BACKGROUND PAPER

Prepared for the Global Assessment Report on Disaster Risk Reduction 2015

BUREF – PRODUCING A GLOBAL REFERENCE LAYER OF BUILT-UP BY INTEGRATING POPULATION AND REMOTE SENSING DATA.

Martino Pesaresi*, Sérgio Freire

European Commission, Joint Research Centre,
Institute for the Protection and Security of the
Citizen; Ispra, Italy

*Corresponding author
(martino.pesaresi@jrc.ec.europa.eu)

30 May 2014

Table of Contents

Abstract

The Global Built-up Reference Layer (BUREF2010) is a spatial raster dataset containing an estimation of the distribution and density of built-up areas using publicly available global spatial data related to the year 2010. In particular, satellite-derived land cover information and population density grid are used within a raster model to infer, per each spatial unit, the percentage of land occupied by buildings. The paper briefly outlines the rationale, the most important methodological steps adopted for the production of BUREF and some examples of outputs.

Introduction and rationale

Global estimation of built surfaces is needed for a variety of applications spanning from climate change adaptation, economical growth monitoring, human ecological footprint analysis, to urban and regional planning. In the context of disaster risk and crisis management, geoinformation on built-up and settlements is required for exposure mapping, and damage and risk assessment. Maps showing the location and extent of built-up areas are especially vital to produce high quality and updated information concerning patterns and processes occurring in the urban environment (Potere and Schneider 2007).

The original purpose of BUREF2010 was to contribute as prior knowledge information used during automatic mapping tasks to produce the global fine-scale human settlement layer. In particular, BUREF was designed as training set in support to the machine learning phase during the automatic image information retrieval tasks applied to high and very-high satellite images input (Pesaresi et al., 2013). More specifically, the purpose was related to i) the calibration of the heterogeneous HR/VHR input data based on information contents, ii) training set collection functional to the learning/classification tasks, and iii) automatic ranking of the information outputs and mosaic of multi-scene processing.

At the time of the study, the most spatially accurate urban global information layer publicly available was created from classification of Moderate Resolution Imaging Spectroradiometer (MODIS) data circa 2001-2002, having a nominal spatial resolution of 463 m (Schneider, Friedl, and Potere, 2009). According to the intentions of the authors, the MODIS Urban Land Cover layer reports about "areas dominated by built environment (coverage >50%), including non-vegetated, human-constructed elements, with minimum mapping unit > 1 km^2". The MODIS "Urban" layer is coded as binary mask reporting the presence or absence of the "Urban" land cover.

For use in the global fine-scale human settlement modeling, the MODIS "Urban" layer shows some drawbacks originated by both sensor technology and data processing methodology applied. More explicitly, the combination of sensor spatial resolution, the minimal mapping unit size and the thematic "dominance" rule translated to a binary map produces a large underestimation of built-up areas in specific settlement patterns. In particular, areas displaying scattered settlements and/or complex mixture of rural-urban uses are expected to be excluded or largely underrepresented in the MODIS "Urban" layer (see Figs. 1 and 2).

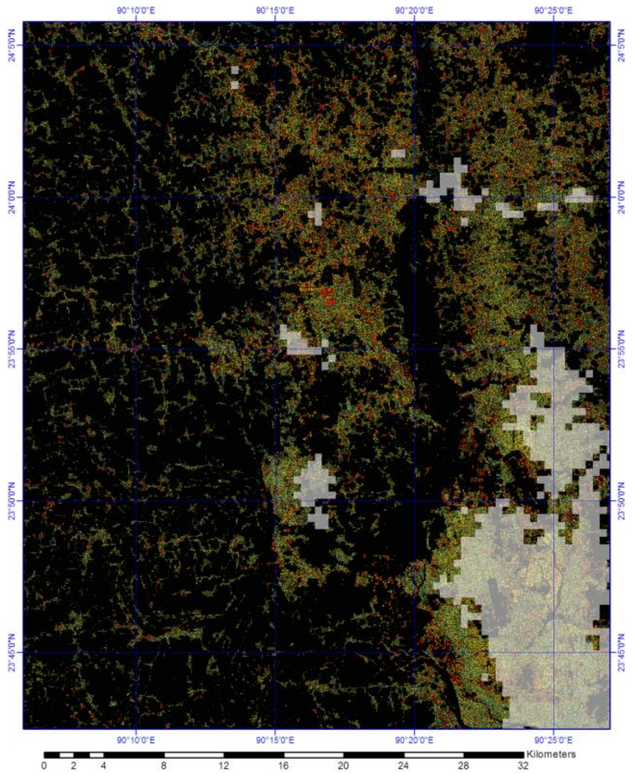

Figure 1 : City of Dhaka, Bangladesh. In white transparency the "urban" areas as reported by the processing of MODIS satellite data (500-m-resolution) (Schneider, Friedl, and Potere, 2009), while the colored dots are built-up structures as detected using high-resolution input imagery (2.5-m-resolution) (Pesaresi et al. 2013). Note the large amount of information related to built-up areas not reported in the low-resolution dichotomy declared in the "urban" layer.

Figure 2 : North of Dhaka, Bangladesh. Detail of the typical settlement pattern not reported in the low-resolution dichotomy declared in the MODIS "urban" layer, despite the fact that a clear dominance of human presence on the ground can be observed using high-resolution sensors. Note how the pattern is connoted by a mixture of

urban / rural residential, productive, and agricultural use, with rural residential structures often spatially related to the presence of trees.

There is a scale gap between (coarse) sensor/model resolution and the size of the elements of interest composing the settlement surfaces at fine scale, such as single buildings and roads. This loss of information may be mitigated by relying on quantitative, continuous geoinformation layers.

Population gridded datasets are semi-continuous information layers reporting the presence of population per regular raster cells (see Deichmann, 1996). The presence of population is strongly linked with the presence of buildings: consequently also global population grids can be potentially used as input for inferring the presence of built-up areas.

There are two main projects that have been producing global population grids: the Gridded Population of the World (GPW) (Balk et al., 2006) and the LandScan Global Population Project (Dobson et al., 2000). LandScan represents ambient and not residential population, but its combination of model approach and higher spatial resolution (0.5 arc-minute vs 2.5 of GPWv3) favor it over GPW 'in places where the census data are spatially coarse and not recent' (NRC, 2007). However, when using LandScan 2010 population grid as input for global estimation of continuous built-up areas, one major difficulty must be addressed: the built-up/population relation embedded in the model is not made explicit and it is merged with other criteria (roads, slope, land cover, administrative units) with no explicit rules available. As corollary of the above, the built-up/population relations are not spatially invariant: consequently global population thresholding or rescaling techniques are not expected to provide consistent results.

The solution adopted for the BUREF2010 production rely on adaptive techniques discovering the built-up/population relations embedded in the population grid, by using an independent and globally-consistent reference layer for systematic comparison. Locally-adaptive methods are expected to mitigate drawbacks that would be generated by direct global population thresholding techniques.

Method

The method uses machine learning techniques to understand the best population thresholds translating population densities to built-up densities. In the proposed methodology the MODIS Urban Land Cover (ULC) 500 m (C5) made by satellite data of the year circa 2001-2002 is used as training set for classification of the LandScan 2010 Global Population Database (LS). Similar techniques are described in Pesaresi et al. (2013) and Gueguen (2014) for the purpose of finding best rescaling parameters translating remote sensing image-derived features to a high-level-abstraction semantic as "built-up areas".

Figure 3 shows the workflow applied in this approach. There are three main processing streams contributing to the final output: two learning and classification processes using ULC as training set (Buref A, B), and one process selecting the information of interest by the definition of prior heuristics (Buref C). The purpose of the processes A, B is to discover general trends in the built-up/population relationships in order to discriminate between background and foreground information. A double inferential approach (A, B) starting from different BU/NBU hypothesis is used in order to improve robustness of the final output. The purpose of the process C is to filter the effect of undesired spatial criteria embedded in the LC model as for example the influence of roads in the spatial population distribution.

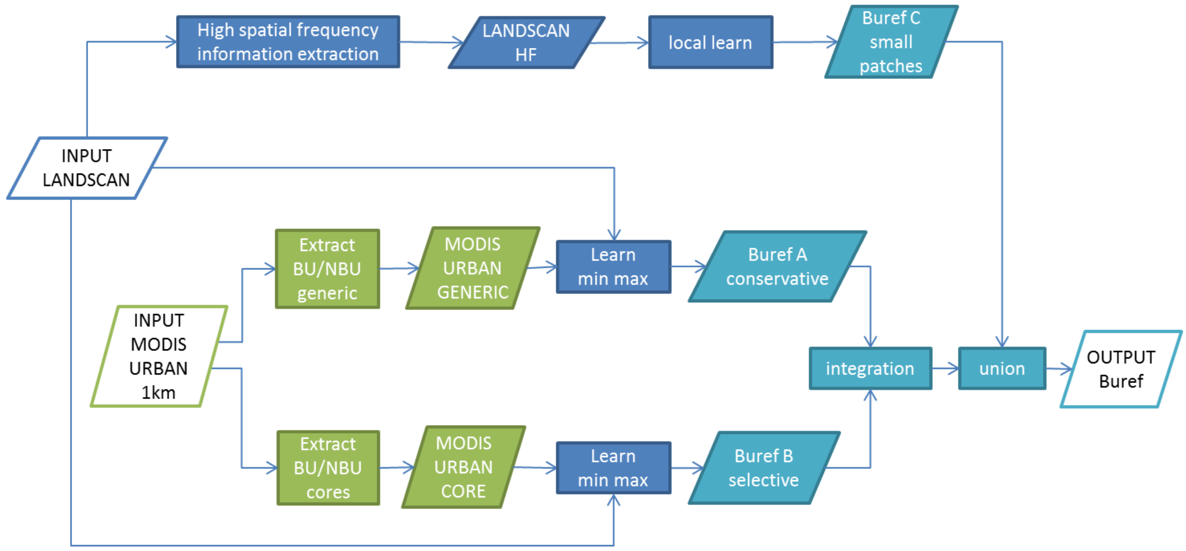

Figure 3 : Workflow applied for the production of BUREF

In order to prepare the ULC for its role as training set it is re-sampled at the same resolution of the LS population grid (30 arc-seconds, WGS84) by summing the binary ULC values falling in the same LS spatial unit (cell). This process ends with a reference "urban" layer (RUL) derived from ULC and reporting about the percentage of urban surface per LS spatial units in the range of [0 to 4] (see Fig. 4).

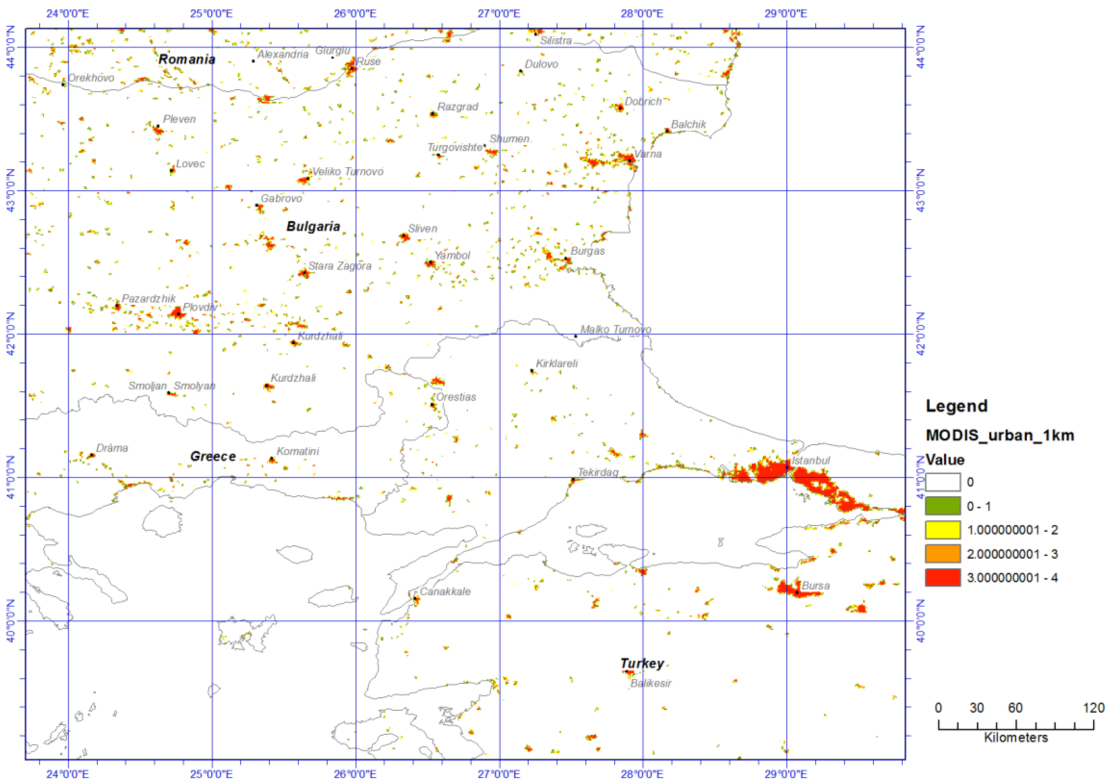

Figure 4 : The MODIS "Urban" layer aggregated at ~1km resolution by sum of the binary values. Parts of Romania, Bulgaria, Greece and Turkey are shown.

This reference information is used for generating two training sets, namely "MODIS Urban Generic" (A) and "MODIS Urban Core" (B), formalizing two different built-up/not-built-up (BU/NBU) prior hypothesis.

In particular, the A learning set is defined as $\mathrm{A} = \begin{cases} \mathrm{BU: RUL} \in [2{,}3] \\ \mathrm{NBU: RUL} \in [0] \end{cases}$. The B learning set is derived from A by adding more conservative bounding conditions. More specifically, i) the $\mathrm{BU_B}$ set must be 3 km away from $\mathrm{NBU_A}$, and ii) the $\mathrm{NBU_B}$ set must be 10 km away from $\mathrm{BU_A}$. In this way, the option B consider as positive/negative samples of BU areas only the inner cores of large urban areas and the inner cores of large not urbanized areas, respectively.

The {A, B} learning sets are used to estimate two *bu = f(pop)* functions using the following formula:

$$\mathrm{BU}_{\{A,B\}}(\mathrm{x}) = \frac{\left(\mathrm{POP(x)} - \bar{\mu}\mathrm{POP}_{\mathrm{NBU}_{\{A,B\}}}(\mathrm{x})\right)}{\left(\bar{\mu}\mathrm{POP}_{\mathrm{BU}_{\{A,B\}}}(\mathrm{x}) - \bar{\mu}\mathrm{POP}_{\mathrm{NBU}_{\{A,B\}}}(\mathrm{x})\right)} \tag{1}$$

bounded in the range $\mathrm{BU}_{\{A,B\}}(\mathrm{x}) \in [0..1]$ with $\bar{\mu}\mathrm{POP}_{\mathrm{BU,NBU}_{\{A,B\}}}(\mathrm{x})$ denoting the average values of population in the built-up and not-built-up spatial domains of the A,B learning sets.

The integration of the two hypothesis of built-up density $\mathrm{BU}_{\{A,B\}}(\mathrm{x})$ obtained by the two learning sets is carried out by a continuous (grey-scale) morphological reconstruction-from-marker algorithm (Vincent, 1993). Assuming two raster data sets (images) X and M, the grayscale reconstruction $\rho_X(\mathrm{M})$ of X from the marker M is obtained by iterating grayscale geodesic dilation of M "under" X until stability is reached, i.e.: $\rho_X(\mathrm{M}) = | \bigvee_{n\geq 1} \delta_x^{(n)}(\mathrm{M})$. In the method discussed here the reconstruction of the $\mathrm{BU}_{\{A\}}$ function is performed from the marker $\mathrm{BU}_{\{B\}}$. The operation propagates the built-up information inferred from conservative training set hypothesis to the connected regions of built-up inferred from more general hypothesis. The expected effect of the operation is an overall increase of the robustness of the overall built-up estimation model. The integrated layer is denoted as $\mathrm{BU}_{\{A*B\}}(\mathrm{x}) = \rho_{\mathrm{BU}_{\{A\}}}\left(\mathrm{BU}_{\{B\}}\right)$

In addition to $\mathrm{BU}_{\{A,B\}}$, a third process generating $\mathrm{BU}_{\{C\}}$ selects the information of interest by the definition of prior heuristics. In particular, the objective of this phase is the detection of the information about the presence of small villages if it is available in the LS source. The operation consists in a high-spatial-frequency band-pass filtering of LS by morphological transforms formalized trough the so-called morphological connected operators or filters by reconstruction (Salembier and Serra, 1995). In particular, the area open (Vincent, 1992) transform $\gamma_\omega^a(\mathrm{f})$ is used for selecting small, relatively higher-value ("brighter") connected components or "regions" in the LS data. In the current implementation, the following formula is applied:

$$\varepsilon = \mathrm{LS} - \gamma_{\omega=2}^a(\mathrm{LS}) \tag{2}$$

This is a “top-hat” filtering by connect component of size 2 pixels corresponding to approx. 2 square kilometers in the LS raster data. The population distribution statistics are observed in the spatial domain defined by a neighboring of 5 kilometers around the $\varepsilon > 0$ set and compared with available RUL density knowledge. Finally, the $\mathrm{BU}_{\{C\}} = f(\mathrm{LS} \in \omega)$ is estimated by bounding the minimal built-up density assumed for small villages by basic heuristics.

The final BU layer is calculated as the union of the three inferential streams. More precisely the final $\mathrm{BU}(x)$ is calculated as

$$\mathrm{BU}(x) = \max\left(\rho_{\mathrm{BU}_{\{A\}}}\left(\mathrm{BU}_{\{B\}}\right),\ \mathrm{BU}_{\{C\}}\right) \tag{3}$$

Let be the general $\mathrm{BU} = \pi(\mathrm{LS}, \mathrm{ULC})$ function estimating the amount of built-up from LandScan (LS) using MODIS “urban” (ULC) as training set as described above. The function π can be estimated using as input the whole global dataset or a sub-spatial domain K of it. In the second case, the output $\mathrm{BU}(X_K)$ will be generated for each K sub-spatial domains making the function π adaptive to local conditions (Equation 4).

$$\mathrm{BU}(X_K) = \prod_{k=1}^{n}\{\mathrm{BU} = \pi(\mathrm{LS}_k, \mathrm{ULC}_k)|k \in K = |1..n|\} \tag{4}$$

In the specific implementation discussed here, a local kernel of K = 500 x 500 pixels (~500 x 500 kilometers) was used for estimation of the π function. In order to improve smooth transitions between π functions estimated from adjacent kernels and prevent “blocking” effects in the final output, an overlapping factor of 50% (250 pixels) in all four directions of adjacent kernels was applied.

Results

The developed approach outputs a global raster layer representing both the spatial distribution and density of built-up areas, for the year 2010. The information about the presence of built-up is expressed as the percentage of built-up area respect to the total surface of the cell. Values are expressed in the range [0 to 100]. The layer is made available as a grid having a spatial resolution of 30-arc seconds (approximately 1 km at the equator), in the WGS84 coordinate system. Being available as a quantitative, continuous raster dataset significantly increases its value by facilitating integration with other spatial datasets for analysis or modeling (Freire, 2010).

Figures 4-6 illustrate differences between input layers and the BUREF2010 output, for an area including part of Romania, Bulgaria, Greece and Turkey. Figure 5 clearly shows how patterns change with administrative borders (i.e., national) due to changes in data availability and consequent modeling adjustments. Figure 6 shows how BUREF2010 successfully mitigates this bias, and puts in evidence the greater number of settlements represented compared to the MODIS urban layer, aggregated at the same 30 arc-second resolution (Fig. 5). Moreover, the spatial patterns of the settlements as extracted from BUREF seem more similar to the results of high-resolution built-up areas detection (as in Figure 7 - see Ferri et al., 2014) than any simple thresholding of the LandScan values.

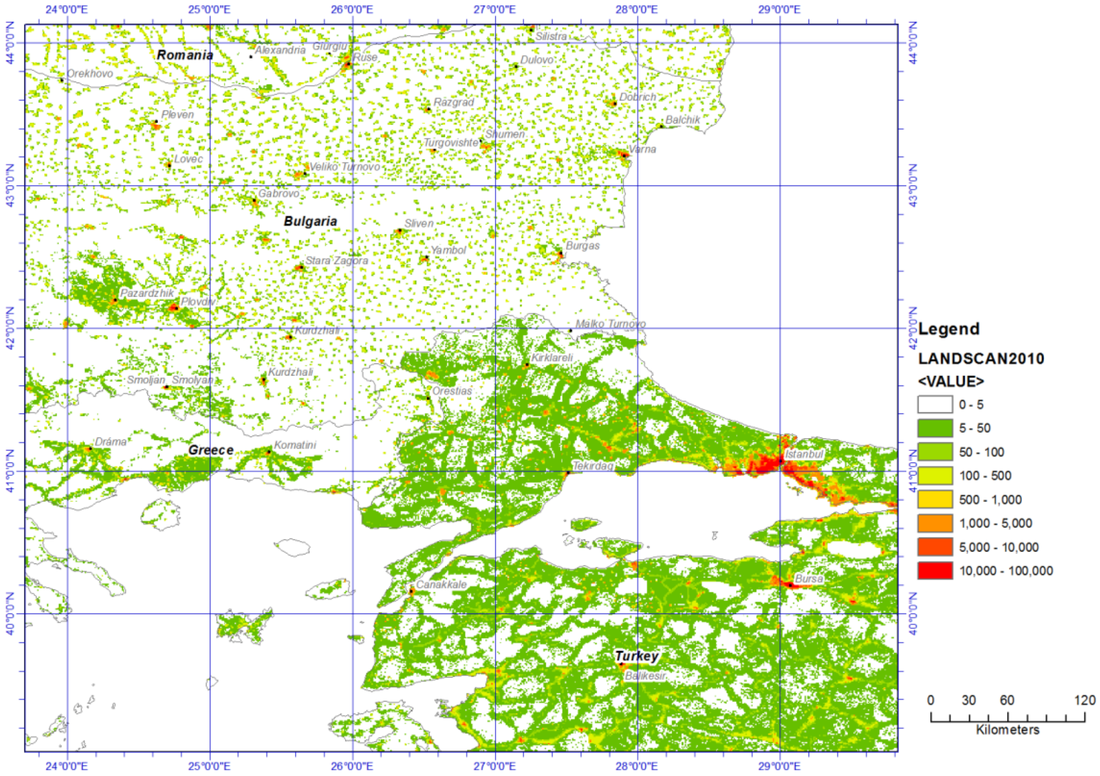

Figure 5 : An example of the LandScan 2010 source: it is clearly visible the different population pattern originated by different spatial criteria (roads) utilized in Bulgaria vs. Turkey.

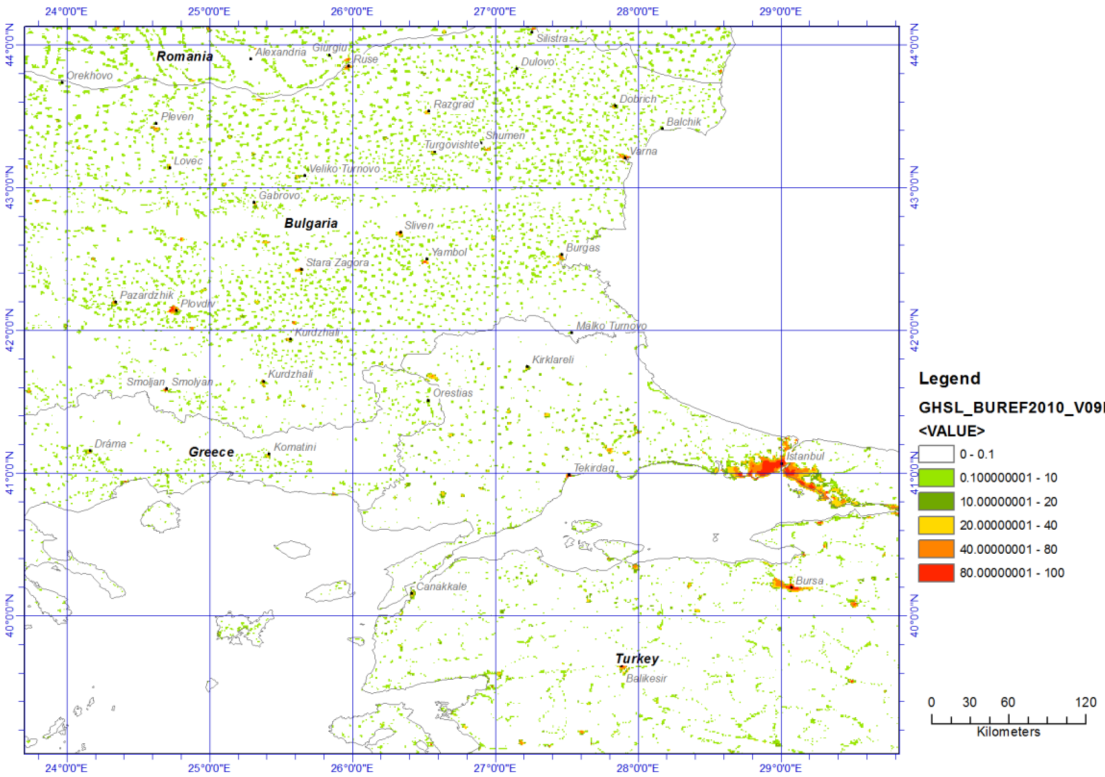

Figure 6 : The output of the proposed BUREF2010 model. Note how the bias introduced by roads in Bulgaria vs. Turkey has been reduced. Note also the greater number of settlements in BUREF reported respect to the MODIS "urban" layer.

The BUREF dataset is a generic representation of the amount of built-up, enabling its use in any analyses or modeling applications where the spatial distribution of this variable may be considered relevant. In the specific context of disaster risk and crisis management, this information can be useful at any stage of the disaster management cycle. In particular, it can be used to improve the spatial assessment of potential or effective exposure to hazards and thus contributing to advancing global risk and impact analyses.

Despite the benefits of BUREF2010, enhanced geoinformation is required to capture built-up areas in more detail, in order to characterize the full range and densities of human settlements. Figure 7 illustrates, for the same geographic area, the result of current efforts at built-up detection using high resolution (2.5 m) satellite imagery, aggregated at the same resolution as previous maps (Ferri et al., 2014). The map shows the improvements in the detection of built-up areas and representation of their densities.

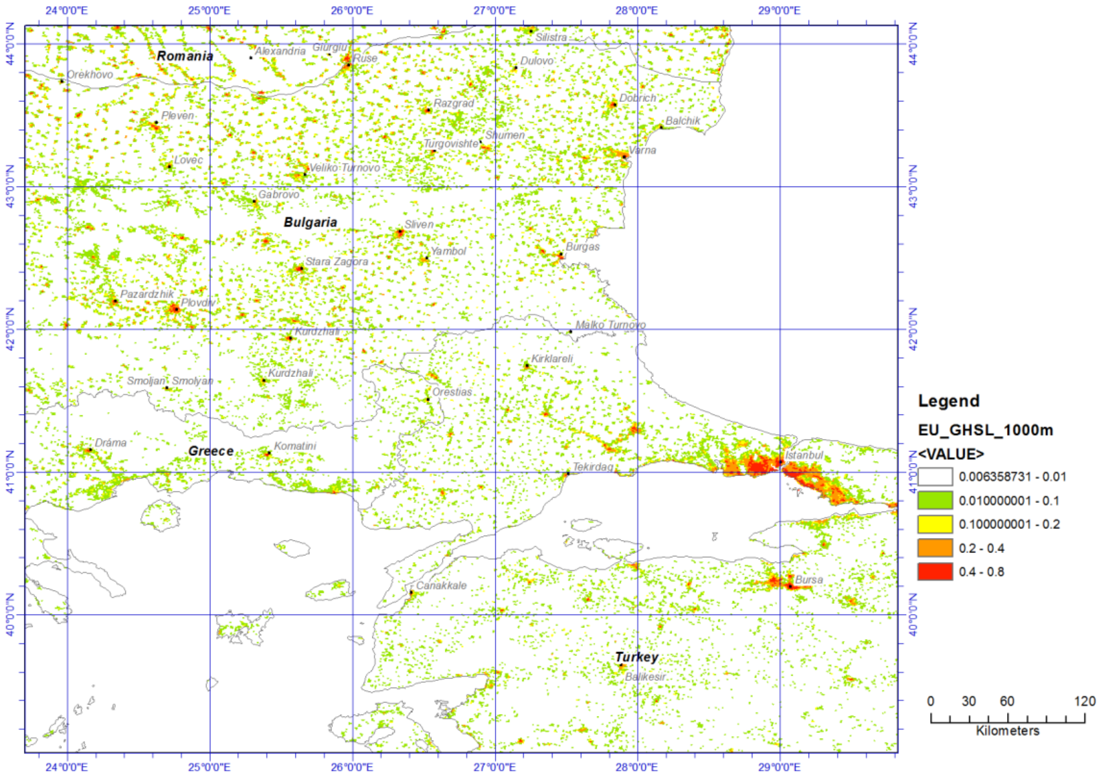

Figure 7 : The built-up areas as detected using high-resolution (2.5m) input imagery.

Conclusions

Mapping and assessing global built-up areas is relevant for many applications, spanning the domains of research, decision and policy-making. While several maps showing global urban extent are available, there are gaps in the representation and reporting of many built up areas. In particular, there is still omission of smaller settlements and scattered or low density built-up areas are not adequately represented.

With the purpose of supporting the extraction of primary information from satellite imagery, we have developed an approach that is both innovative and effective at mapping the distribution and density of built-up areas. The method combines satellite-derived land cover information and a population density grid through machine learning techniques in order to infer the percentage of land occupied by buildings. The first output is a spatial raster dataset with 30-arc second resolution, known as Global Built-up Reference Layer (BUREF2010). Results indicate that the BUREF layer improves the representation of global built-up areas compared to existing maps, while being suitable to integrate with other spatial datasets for analysis or modeling.

Still, superior geoinformation on built-up is required, and we are currently using high resolution satellite imagery in order to better characterize the full size range and densities of human settlements.

References

Balk, D. L., U. Deichmann, G. Yetman, F. Pozzi, S. I. Hay and A. Nelson, 2006. Determining Global Population Distribution: Methods, Applications and Data. *Advances in Parasitology*, vol. 62: 119-156.

Deichmann, U. 1996. A review of spatial population database design and modeling. Technical Report 96-3, National Center for Geographic Information and Analysis (NCGIA), University of California, Santa Barbara, USA.

Dobson, J. E., E. A. Bright, P. R. Coleman, R. C. Durfee, and B. A. Worley, 2000. A Global Population Database for Estimating Population at Risk. *Photogrammetric Engineering & Remote Sensing*, 66(7): 849-857.

Ferri, S., V. Syrris, A. Florczyk, M. Scavazzon, M. Halkia, and M. Pesaresi, 2014. A new map of the European settlements by automatic classification of 2.5 m resolution SPOT data. in *Proceedings of the International Geoscience and Remote Sensing Symposium (IGARSS)*, Québec, Canada, July 2014.

Freire, S., 2010. Modeling of spatiotemporal distribution of urban population at high resolution - Value for risk assessment and emergency management. In: Konecny M, Zlatanova S, Bandrova TL (eds) Geographic information and cartography for risk and crisis management. *Lecture Notes in Geoinformation and Cartography*. Springer, Berlin, pp 53–67.

Gueguen, L. 2014. Mash up of VHR image corner density with kilometric population density for the automatic detection of built-up extent. In Pierre Soille, editor, *ESA-EUSC-JRC 9th Conference on Image Information Mining*, pages 49–54. European Commission JRC, March 2014.

NRC (National Research Council), 2007. Tools and Methods for Estimating Populations at Risk from Natural Disasters and Complex Humanitarian Crises. Report by the National Academy of Sciences, Washington, D.C.: National Academy Press, 264 p.

Pesaresi, M., Guo Huadong, X. Blaes, D. Ehrlich, S. Ferri, L. Gueguen, M. Halkia, M. Kauffmann, T. Kemper, Linlin Lu, M.A. Marin-Herrera, G.K. Ouzounis, M. Scavazzon, P. Soille, V. Syrris, and L. Zanchetta, 2013. A global human settlement layer from optical HR/VHR RS data: Concept and first results. *Selected Topics in Applied Earth Observations and Remote Sensing, IEEE Journal of*, 6(5):2102–2131.

Potere, D. and Schneider, A. 2007. A critical look at representations of urban areas in global maps. *GeoJournal*, 69: 55–80.

Salembier, P. and J. Serra, 1995. Flat zones filtering, connected operators, and filters by reconstruction. *IEEE Transactions on Image Processing*, 4(8):1153–1160, 1995.

Schneider, A., M.A. Friedl , and D. Potere. A new map of global urban extent from MODIS satellite data. *Environmental Research Letters*, 4(4):044003, 2009.

Vincent, L. 1992. Morphological area openings and closings for greyscale images. In *NATO Shape in Picture Workshop*, pages 197–208. Springer-Verlag, September 1992.

Vincent, L. 1993. Morphological grayscale reconstruction in image analysis: applications and efficient algorithms. *Image Processing, IEEE Transactions on*, 2(2):176–201.