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ORIGINAL PAPER

Optical satellite imagery for quantifying spatio-temporal dimension of *physical* exposure in disaster risk assessments

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Abstract This work addresses the use of remote sensing imagery to quantify the built environment and its spatial and temporal changes. It identifies building footprint map, building location map and built-up area map as information products that can be used to quantify physical exposure, one of the variables required in disaster risk assessments. The paper also reviews urban land use maps and urban classes in land cover maps as potential source for deriving exposure information. The paper focuses on the latest generation of satellite-borne remote sensing imaging systems that deliver high-resolution optical imagery able to resolve buildings and other three-dimensional man-made constructions. This work also reviews the semantics, the spatial unit used to define physical exposure, image processing procedures and change techniques.

Keywords Remote sensing · Built-up mapping · Exposure · Building stock · Urban · Change detection

1 Introduction

The number of scientific international initiatives, advocacy documentation and policy paper on disaster risk, indicates that the topic is high on scientific and policy agendas. Policy provides the directions and funding, and international research programs provide the research to make up for insufficient knowledge on disaster risk. The devastating outcomes resulting from the impact of hazards such as earthquakes, flash floods, cyclones, volcano eruptions and tsunamis may be reduced if appropriate disaster risk reduction measures are put in place. Precondition to reducing risk is a proper quantification of risk. For many locations on Earth, often where mostly required, risk is not quantified because hazard and especially exposure

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data are not available. Also, risk may be quantified, using available hazard and exposure data that are not standardized and thus not suitable for comparison in space and time.

Exposure is the collection of the elements at risk that are subject to potential losses (ISDR 2009a) or that may suffer damage due to the hazard impact. This paper addresses specifically the quantification of the building stock—the inventory of buildings—referred herein as physical exposure. Exposure is reported to be increasing due to population growth and urbanization and to be accounted as a major factor in increased disaster risk in hotspot countries (ISDR 2009b).

Mapping buildings is important for a number of reasons. (1) Buildings are the characterizing element of human settlements, villages and cities. In fact, urban sprawl is measured primarily based on buildings, as well as other man-made structures on non-constructed land. (2) Building collapse is the major source of casualties in earthquake disaster scenarios (Taubenböck et al. 2009a). (3) Building inventories can be used to estimate population distribution (Wu et al. 2008; Silván–Cárdenas et al. 2010; Dong et al. 2010; Lu et al. 2010)—especially when no other population information is available—and affected population in case of disasters (Ehrlich et al. 2009a; Taubenböck et al. 2009b). (4) Disasters risk assessment models use building counts, as well as statistic aggregations of buildings at different areal units, for physical damage estimations. In fact for what concerns earthquakes, "The simplest earthquake loss model for an urban area aims to estimate the damage to the building stock due to a specified earthquake scenario, and then translate the estimate of physical damage into a cost in terms of repair and rehabilitation" (Bal et al. 2010).

Earth observation is an efficient tool for enumerating buildings, quantifying built-up areas and defining the building's geometric parameters, this for a number of reasons; first, imagery provides a synoptic overview and delivers geographic specific information. Disaster risk assessment is based on spatially explicit models that link hazards that occur in geographically confined location on Earth with corresponding exposure data. Second, remote-sensed measurements are consistent, collected through engineered parameters characterized by imaging sensors and orbiting platform parameters. These measurements can be calibrated and can be made comparable in space and time. Third, satellite data are available and accessible, either commercially or as open source, over most of the Earth's inhabited land surface, and the constellation of satellites with imaging sensor is increasing.

The paper reviews scientific literature in the use of imagery collected from optical satellite-borne platforms to quantify physical exposure. When available, it reviews the work used to measure changes of the built environment over time. It focuses on very high-resolution (VHR) imagery—with spatial resolution lower than 1×1 m; high-resolution (HR) imagery—with spatial resolution between 1×1 m and 10×10 m; and reviews the most relevant development in medium-resolution (MR) imagery—with spatial resolution coarser than 10×10 m, following the grouping proposed by Taubenböck et al. (2012). This paper does not address the use of SAR imagery for exposure mapping. The topic is too important to be treated as complement to optical imagery, and it requires a separate review and analysis.

The point of view of this paper is that of the user that aims to access exposure information with local detail and for use in global applications. It is also the view of the validator of global exposure databases that uses fine detail data derived through remote sensing to benchmark coarser exposure information products. This work aims to contribute to the development of sound concepts to be used for implementing, validating and updating a global exposure dataset, such as that produced within the Global Earthquake Model (GEM 2012).

2 Background

The background section provides a brief overview to the concepts aiming to link terms and definitions used by the remote sensing/image processing community with those of the disaster risk community.

2.1 Exposure and vulnerability

Assessing disaster risk boils down to quantifying hazard information and exposure, where exposure refers to the exposed assets (referred also as elements at risk) present in hazard-affected areas of the world, which are subject to potential losses (ISDR 2009a). Exposure is thus a general term that may contain several physical and socio-economic elements at risk, including the building stock, lifelines, transport network, population, economic activities or other services that can suffer damages in case of hazard impact. This paper focuses only on the inventory of buildings—the building stock—referred to as physical exposure.

This paper uses the term vulnerability as used by the engineering sciences where it indicates the propensity of the exposed assets/elements at risk to suffer damage (ISDR 2009a) due to the hazard impact. In fact, the important building stock attribute used in disaster risk assessment is its structural characteristic related to construction material, construction codes and practices (Blolkley et al. 2002; Vamvatsikos et al. 2010). The structural characteristics define the vulnerability functions that describe the probability of losses given a level of hazard (Calvi et al. 2006). Engineering sciences also use fragility functions that describe the probability of exceeding different limit states (FEMA 2003, Vamvatsikos et al. 2010). Buildings are typically grouped in building types, and at each building type is associated a fragility and vulnerability function (Erberik and Cullo 2006; Jaiswal et al. 2010). This attribute information complement the information related to the geographical position and geometric properties of the building.

Building stock information for disaster risk analysis and urban/regional planning is typically stored in geographic specific databases. The building stock is typically geographical data (Deichmann et al. 2011) consisting of two parts: the *spatial* part that defines the geographical position and, if represented by a polygon, its geometric properties, and the *attribute* part that defines building characteristics. Exposure databases typically include attributes such as structural type, age, number of storeys or height, as well as occupancy and use.

The separation of the physical exposure datum in a spatial and an attribute part suites well remote sensing image analyst and image processing professionals because the two parts are usually measured separately and with different techniques. The spatial part can, by and large, be "objectively" measured from optical VHR and HR satellite imagery as reviewed in this paper.

Building height is a building attribute that can also be derived from remote sensing. In fact, optical remote sensing can provide building height from shadow information if acquisition angles, spatial arrangement of buildings and acquisition dates are optimized (Lin and Levatia 1998; Miura et al. 2004; Miura et al. 2006; Brunner et al. 2010; Shao et al. 2011). Building height is also typically derived from stereo imagery (Toutin 2004a, b, 2006a, b; Poli 2010; Poli and Caravaggi 2012).

Buildings or built-up area attributes for quantitative vulnerability estimation can only in part be extracted from remote sensing imagery (Wieland et al. 2012). Mueller et al. (2006) investigate the potential of VHR imagery to derive structural characteristics of buildings and identify the limitations of VHR satellite imagery for this task. Roof characteristics as depicted on imagery can provide structural information on buildings for those areas where the relations between building roof and building type are well established. Shape, perimeter and size are often used to characterize structural attribute information. These geometric properties are also used, together with context information, to infer the building use that may in turn provide structural information on buildings. The age of buildings can be inferred from change detection in satellite images. The age provides insights into construction practices and standards that define the structural solidity (Deichmann et al. 2011). However, the operational uses of optical satellite imagery and image processing research in satellite remote sensing have focused primarily on deriving the spatial part of the datum, which is the topic of this paper.

2.2 Imagery for building stock and built-up

The detection and extraction of building stock and built-up area from remotely sensed imagery depends on the spatial resolution of the imagery (Table 1), the size and spatial arrangement of buildings and the processing technique used. It also depends on the spectral resolution, the viewing and illumination angles. The spatial resolution is the most critical parameter in settlement analysis because it defines the ability to resolve single elements from the image. In this paper we primarily address imagery classed as VHR, and HR, as listed in Table 1. We also briefly review exposure mapping from MR satellites that have been used for urban area detection and change analysis.

For the purpose of information extraction from remote sensing addressed in this paper, we refer to buildings as three-dimensional man-made structures hosting people and/or societal functions. On VHR and HR satellite imagery, buildings are distinguishable from other objects by their regular shape, regular arrangement in space, casted shadow that indicates the height and their proximity to the transport network.

The information on buildings extracted from imagery can be visualized in three information products: (1) building footprint maps, (2) building location maps and (3) built-up area maps (Fig. 1). Two more remote sensing–derived products may provide information on buildings and thus exposure: urban land use map and “urban” classes in land cover maps. These two last products are discussed separately because their semantic is not centred on the concept of building alone, and their production relies also on information not directly measurable from the imagery.

Building footprint and location maps are also often referred to as building stock maps because they detail single buildings. Maps should be intended as information layers stored in GIS databases. Figure 1 aims to clarify the relation between spatial resolution and the three information products. It shows a 2 km^2 large area covering portion of the island of Guadalupe on a QuickBird image collected on 29 March 2007.

The sequence of images (a–e) show decreasing spatial resolution from 0.6 $\times$ 0.6 m (VHR) to 2.5 $\times$ 2.5 m, 5 $\times$ 5 m, 7.5 $\times$ 7.5 m and 10 $\times$ 10 m (HR), respectively. The figure shows that the building stock is made up of very large buildings, medium-size buildings and small scattered buildings and that the finer the resolution the likelier to detect and outline buildings. Figure 1b–e is generalized—using an averaging rule—from the finer panchromatic information to simulate the coarser spatial resolution available from HR sensors as listed in Table 1, since the authors did not have at disposal other images for that area and that date.

Figure 1 aims also to show that the building stock can be quantified with VHR and HR imagery with the following constraints. The coarser the resolution and the smaller the average building size, the more difficult to detect single building units. When imagery is

Table 1 VHR and HR Satellite-Sensors imaging systems providing imagery with the following characteristics

Satellite	Spectral resolution	Spatial resolution (m)	Scene size (kmq)	Collection window (days)
GeoEye-1	PAN* + 4 MS** (blue, green, red, near-IR)	PAN 0.50 MS 2.0	49–100	60
WorldView-1	PAN	0.55	246.4	1.7–5.9
EROS-B	PAN	0.7	49	2–4
Quickbird	4 MS (blue, green, red, near-IR)	PAN 0.61 MS 2.8	272	3–11
IRS Cartosat-2	PAN	0.8-1	92	4
EROS-A	PAN	PAN1 1.0 PAN2 1.9	100 196	2–4
Ikonos	PAN + 4 MS (blue, green, red, near-IR)	PAN 1.0 MS 4.0	49–100	60
Kompsat-2	PAN + 4 MS (blue, green, red, near-IR)	PAN 1.0 MS 4.0	225	14
OrbView3	PAN + 4 MS (blue, green, red, near-IR)	PAN 1.0 MS 4.0	64	3
WorldView-2	8 MS (red, blue, green, near-IR, red edge, coastal, yellow, near-IR2)	1.8–2.4	490	1.1–3.7
Formosat-2	PAN + 4 MS (blue, green, red, near-IR)	PAN 2.0 MS 8.0	576	1
SPOT-5	PAN + 5 MS (blue, green, red, near-IR, Shortwave IR)	PAN: 2.0 MS: 10 SWI: 20	3,600–7,200	2–3
THEOS-PAN	PAN	2.0	484	26
IRS-P5 Cartosat-1	PAN	2.5	900	116
ALOS	PAN + 4 MS (blue, green, red, near-IR) + Synthetic Aperture Radar (L-band)	PAN: 2.5 MS: 10 L-band: 10-100	30–350	46
CBERS-2B (HRC camera)	PAN	2.7	729	130
RapidEye	5 MS (blue, green, red near-IR, red edge)	5.0	6,000	1–5.5
Resourcesat-1/2—LISS-IV sensor	PAN + 3 MS (green, red, near-IR)	5.8	4,900	5

* *PAN* Panchromatic band

** *MS* Multispectral bands

Sources CBERS (http://www.cbers.inpe.br/), Satellite Imaging Corporation (http://www.satimagingcorp.com/), ImageSat International (http://www.imagesatintl.com/), European Space Agency (http://earth.esa.int/), Indian Space Research Organization (http://www.isro.org/)

coarser, typically at resolution of 7.5 × 7.5 m and 10 × 10 m, it may not be sufficient to identify the smaller buildings. The general rule often adopted by image processing specialists is that all products as shown in Fig. 1 (sub-images a–e) can be used to generate the built-up area map (sub-image 3). Imagery with spatial resolution from 0.6 × 0.6 m to

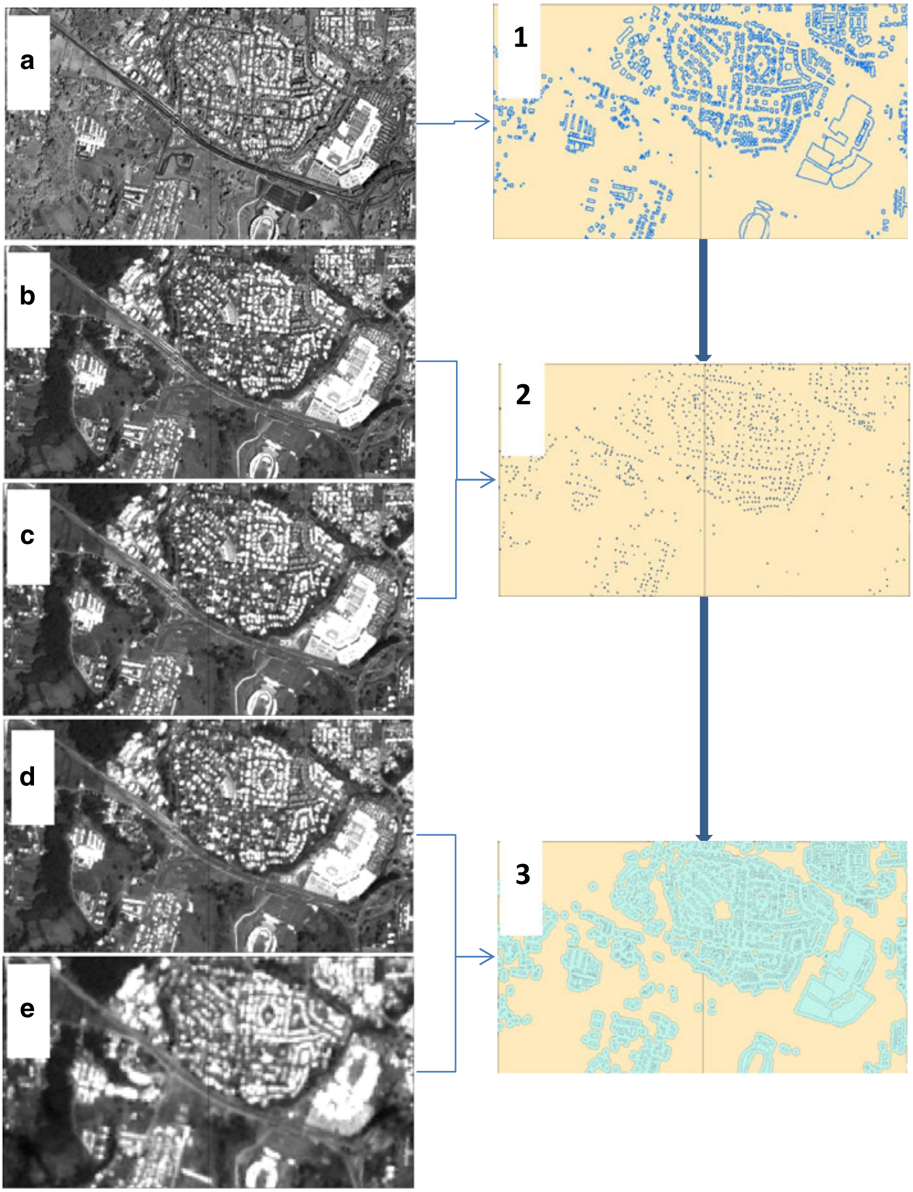

Fig. 1 Two *square* kilometres for the island of Guadeloupe from Quickbird imagery collected on 29 March 2007. The figure shows the image at spatial resolution from 0.6 × 0.6 (**a**), 2.5 × 2.5 (**b**), 5 × 5 m (**c**), 7.5 × 7.5 (**d**) and 10 × 10 (**e**). The images were degraded to coarser resolution from a single QuickBird panchromatic image. The images also show three information products, building footprint map (1), building location map (2) and built-up area map (3), which can be generated from the imagery

5 × 5 m can be used to detect building location (sub-image 2), while only imagery with resolution finer than 1 × 1 m can be used to outline building footprints (sub-image 1).

The building footprint map (Fig. 1, sub-image 1) provides outlines of buildings based on their planar cross section. It is traditionally produced from aerial photography.

In well-mapped locations, these are produced and updated regularly at scales of 1:5,000–1:10,000 and now updated using also VHR imagery (Tao et al. 2004; Miura et al. 2006; Gianinetto 2008; Freire et al. 2010). Building footprint maps explicitly define the geographical location and the geometrical parameters of buildings such as shape, perimeter and size. The delineation of footprints requires imagery at the finest spatial resolution. Only then the edges of building can be identified. Figure 1 shows that the large majority of buildings are clearly identifiable from VHR imagery. Very small buildings closely spaced may not be resolved even at the resolution available from the finest spatial resolution satellite imagery.

Building location map (Fig. 1, sub-image 2) is a simplified building stock map when compared to the building footprint map. It only reports the geographical location of the building represented typically as the building centroid.

Built-up area map (Fig. 1, sub-image 3) is a binary map of the built environment that outlines areas with buildings as well as landscape elements adjacent to buildings, including green areas and transport network (Pesaresi and Ehrlich 2009). The built-up area map is typically produced as a binary map—built-up/non-built-up—but can also be represented with continuous values and take the form of fuzzy indexes, or soft classification, where the different values indicate the built-up density. In this paper we discuss the built-up area map as a binary map unless otherwise specified in the reviewed papers, in order to facilitate the discussion on definitions and semantic content.

Built-up area maps can be generated from computer-aided visual interpretation (photo-interpretation) or using automatic classification procedures. In photo-interpretation and manual digitizing, the map is produced by outlining concentration of buildings. Built-up area maps are also used as typical product of automatic or semi-automatic image processing routines (Pesaresi et al. 2011). They are generated from remote sensing data as surrogate to building stock map when the resolution of the imagery does not allow to resolving single buildings. Built-up area maps are also generated when large volume of data needs to be processed, or when rapid assessment is required.

Contrary to building footprint maps, built-up area maps are not semantically well defined. This section proposes some rules that can be used to define a built-up area map based on building footprints or building location maps. Binary built-up area maps can be generated by defining three elements: (1) the characterizing landscape element—the building; (2) the spatial unit of reference that should be linked to the characterizing element; and (3) the spatial rule that links spatial unit of reference and the characterizing element.

To facilitate explanation of the information content of a built-up area map, we describe a process of built-up area map creation starting from a building footprint map. In this example the building footprint map has been generated through computer-aided visual interpretation. The built-up map of Fig. 1 (sub-image c) was produced using a spatial rule that spatially expands by 15 m the area covered by buildings along its perimeter. The buffer distance of 15 m corresponds to the estimated average length of buildings in the settlement pattern of Fig. 1. The analysis of settlement patterns with different building sizes and spatial arrangements may require different buffer distances that the one used in Fig. 1. Also, buffer distances are selected based on the scale at which the maps are produced and its application.

Other criteria can be used to generate a built-up map from footprints. For example, Tenerelli and Ehrlich (2011) have generated built-up area maps from a building footprint map using grid cells as spatial unit and defined a spatial rule that links the buildings to the grid cell. This simulates built-up area maps produced using imagery at different resolution.

The cell is labelled as built-up if it overlaps (intersects) with one or more buildings. Larger grid cells include proportionally more space-in-between-buildings than smaller cells, and this is quantified for the different settlement patterns in Tenerelli and Ehrlich (2011).

Urban land use maps are commonly derived from VHR and HR data. Urban land use maps outline areas with different uses including "industrial", "commercial" and "residential" classes, as well as roads and non-impervious areas (e.g. green spaces). Urban land use classes may also contain building density information (EEA 2000; Urban Atlas 2010). Urban land use maps are typically created using machine-assisted procedures using information from the imagery and ancillary information or knowledge on the stud area. In fact, the fully automatic classification of imagery into a land use map remains a research challenge due to the complexities of built-up environments and the rules required to generate the map.

MR remote sensing, such as Landsat Thematic Mapper (TM), has also been used to derive urban land cover classes within land cover maps. The term urban in this case relates to an unspecified density of buildings found in cities and large settlement agglomerations (Comber et al. 2005). Urban land cover classes derived from MR imagery may not be converted in accurate physical exposure maps. In fact, the building stock is not the only landscape element classified as "urban" in land cover classification due to its bright (high) spectral reflectance values when viewed in different band combinations. Many built-up areas may display spectral characteristics (dark roof) not identifiable from other landscape elements. In addition, scattered buildings and small human settlements may not be resolved from MR imagery and thus captured in "urban" cover classes. In short, deriving urban land cover information from MR satellite imagery is prone to commission and omission error that is not easily quantifiable for two reasons: The imagery itself cannot be used as a source of reference data, and it is very costly to collect reference validation data for the vast area covered by Landsat TM imagery. Yet, Landsat TM data remain very valuable imagery for the global availability, the consistent geometric properties (Tucker et al. 2004), and for the time span it covers, that provides an excellent basis also for land cover change analysis in general.

Exposure databases detailed to single building units are seldom available for disaster modellers. Exposure data are more often available in aggregated level for larger spatial units related to arbitrary areal subdivision of the settlements, census block, postal codes, city blocks or more regular gridded subdivision. A spatial unit may contain a statistic summary of building information such as average size and average height, density or even relative distribution of building types.

3 Literature review

This review focuses on techniques and procedures employed to derive the building footprint map, the building location map and the built-up area map as derived from VHR, or HR. The review summarizes the operational ways to extract information and focuses on the innovations in image analysis that may allow for fast processing of large volume of data over large geographical regions and change detection techniques.

This work also briefly reviews the production of urban land use maps from HR, and "urban" classes from MR classifications (land cover classifications), when it applies to one or more points as follows. (1) It includes information that is specifically derived to assess the constructed environment and not as a by-product of an environmental research applications, (2) the information products cover large geographical areas, countries or continents, and (3) the techniques used have been tested across large geographical areas or are deemed to have the potential to be used across large regions of the Earth for exposure mapping.

The following sections review references for the five product types: (1) building footprints maps, (2) building location maps, (3) built-up area maps, (4) land use maps and (5) land cover maps, respectively, in Sect. 3.1 to 3.5. Each section first describes the operational techniques, then it addresses research innovations towards automatic classification, and finally, it reviews the techniques used for change detection.

3.1 Building footprints maps

The building footprints map is a well-accepted product used for planning purposes, urban sprawl analysis and disaster risk assessments. Footprint maps are typically produced from aerial photography using photo-interpretation techniques and manual digitalization of image objects. The process is based on encoding the digital data based on texture and tone information, together with context information, available from the aerial photography. The encoding is typically carried out using Geographic Information System tools. A number of authors have tested VHR satellite imagery for producing or updating building footprints maps (Miura 2006; Gianinetto 2008; Freire et al. 2010). The manual extraction of information is extremely labour intensive and thus conducted typically for single municipalities and if governmental programs are in place also for larger regions, such as for the study area of Guadalupe (IGN 2002).

The image processing community is actively engaged in developing automatic and semi-automatic procedures to derive building footprints. Semi-automatic procedures are based on algorithms that use rules to aggregate pixels based on the spectral similarity, spatial parameters (i.e. texture, scale, shape, size, brightness) or the combination of both spectral and spatial parameters (Stassopoulou and Caelli 2000; Lee et al. 2003; Taubenböck and Roth 2007; Liu et al. 2008; Gamba et al. 2009; Freire et al. 2010; Taubenböck et al. 2012). For example, Gamba et al. (2009) have developed a semi-automatic method referred to as Built-up area Recognition tool (BREC) that “extracts man-made structures”, as well as land cover classes and can be used for analysing changes as well. The algorithm is based on neural networks and edge detection filtering algorithm that isolates single-image elements and can re-combine them in an interacting “bottom-up” approach to obtain the image object required by the application. The BREC algorithm is used to generate building footprints for vulnerability assessment of man-made structures (Polli et al. 2009, 2010).

The image processing community is defining new paradigms for information organization and extraction. Examples are the advanced segmentation algorithms that take into account connectivity relations along with radiometric properties (Soille 2008, 2010; Ouzounis and Soille 2012). Efficient multiscale methods are reported in Ouzounis et al. (2012). These algorithms aim to process large volume of VHR data covering massive regions or countries (Pesaresi et al. 2012). Benchmarking these new methods, procedure and algorithms, as carried out by Ozdemir et al. (2009), is forthcoming work.

Monitoring changes in the building stock requires change analysis of the building footprint maps. Change detection analysis relays on the following preconditions. Multidate imagery needs to be georeferenced and co-registered in order to have spatially consistent building footprint maps. Georeferencing has to match the precision of the change analysis required. For example, changes in shape and size of building footprints would require very fine-resolution aerial photography with accurate digital encoding of the building footprint and very precise georeferencing of the input imagery.

3.2 Building location maps

The information content of building location maps is lower than that of footprint maps. It does not provide information on the geometry of buildings, but only its location. Disaster risk models do not yet use exposure databases in the form of building location maps. Data are rather stored as building footprints or as building counts aggregated at coarser spatial units, such as district census or building blocks. Other applications do, however, produce building location maps that can be used for generating exposure data or validation datasets.

Building counts information layers are generated for building stock assessment in time or resource constraint applications, when input satellite information does not provide the spatial detail to derive footprints, or when the enumeration alone fits the information request. Building count maps are primarily used in enumerating buildings and dwellings in humanitarian crises for post-disaster damage assessments. For example, VHR imagery was used to assessing population from enumerating dwellings and thus quantifying population in refugee camps (Giada et al. 2003) using morphological operators. The work was adapted to accommodate the new imagery and landscape settings and has been used to map changes in temporary camps in Sri Lanka (Kemper et al. 2011a) and Darfur (Kemper et al. 2011b).

VHR imagery and aerial photography have been used to rapidly count and encode collapsed buildings as single building entries during 2010 Haiti earthquake for post-disaster damage assessments (Corban et al. 2011). Gueguen et al. (2012) have developed automatic based procedure to directly identify buildings damaged in conflict area where roofs have collapsed and only the perimeter walls can be seen on VHR imagery. Change detection between two VHR images allowed detecting changes of building distribution in post-conflict scenarios (Pagot and Pesaresi 2008).

3.3 Built-up area maps

Built-up area maps are typically produced from HR and VHR data. These maps are derived from photo-interpretation by outlining adjacent buildings according to given specifications. Image processing algorithms have been developed to automatize the outlining of built-up areas. The information extraction process is based on classification algorithms that analyse and aggregate data into given classes based on statistical decision rules in the multispectral domain or on logical decision rules in the spatial domain, where the spatial domain includes shape, size, texture and patterns of pixels or group of pixels (Gao 2009). For example, the "built-up area presence index" was developed and tested for processing SPOT panchromatic imagery (Pesaresi et al. 2008). The built-up area presence index is an anisotropic texture measure based on the grey-level co-occurrence matrix (Haralik 1979). It is used to exploit the high texture typical of the built-up environment as seen in HR and VHR imagery. The index returns very high Digital Number for image regions characterized by high texture typically found in built-up areas. These high texture regions are classified into the built-up area map using typically a binary threshold. The built-up area presence index has been extensively tested also to derive built-up area information over a number of large cities in four continents, based on information contained in the three visible bands of Ikonos and QuickBird (Pesaresi et al. 2011). The built-up area presence index algorithm was also tested on landscapes containing both dense urban centres and sparse scattered human settlements over the island of Guadeloupe (Ehrlich et al. 2009b). Niebergall et al. (2007) have applied a semi-automated classification procedure for mapping human settlements from VHR data in

Delhi (India); this procedure was customized for informal settlements typical of the study area, with the aim of monitoring the urban and population growth.

Spatial temporal changes in built-up area can be measured when the built-up layers in different times are computed. However, change detection techniques have been developed to directly identify changes from image data. Moeller and Blaschke (2006) tested three indices to identify changes from QuickBird imagery that included two spectral band transformations, Intensity-Hue-Saturation transformation and principal component analysis (PCA), as well as band rations in the form of Normalized Difference Vegetation Index and the combination of the above. Doxani et al. (2010) analysed changes over two QuickBird images, by first simplifying images using a morphologically based object-oriented approach, and then performing changes using the multivariate alteration detection (MAD) transformation. Bustos et al. (2011) computed PCA to multispectral bands of CBERS-2B sensors taken in pairs over an interval of time; the changes were then detected by calculating a PCA, where the changes are captured in the second component. Ehrlich and Bielski (2011) located changes on SPOT 4 panchromatic channel at 10×10 m resolution and Spot 5 Panchromatic channel at 2.5×2.5 m resolution imagery, using the built-up area index and PC analysis. Gueguen et al. (2011) used the built-up area index on two SPOT 5 2.5×2.5 panchromatic imagery and the mutual information change detection technique that seems to better capture changes in the built-up if compared to PCA because it is less sensitive to atmospheric contamination.

3.4 Urban land use maps from HR and VHR data

Urban land use maps outline regions within a city with homogeneous building densities and include classes with transport networks and other uses of the land. For example, the European Urban Atlas (Urban Atlas 2010) uses a refined legend on classes available from CORINE Land Cover (EEA 2000), which is used to derive also urban indicators. Over 300 European cities are mapped with Urban Atlas standards (Seifert 2009). It discriminates, at the building blocks level, between five built-up density classes, two built-up uses and three transportation network classes (Urban Atlas 2010). Some classes (e.g. “Sport and Leisure facilities”, “Construction sites” and “Railways and associated land”) do not report the presence of building even when buildings are present. In fact, if the Urban Atlas would be considered to derive exposure information, those buildings would not be accounted for.

Because of the complexity of the semantics, urban land use maps are not easily reproducible with automatic techniques. The European Urban Atlas is mainly based on the photo-interpretation of HR imagery with support of other reference data. Some authors use automatic and semi-automatic classification of HR data for urban land use mapping. Stow et al. (2007) mapped the residential land use of Accra (Ghana) from QuickBird data using a semi-automated approach that details classes by socio-economic characteristics, obtaining an overall percentage accuracy of 75 %. Liu and Clarke (2002) classified the urban land use of Santa Barbara (USA) using Ikonos data for estimating the residential population. They exploited the image texture to extract seven different land use classes with an overall accuracy of about 55 %; this low accuracy confirms the difficulty in automatically classifying different patterns of land use within urban areas.

Land use maps produced at different interval of time can in principle be used to derive changes in land use. The preconditions for such change analysis are an accurate geometric map registration, the consistency of the input data and semantic information, and a quantified accuracy of the two land use maps.

3.5 Urban land cover maps from MR data

Landsat TM-derived "urban" classes suffer from limitations in accuracy. In fact, the classification of Landsat TM for built-up area estimation is notoriously hampered by the high spectral heterogeneity (Small 2003). Even fine spectral resolution may not provide sufficient discriminatory power to automatically differentiate landscape elements in built-up areas (Herold et al. 2004). Herold et al. (2003), Griffiths (2010) and Taubenböck (2009a, 2012) report that urban landscapes are the most challenging environment to be analysed due to the spatially and spectrally heterogeneous nature of artificial and natural surface types.

This document restricts the review of MR data to research for deriving physical exposure information as defined in this paper. One study uses Landsat imagery for exposure mapping. Wieland et al. (2012) have classified Landsat imagery into an urban land cover map using a supervised approach. The urban land cover is then used to derive a building inventory. Ancillary information such as field-collected images is used to label buildings into typologies and vulnerability classes.

There is a vast literature that considers impervious surfaces, a proxy variable used in urban areas mostly for environmental analysis, as reported in Weng (2008). That literature is beyond this paper since it does not match the semantic required for exposure information from satellite imagery. We limit the review and analysis to applied methodologies that have produced continental datasets, or for procedures and algorithms that are applied locally, but have the potential to be applied globally for deriving physical exposure information.

Three continental land cover databases have been produced from Landsat TM data, CORINE Land Cover (EEA 2000), Africover (LCCS 2005) and Land Cover Characterization of North America (Vogelman 1988; 2001). Each contains information on the built environment that is defined differently. Vogelmann (1988) defines low-intensity developed land and high-intensity developed land when man-made artefacts cover, respectively, between 50 and 80 %, and more than 80 % of the land as visible on the Landsat TM imagery. CORINE Land Cover describes two "urban" classes, "continuous" and "discontinuous" urban fabric, when man-made artefacts that make the land "impermeable" cover, respectively, 80 % or more of the total surface, and 30–80 % of the total surface. Africover defines one class—developed land—to indicate built-up land in cities and settlements as seen from MR imagery. The value of these continental datasets rests with the effort of mapping the built environment at continental scale. Should these datasets be used to generate exposure information, they would require additional processing, and assigning quantitative building stock information to the existing land cover classes based on ancillary information.

In fact, spurred by the demand of exposure information, these continental datasets have started to be considered to generate Exposure maps. The Earthquake Loss Estimation Routine project (Hancilar et al. 2010) assigns building counts to selected CORINE Land Cover classes using open source satellite data. The database then uses the classification typologies used in PAGER (Jaiswal et al. 2010).

A number of studies have produced procedures and indicators to measure urban areas from MR imagery. All aim to be robust in space and time allowing for wide area mapping. Guindon et al. (2004) applied a spectral clustering and image segmentation by combining both spectral and spatial parameters. The results are then re-combined in predefined classes. Tatem (2004) used a number of spectral based parametric and nonparametric classifiers, including neural networks for Landsat TM Imagery with the inclusion of SAR information, and used the results to optimize the classification of human settlement in Kenya. Zha et al. (2003) introduced the Normalized Difference Built-up Index (NDBI) based on band ratio between visible, Near Infrared and Medium Infrared bands of Landsat TM to be used for built-up analysis. Xu (2007) used a combination of previously published indices to map built-up land features from Landsat TM using PCA. Taubenböck et al. (2009b, 2012) use commercial object-oriented image analysis software to segment images and then re-combine the segments into useful built-up information. Taubenböck et al. (2012) tested a methodology on a number of megacities for which they have derived spatial indicators of urban growth and used buildings, roads and impervious surfaces as the characterizing elements of the urban footprints. Novel research from Angiuli and Trianni (2012) based on systematic analysis of band ratio from Landsat might provide improved algorithms for continental built-up mapping.

CORINE Land Cover products have been used to map the land cover changes in Europe between two different time periods (1990-2000 and 2000-2006), by post-classification comparison (EEA 2011a; b). Landsat TM has often been used to map the changes in built-up for analysing sprawl and sprawl patterns. As reviewed in Ji (2001) MR imagery is used to detect changes in built-up by comparing remote sensing–derived urban classification, through image differencing, PCA analysis and by comparing Tasseled Cap transformation or Gramm-Schmidt transformations. For example, Taubenböck et al. (2012) use a variety of sensors from Landsat ETM, TM and MSS in addition to TerraSar-X data mapping urban footprints. Li and Yeh (1998) use PCA on staked multitemporal imagery. Seto et al. (2002) use the Landsat TM Tasseled Cap transformation, to extract information related to biophysical properties of the landscape and changes in built-up land. All of the reviewed papers are driven by the need to quantify urban change information and apply it to urban studies, rather than defining the accuracy of the change detection and the consistency of the methods.

4 Discussion

This paper identifies three information products that are derived from remote sensing data and that can be used to derive physical exposure information: the building footprint map, the building location map and the built-up area map. The urban land use map and urban classes in land cover map are also discussed. The semantics for two products, building footprint map and building location map, are well understood and used. The built-up area maps on the other hand often lack a precise semantic. A definition of built-up area map is proposed in this document. This definition is scalable—to take into account maps derived from satellite imagery with different spatial resolution—and is based on the presence of buildings and the size of the spatial unit of reference. This definition can be used with satellite imagery, which displays single building units, namely VHR and HR imagery, and thus not on MR imagery. Such definition can be used to implement validation protocols that aim to attach accuracy values to built-up maps.

The review showed that VHR satellite imagery has started to be used to produce and update the building footprint maps. The precision of the updating depends on the spatial resolution of the input imagery. The high demand for building footprint maps has spurred the community to develop semi-automatic and automatic procedures for building encoding. Benchmarking of these algorithms has just started and needs to be carried out on built environments with different settlement patterns and ecological settings. Changes in the built environment can then be detected by comparing building footprint maps created at different dates. The comparison will require accurate georeferencing and consistent information products.

The review shows that building location maps can be generated more rapidly than building footprint maps. In fact, they are now produced for post-disaster assessments and other humanitarian purposes when time constraints require fast processing. The techniques developed to generate building location maps should also be used to target physical exposure mapping over large areas.

The built-up area maps may be produced with different input data and techniques. In fact, the range of automatically produced built-up area maps may vary significantly. Attaching proper scale and information content parameters to built-up maps is important for defining the semantics and the reference spatial unit. This is also important for validation, especially when the built-up layer is used to extrapolate building stock information using statistical techniques (Ehrlich et al. 2010).

The reviewed papers addressing automatic change detection procedures based on built-up area show that they successfully detect changes. However, the procedures are not error free, and the accuracy is not always properly quantified. The change in built-up area, detected with the reviewed techniques, is not sufficiently precise for quantitative change assessments in operational exposure mapping. The change products may be used as alerts for change that can then be revisited with more accurate techniques.

Urban land use maps such as the Urban Atlas produced from VHR and HR imagery can be used for mapping exposure with the following advantages and limitations. The Urban Atlas follows production specifications that are standardized across Europe. The over 300 cities covered are thus mapped in a consistent way. Several classes contain quantitative information on building density that can be turned into building stock information. However, other classes contain building information that cannot be accounted for. In addition, the Urban Atlas only covers main European urban areas (with more than 100,000 inhabitants) ignoring smaller centres that should also be mapped.

The procedures described for mapping urban areas from MR imagery use definitions that do not relate strictly to building stock but rather to proxy of the building stock such as artificial surfaces, sealed surfaces, impervious surfaces and developed land. These definitions are then used to derive information products, such as "urban footprint", used interchangeably with "urbanized areas" and "settlement mask" (Taubenböck et al. 2012). These terms lack a precise semantic and thus cannot be—in this form—used to quantify physical exposure.

For the lack of precise semantic and processing algorithms, MR data such as Landsat TM imagery remain an untapped resource for quantitative exposure mapping. The continental land cover data layers including CORINE Land Cover, Land Cover characterization of North America and Africover have each strong points and weaknesses. The main advantage is that they can deliver absolutely unique information for environmental applications over large areas (continental scale). The weaknesses for physical exposure mapping are as follows. First, the continental datasets cannot be compared because their semantic is often different. Second, few classes provide quantitative information on the built-up. Also, a large part of the built-up area is unaccounted because too small or too scattered to be mapped with automatic or semi-automatic techniques. Third, there is a lack of robust methodologies that can reproduce these information products in automatic and semi-automatic way for future updating. Despite these limitations, CORINE Land Cover was used to generate a European-wide exposure map that has used VHR open source information to assign density values to the different CORINE land cover classes (Hancilar et al. 2010). Future work should release updated version of these continental datasets with sound statistical accuracy assessments.

5 Conclusions

The usefulness of VHR and HR satellite imagery for physical exposure mapping is beyond dispute. Satellite imagery's most peculiar characteristics are its synoptic overview that provides a number of advantages for exposure mapping. (1) The full landscape is imaged and the entire built-up environment can be detected and measured, including small settlements, scattered settlement typical of rural areas and dense city centres. (2) The information collected is geographic specific, and the precise location of buildings can be measured. When of fine resolution, such as aerial photography or VHR imagery, it allows us to detect and measure the geometry of every physical element. (3) The data are available globally and accessible, provided the resources are at hand.

This document has identified information products derived from optical remote sensing that can be used for physical exposure mapping. The paper also identifies shortcomings in standards and semantics that require to be addressed. It proposes a semantic definition of built-up area map and recognizes there is no accepted methodology for extraction of built-up information from MR land cover products. It also argues that analysis of built-up and change detection performed on MR would be difficult to use in a consistent exposure database, because of the lack of quantitative definitions of the built-up and precise semantics.

Remote sensing and image processing specialists using HR and VHR should have the building stock information (building footprints or building location maps) as the ultimate objective of their analysis. In fact, single building information layers would be of extreme value also for validation purposes. Exposure data layers are often produced at coarse spatial scale because of the limitation of risk models to process the vast amount of exposure information at global and national scale. However, there are initiatives that aim at capturing exposure information at many different scales. For example, comprehensive exposure databases such as that envisioned by the Global Exposure Model developed within the Global Earthquake Modelling (GEM) initiative will include a hierarchical set of building stock information with fine detail entries at the building level, as well as aggregated values at grid cells of 30 × 30 arcsec. When available, exposure data at the building level can be used to calibrate or validate that at coarser 30 × 30 arcsec large spatial units.

Until recently, it would have been unthinkable to have exposure information available from satellite remote sensing at very fine scale with the precision required for local application. This should be no longer considered an unachievable result. A spatially consistent, standardized, fine scale global physical exposure information layer could be obtained from VHR data collected over the past 10 years over the Earth's inhabited land surface. The ever increasing supply of VHR imagery should then be used to improve and update the database. Converting imagery into exposure information will require processing chains and an information infrastructure capable of processing massive data volumes, validation protocols and a community of validators, possibly recruited through the crowd sourcing community. The task is now at hand.

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