The spectral information helps therefore to improve the selection of 3D points which represent ground, in order to increase the quality of the calculated DTM. It relies on an object-based image analysis approach (OBIA, Blaschke et al., 2014) to also incorporate topological and non-topological object-relationships in the analysis, and has shown satisfying results compared to LiDAR-derived models.

The following workflow from Luethje et al. (2017) has been applied (cf. Figures 1 and 2) to Pléiades Tri-

stereo satellite imagery and the derived DSMs acquired on 1 September 2015 (Salzburg) and 6 July 2013 (Port-au-

Prince), respectively.

- Initial land cover classification for the four basic classes water, vegetation, impervious surface and shadow based on the spectral information of the satellite images
- Increasing of the semantic depth of the classes regarding the differentiation of elevated and non-elevated areas, by incorporating information from the DSM (surface roughness, local height differences between objects, see Luethje et al., 2017). This results in the land cover (LC) classes: water, vegetation elevated, vegetation flat, impervious flat, impervious elevated (mainly buildings) and clearings within elevated vegetation
- Stratified selection of areas for the DTM interpolation based on the derived LC classes and interpolation of the DTM using the natural neighbour interpolation (based on Voronoi tessellation, Sibson, 1981), suited for heterogeneous point data sets (including gaps)

Figure 2 (right) shows the nDSM result for the Salzburg test area which has been used for the urban population estimation. Some artefacts resulting from the stereo-model-derived DSM are still present; also, the DTM extraction in hilly areas covered by higher vegetation is error-prone (overestimation of terrain in steep slopes, underestimation of vegetation volume in densely vegetated areas and steep slopes). Nevertheless, built-up areas – the focus of this study – were less affected by terrain problems (smaller problems are visible at building borders and shadowed area). The same
approach has been transferred to the study area in Port-au-Prince, Haiti.

Population scenarios for Salzburg

The Salzburg test site was chosen as a test bed due to its availability of complete data sets including independent reference data for population. Five top-down scenarios and one bottom-up scenario were modelled and compared with the reference data set for evaluation.

Data sets

The test site comprises an area of $5 \times 5 \text{ km}^2$ covering the central part of the city of Salzburg (Figure 3, left). The reference data are a population grid with 100-m cell size, representing residential population per grid cell. It is the official population grid provided by Statistik Austria, derived from the population register linked with geocoded address data; the former gives the number of people per household and the latter indicates the location. However, the geocoding in some cases is not on a single-building level: for apartment buildings, inhabitant numbers are attributed to the grid cell containing the street address point of the building, thus causing population shifts between neighbouring grid cells. We corrected manually for obvious displacements, but there might be inconsistencies left in the reference data set that will have a slight impact on the evaluation of the scenarios.

The data used for the development of the scenarios comprise two different nDSMs – one based on Lidar and the other on Pléiades stereo imagery. Figure 3 (right) shows the Pléiade-derived nDSM intersected with the building footprints from Open

Figure 1. Initial land cover classification based on spectral information and increased semantic depth (elevated/non-elevated land cover classes), by including DSM and DSM derived information (left). Right image: impervious elevated (red colour), impervious flat (grey colour), vegetation elevated (dark green), vegetation flat (light green), water (blue), clearing within elevated vegetation (pink).

Figure 2. Stratified sampling (selection of non-elevated areas based on the initial classification) as basis for the DTM interpolation (bright areas, left), final nDSM (right).
Street Map – OSM. Additional data comprise ancillary polygon and point data, satellite imagery and the SAR-derived Global Urban Footprint – GUF (Esch et al., 2017, 2012) provided by the German Aerospace Centre DLR. A detailed list of the used data sets is given in Table 1.

Based on these data sets, the following top-down scenarios were developed:

- scenario 1: Complete 3D, using 3D building models and all ancillary data sets
- scenario 2: Complete 2D, using building footprints and all ancillary data sets
- scenario 3: Limited 3D, using 3D building models and a limited set of ancillary data
- scenario 4: Limited 2D: using building footprints and a limited set of ancillary data
- scenario 5: Alternate scenario, using GUF and a limited set of ancillary data

In addition, a bottom-up scenario was developed, using 3D building models and all ancillary data sets.

**Methodology**

All top-down scenarios (Scenarios 1 to 5) followed the same methodology for population modelling.

First, the geometry of the buildings was modelled – either as building blocks for the 3D buildings or as footprints for the 2D building representation. Next, residential buildings were selected by excluding buildings with non-residential use, such as commercial and industrial areas, office buildings or public service facilities. For the “Complete” scenarios (Scenario 1 + 2), geocoded company data and zoning information were used, leading to a very precise selection of non-residential buildings. For the “Limited” scenarios (Scenario 3 + 4), visual interpretation of satellite imagery was used to define non-residential areas, which only allows the detection of larger commercial or industrial areas, thus providing a less precise selection of non-residential areas. For the final selection buildings with a height of less than 2.5 m and/or an area less than 25 m$^2$ were excluded, as they are not likely residential buildings but rather auxiliary buildings such as garages.

The distribution of the population starts from the total number of population calculated by summing up all population numbers per grid cell of the reference data. This total is then disaggregated to the selected residential buildings weighted per volume (3D) or area (2D) of the buildings. The resulting building layer provides the number of persons per building, which are then aggregated to the regular population grid.

**Table 1.** Data sets used in the development of scenarios for the Salzburg test site.

| Input data sets          | Data source                                      | Data type     |
|--------------------------|--------------------------------------------------|---------------|
| nDSM                     | Lidar (acquired 2016)                            | Grid, 1 m/cell|
| nDSM                     | Pléiades, tri-stereo, (01/09/2015)               | Grid 2 m/cell |
| Satellite data           | Pléiades acquisition date (01/09/2015)          | Image 0.5 m/cell|
| Building footprints      | Open Street Map (OSM, 2017)                      | Polygon       |
| Zoning data              | Salzburg administration (Salzburg, 2017)         | Polygon       |
| Geocoded company data    | Company Database (Bisnode, 2016)                 | Points        |
| Global Urban Footprint   | DLR                                              | Grid, 12m/cell|
| Reference Data set       | Data source                                      | Data type     |
| Population grid          | Statistik Austria (2017)                         | Grid 100 m/cell|
grid for comparison with the reference data as described in the next chapter. Figure 4 shows the workflow for the first four scenarios.

The development of the “Alternate” scenario 5 follows a slightly different approach, as the input data are not building structures but a 2D built-up grid represented by the GUF. As the name says, Global Urban Footprint is a globally available data layer of human settlements. It has a spatial resolution of 12 m/pixel and was calculated from TerraSAR-X data with an original resolution of 3 m/pixel, collected between 2011 and 2012 (Esch et al., 2017). It is a binary layer with the values “settlement” and “not settlement”. An improved version of this product is the so-called GUF-DenS, that provides built-up densities for the settlement areas of the original GUF. The GUF-DenS was used as input for the Alternate scenario. For the selection of the residential areas, the GUF-DenS was masked with the same visually interpreted land use data that were used for the “Limited” scenarios. The outcome is a residential density grid that is used for disaggregating the total population of the test site. Figure 5 shows the workflow for the “Alternate” scenario.

While the methodology for the top-down scenarios follows a general approach that is easily transferable to other cities, the bottom-up approach requires specific input data such as building typologies and population per building type. Based on the selection of residential buildings from the “Complete 3D” scenario, we differentiate between three building types – single family houses, row houses/apartment buildings, and high-rise buildings. Based on statistics of household sizes and average apartment sizes, different population densities are estimated for these building types. For the calculation of the bottom-up scenario, the volume of each residential building is multiplied by the estimated population density of its building type thus leading to population numbers per building for the entire test site. Figure 6 shows the workflow for the bottom-up scenario.

**Evaluation**

For evaluation, the scenarios are compared to the reference population grid. The comparison is performed on a cell per cell basis, not considering neighbouring cells. Figure 7 shows the difference grids between four scenarios and the reference grid. All four scenarios show a general pattern with an underestimated population in the northern part of the area and an overestimated population in the very centre of
the city. Scenario 1 gives the best results, as expected, as all available data sets were used. Scenario 3 (Figure 7, upper right) has a strong overestimation in the city centre, that is due to high buildings and limited information on building use – i.e. the entire centre is assumed to be residential areas. In scenario 4 (Figure 7, lower left), the overestimation of the centre decreases, as the no information on building heights is considered (2D scenario). Finally, the alternate scenario based on the GUF is comparably good, taking into account that only built-up densities are considered.
For quantitative analysis the total relative error (TRE) was chosen as a measure of deviation (Goerlich & Cantarino, 2013):

$$\text{TRE} = \frac{\sum |\text{Pop}_{\text{ref}} - \text{Pop}_{\text{est}}|}{2 \times \sum \text{Pop}_{\text{ref}}}$$  

(1)

The TRE calculates the absolute difference between the estimated ($\text{Pop}_{\text{est}}$) and the reference population ($\text{Pop}_{\text{ref}}$) per grid cell, adds up the differences and normalises the result. This measure is a good indicator for comparing grids, but is limited as an absolute error measure, as it does not account for population displacements between neighbouring grid cells. To compensate for this drawback, we made the comparison on two aggregation levels: first on the original 100 m cells, then on aggregated 500-m grid cells. Table 2 shows the TRE for all scenarios, also indicating the difference between nDSMs derived from Lidar and from Pléiades.

Looking at the general trend of TREs in Table 2, it is obvious that the availability of good ancillary data has the strongest impact on the quality of the scenarios. The “Complete” scenarios are better than the “Limited” and the “Alternate”. The difference between Lidar and Pléiades based nDSMs is not significant – independent from the scenario – thus indicating that the quality of the tri-sensor derived-models is clearly sufficient for population modelling. On the other hand, there is a significant difference between the 2D and the 3D scenarios – in particular between the “Complete” 2D and 3D scenarios. This seems to be self-evident – as the height of buildings obviously has an impact on the number of people living in it – and holds for the “Complete” 2D and 3D scenarios, but is less distinct for the “Limited” scenarios. The underlying reason is the limited information on land use that leads to non-residential buildings being included in the disaggregation process. If these buildings are high, their erroneous impact is stronger in the 3D scenarios than in the 2D scenarios. The “Alternate” scenario is in the range of the “Limited” scenarios, indicating that the GUF is a valuable alternative to building models for the population modelling approach. Finally, the bottom-up scenario delivers results that are close to the best, but are the costliest ones in terms of labour and input data, because average household sizes would have to be estimated from field surveys.

**Population scenarios for Port-au-Prince**

Port-au-Prince was selected as a test site in order to test built-up living space modelling in a more data-scarce environment commonly found in humanitarian relief organisations activities. Due to the humanitarian activities following the earthquake of 2010, at least some datasets are available, including a Lidar DSM. Seven bottom-up scenarios and one top-down scenario were modelled. As no population grid was available comparable to the data on Salzburg, which could have been used as a reference to the data on Salzburg, which could have been used as a reference dataset to validate these scenarios against, the scenarios were evaluated relative to the most sophisticated scenario, which was considered to yield the best results.

**Data sets**

A large set of ancillary data and documents were collected and viewed as input data. It is important to underpin that the lack of reliable survey data on occupancy has prevented the possibility to estimate correctly and validate the final value of the population. Instead, only the living space (building area multiplied by the assumed number of storeys) was modelled, except for the top-down scenario based on GUF.

The most detailed data on population numbers is the OCHA-Haiti, 2015 census, which provides an estimation of the total population distribution in Port-au-Prince by administrative units, with a resolution up to level 3 (“sections”). Table 3 gives an overview of the datasets used for the development of scenarios. Unfortunately, these data have a scattered spatial distribution for the Port-au-Prince region. This has led to focus the analysis in three study areas (Car, Pap and PaPout) where nDSM was available (Figure 8).

The following observations emerge from the overlay of these data sets and satellite imagery:

1. OSM only partially covers the Port-au-Prince region, and overlay PaP and PaPout in a very small percentage of the area
2. The various data related to building location points and footprints do not overlap properly, leading to over or under-estimation (depending on the area)
3. Population data are only available at administrative unit level 3
4. None of the study areas contains an entire administrative unit at level 3
5. Reliable local survey data are absent (e.g. roof area per person), therefore a bottom-up population...
estimation depends on literature (such as Aminipouri, Sliuzas, & Kuffer, 2009; Hillson et al., 2014), or “expert knowledge.”

(6) Copernicus EMSR185 data clearly overestimate residential buildings. To be able to use this data, a visual correction (using Digital Globe imagery through Google) was performed, excluding at least those buildings from the residential areas that are clearly not of residential use.

Consequently, the present analysis focuses on modelling the built-up living space (surface or volume, depending on the scenario). Resulting data could easily be used as a proxy for population distribution by applying an appropriate number of people living in a given space, if either the total number of people living in a given study area, or the number of people living in a selection of neighbourhoods are available (Checchi, Stewart, Palmer, & Grundy, 2013).

Moreover, it was not possible to carry out a top-down scenario using the nDSM due to the mismatch of extension of population at administrative level and imagery (as reported in point 4 of the previous list).

Based on the ancillary data availability and quality, seven bottom-up scenarios were developed; their workflow is detailed in Figure 9. Table 4 presents an overview of the scenarios composition and on which study area they were applied. Due to the lack of a reference dataset, the scenario 1 is named “Reference” as it takes advantage of all (presumably) “best” data available (including building use from Copernicus EMSR185, 2016). This is the scenario that will be used as reference, and compared to the following scenarios.

Complete scenarios take advantage of OSM footprints data with Lidar nDSM in the case of the 3D version. Lidar scenarios derive both building footprints and building heights by Lidar nDSM, without using OSM footprints. 2D versions only use built-up footprints derived from the nDSM as a replacement of OSM. Pléiades scenarios are defined similarly, but use the Pléiades nDSM instead of the Lidar nDSM.

A supplemental scenario was generated using a top-down approach (Figure 10). It downscales OCHA level 3 population level to block level, using GUF data and a vegetation mask. This last scenario simply

Table 3. Data sets used in the development of scenarios for the port-au-prince test site.

| Data set                          | Data source                                      | Data type      |
|----------------------------------|--------------------------------------------------|----------------|
| nDSM                             | Lidar World Bank (2010), Pléiades tri-stereo     | Grid, 0.5 m/cell|
|                                  | imagery (6/7/2013)                               | Grid, 0.5 and 2 m/cell |
| Building footprints of the city  | Open Street Map (OSM; 3/10/2017)                 | Polygon        |
| Zoning data                      | Not available                                    | –              |
| Geocoded company data            | Not Available                                    | –              |
| Satellite data                   | Digital Globe, Google                            | Image          |
| Global Urban Footprint           | DLR                                             | Grid, 12 m/cell|
| Building typology, residential vs non-residential | Copernicus EMSR185                             | Points         |

Figure 8. Overlay of areas of available geospatial datasets for Port-au-Prince test site.
called “top-down scenario” can be compared with Salzburg scenario 5 (alternate).

**Methodology**

The reference-modelling units correspond to true subdivisions of the field and are based on neighbourhoods or building blocks (called here simply blocks). All the results of the different analyses are aggregated and integrated into the blocks. Blocks were created by using linear features (roads and waterlines) from the OSM layers by aggregating each block until its area reaches a given minimum value. They were generated at several scales (15,000, 10,000 and 5,000 m²). The scale of 5,000 m² was used for the modelling. Results were then aggregated at other scales. Using blocks has several advantages:

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**Table 4. Overview of scenarios and application sites.**

| Model       | Scenario number | Name       | Geographic areas & nDSM used | Car   | PaP   | PaPout |
|-------------|-----------------|------------|-------------------------------|-------|-------|--------|
| OSM + nDSM  | 1               | Reference  | OSM & Lidar                  | OSM & Lidar | OSM & Lidar | OSM & Lidar |
|             | 2               | Complete 3D| OSM & Lidar                  | OSM & Lidar | OSM & Lidar | OSM & Lidar |
|             | 3               | OSM 2D     | OSM                           | OSM   | OSM   | OSM   |
| Lidar       | 4               | Lidar 3D   | Lidar                        | Lidar | Lidar | –      |
|             | 5               | Lidar 2D   | Lidar                        | Lidar | Lidar | –      |
| Pléiades    | 6               | Pléiades 3D| –                            | –     | –     | Pléiades |
|             | 7               | Pléiades 2D| –                            | –     | –     | Pléiades |

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**Figure 9.** Workflow for bottom-up scenarios of Port-au-Prince test site.

**Figure 10.** Workflow for top-down scenario of Port-au-Prince test site.
blocks are more realistic than a virtual grid as they are created using physical features existing in the real world.

- road features in OSM data are generally quite complete and available worldwide, and even if missing, they can be quickly digitalised using existing imagery: this approach is therefore exportable in other parts of the world.

- each block can be categorised on the base of the type of building, percentage of vegetation, etc., allowing the end users to apply different parameters during the estimation of the population distribution.

- organisations active on the field can easily perform surveys on a representative selection of blocks in order to evaluate and calibrate the population distribution model.

- moreover, blocks are customisable and they can be easily modified to meet the specific needs of a particular neighbourhood.

**Top-down approach based on GUF**

The top-down approach based on GUF-DenS represents a simple alternative to using rather complex 3D data, OSM and building use data. It uses the GUF density layer as a proxy to spatially distribute the total population numbers at admin level 3. These total population numbers stem from OCHA-Haiti, 2005). More sophisticated models involving harder-to-get data such as nDSMs and building use therefore have to exceed the accuracy of the GUF-based model to justify the added effort required for their set-up and calculation.

In order to use the GUF-DenS as a proxy for population densities a conversion factor was calculated. The conversion factor is the ratio between the total of all GUF-DenS cell values within an administrative unit and the total population of that unit. Even if the average conversion factor is 8.9, large variations exist in a few administrative units (28.6 in Bellevue and 117.8 in Montagne noire). Although such large differences remain unexplained, none of the selected study areas intersects with them and consequently do not affect our study. Finally, the population of each block was divided by its area in order to get the population density (Figure 11).

**Bottom-up approaches**

Built-up surfaces were extracted from the Lidar and Pléiades nDSMs generated within the frame of this project by performing a segmentation with GRASS GIS software using nDSM combined with derived products such as variance (https://grass.osgeo.org/grass74/manuals/r.neighbors.html), generalisation (https://grass.osgeo.org/grass74/manuals/v.generalize.html) and aspect (https://grass.osgeo.org/grass74/manuals/r.slope.aspect.html). Multi-spectral layers were not used as they did not improve significantly the results and slowed down the segmentation process.

Before running the segmentation process, a mask was applied into filter out structures with elevations below 1.8 m (which are not considered living quarters) and vegetation (based on NDVI). Once the building surfaces were obtained, several elevation parameters were calculated for each of them (minimum, maximum, average, standard deviation) in order to generate the built-up volume.

![Figure 11. Population density per block calculated from GUF and population by administrative level 3.](image-url)
All bottom up scenarios followed the same methodology for living space modelling: the only difference is the amount/quality of data available. The first step consists of the integration of the nDSM geometric data: roof surface and height with all the other available elements: building footprint, building use and a vegetation mask. All buildings higher than 1.8 m were considered as inhabitable. In the case of scenarios 1, 2 and 3, OSM buildings provide reference and consequently the nDSM data are transferred on the OSM footprints.

In the second step, the number of floors is calculated from the building heights, based on the references given in Alahmadi, Atkinson, and Martin (2013). The last step consists of the aggregation of all data to block level. Finally, for each block, it is possible to obtain:

- ground surface
- built-up density
- living space for 3D scenarios (taking into account the number of floors)
- number of buildings (scenarios including OSM only)
- fraction of surface covered with vegetation
- fraction of surface covered with low build-up structures like roads, courts, parking lots, etc.

The living space calculated using the building footprint from OSM and the heights from nDSM (scenarios1 and 2) and those calculated using only the nDSM present quite good correlations (Figure 12) that will allow a more correct evaluation of the volumes in those areas where OSM is not present.

The living spaces calculated using OSM footprints and building heights from Lidar are generally slightly lower than the living spaces calculated from Lidar alone, but the correlation is high. The blocks were successively differentiated into four classes based on the fraction of vegetated and built-up surfaces using the 25th, 50th and 75th percentiles, from high-density low vegetated to low-density low vegetated. Finally, if robust data on the living area per person (“roof area”) are available, preferably stratified according to the type of block, it is possible to calculate the number of inhabitants per block using the following formula (Aminipour et al., 2009):

\[
\text{TRE} = \frac{\text{EBA}}{\text{RAP}}
\]

With: \(\text{TRE}\) = Total Estimated Population; \(\text{EBA}\) = Total Extracted Building Areas; \(\text{RAP}\) is the Roof Area per Person.

**Comparison of the results and discussion**

The comparison of the results of the various scenarios was done on the blocks evaluated as having a satisfying OSM building coverage, as the reference model rely highly on this dataset.

TRE was calculated, as in the Salzburg section, for the different scenarios and study areas at each level of blocks aggregation (see Table 5). Due to the lack of reference data set, the Reference scenario was used as reference for the TRE calculation. The error calculation could only be performed in selected areas of interest, where the data availability was sufficient. Following conclusions emerge:

- top-down scenario shows always by far the worst TRE values
- TRE values for Complete 2D scenario in PaPout study area are much lower than in other locations, this could be due to a low number of blocks with satisfying OSM coverage in PaPout
- TRE values of Complete 3D scenario are very close to the reference scenario, which indicates that the building use parameter do not influence much the model. This is probably due to a lack of representativeness of the building use parameter, as it was evaluated as overestimating residential buildings at the beginning of the project
- there are no large TRE differences between all other scenarios (TRE values range between 15 and 23%)
- level of blocks aggregation did not show significant changes in TRE values

The various scenarios were constructed taking into account the progressive lack of data. Considering the PaP and PaPout sectors, only a part of their surface is effectively covered by OSM + nDSM (scenarios 1 and 2). Nonetheless, considering the correlations between the blocks’ surfaces calculated with OSM + nDSM and those calculated only with nDSM (Figure 12), it is possible to estimate, based on these correlations, the values of the surfaces for those sectors where OSM is not present.

Several sources of uncertainties were identified during the study. In its current state, building use data (EMSR185, Copernicus) is not representative of the reality and has no significant influence on the model, probably because most of the analysed sectors include mainly residential dwellings and a manual correction was made for the less residential neighbourhoods. Mixed building use (commercial and residential use in the same building) should also be considered in a context such as Port-au-Prince. The estimation of number of storeys from building heights is also a source of incertitude. nDSM analyses should be always coupled with 2D digitalised buildings (ex OSM) in order to calibrate the system. Pléiades (Tri-stereo) imagery shows a reliability comparable to those of Lidar.

Further developments could be done together with GIS analysts and field workers, by organising...
targeted survey in the field after a solid categorisation of block types. Such survey should allow to precise the point mentioned above as well as define the proper factor in order to estimates population from living space or volume.

**Conclusions**

The objective of this study is to test the feasibility of Pléiade-derived nDSMs for the estimation of residential population distribution in urban areas. Two test sites are analysed, one providing an optimum setting in terms of data availability for the city of Salzburg, Austria and the other representing a reality setting in Port-au-Prince, Haiti.

The feasibility study of Pleiade-derived nDSMs is fundamental for the estimation of population in crisis areas as support for humanitarian organisations. It showed that it is possible to obtain comparable results from satellite imagery as can be derived from Lidar nDSMs but for minor costs. The experiment in Salzburg proved the

**Table 5. Total relative error – TRE of scenarios per aggregation level 5,000 m².**

| Number | Scenario   | Car  | PaP  | PaPout |
|--------|------------|------|------|--------|
| 2      | Complete 3D| 3.2% | 2.9% | 2.1%   |
| 3      | OSM 2D     | 12.8%| 17.1%| 29.8%  |
| 4      | Lidar 3D   | 15.0%| 22.8%| –      |
| 5      | Lidar 2D   | 15.3%| 16.5%| –      |
| 6      | Pléiades 3D| –    | –    | 18.8%  |
| 7      | Pléiades 2D| –    | –    | 20.5%  |
| –      | Top down (GUF)| 37.4%| 48.2%| 37.6%  |
general quality of the chosen approach, although the data availability will always be limited in crisis situations.

The analyses of the Salzburg test site proved the feasibility of Pléiade-based nDSMs and derived building models for population modelling. There is no significant difference between Lidar- and Pléiades-based nDSMs and derived population distributions. The impact of using 3D building models instead of 2D building footprints is positive, but only if building use is known and residential buildings can be selected for modelling. If urban land use is only generally available, the use of building heights might cause larger errors than applying 2D information.

The GUF, representing 2D built-up areas, in combination with general information on urban land use proves to be a valuable alternative, if nDSMs are not available. Finally, the bottom-up method, where population densities per housing type are estimated from field surveys or statistical data on households and aggregated to larger urban areas, delivers very good results for population modelling, but is the costliest approach in terms of labour and input data.

The main purpose of the work, in the test site Port-au-Prince, lies in providing and testing a methodology for the rapid estimation of urban populations in a crisis situation, using available data. The development of a simple and rapid methodology for dividing the urban area in neighbourhoods (blocks), based on the use of physical features existing in the real world, represents an effective tool. The blocks can greatly facilitate subsequent work on the ground, focusing on the most significant sectors for the collection of statistical data samples. The use of local and reliable survey data would have allowed going further and being able to calculate and above all validate the population using a bottom up approach.

Unfortunately, due to lack of reliable data, it was not possible to produce figures with respect to the population, but on the other hand, an essential result was achieved with regard to the calculation of the available living space: The combination of OSM building footprints and nDSM produced results with satisfactory relative error margins.

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