CHAPTER 2 UNDERSTANDING DISASTER RISK: RISK ASSESSMENT METHODOLOGIES AND EXAMPLES

2.2 Current and innovative methods to define exposure

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2.2.1 What is exposure?

Exposure with vulnerability (see Chapter 2.3) and hazard (see Chapter 3) is used to measure disaster risk (see Chapter 2.3). It is reported that exposure has been trending upwards over the past several decades, resulting in an overall increase in risk observed worldwide, and that trends need to be better quantified to be able to address risk reduction measures. Particular attention to understanding exposure is required for the formulation of policies and actions to reduce disaster risk (UNISDR, 2015a), as highlighted by the Sendai Framework for Disaster Risk Reduction (UNISDR, 2015b): ‘Policies and practices for disaster risk management should be based on an understanding of disaster risk in all its dimensions of vulnerability, capacity, exposure of persons and assets, hazard characteristics and the environment. Such knowledge can be leveraged for the purpose of pre-disaster risk assessment, for prevention and mitigation and for the development and implementation of appropriate preparedness and effective response to disasters.

Exposure is a necessary, but not sufficient, determinant of risk (Cardona et al., 2012) (see Chapter 2.1). According to available global statistics, least developed countries represent 11% of the population exposed to hazards but account for 53% of casualties, while the most developed countries account for 1.8% of all victims (Peduzzi et al., 2009) with a population exposure of 15%. These figures show that similar exposures with contrasting levels of development, of land-use planning and of mitigation measures lead to drastically different tolls of casualties. Hence it is possible to be exposed, but not vulnerable; however, it is necessary to also be exposed to be vulnerable to an extreme event (Cardona et al., 2012).

Due to its multidimensional nature, exposure is highly dynamic, varying across spatial and temporal scales: depending on the spatial basic units at which the risk assessment is performed, exposure can be characterised at different spatial scales (e.g. at the level of individual buildings or administrative units).

Exposure represents the people and assets at risk of potential loss or that may suffer damage to hazard impact. It covers several dimensions like the physical (e.g. building stock and infrastructure), the social (e.g. humans and communities) and the economic dimensions.

Population demographic and mobility, economic development and structural changes in the society transform exposure over time. The quantification of
exposure is challenging because of its interdependent and dynamic dimensions. The tools and methods for defining exposure need to consider the dynamic nature of exposure, which evolves over time as a result of often unplanned urbanisation, demographic changes, modifications in building practice and other socioeconomic, institutional and environmental factors (World Bank, GFDRR, 2014). Various alternative or complementary tools and methods are followed to collect exposure-related data; they include rolling census and digital in situ field surveys. When the amount, spatial coverage and/or quality of the information collected in the ground is insufficient for populating exposure databases, the common practice is then to infer characteristics on exposed assets from several indicators, called proxies. Exposure modelling also has a key role to play in risk assessment, especially for large-scale disaster risk models (regional to global risk modelling (De Bono and Chatenoux, 2015; De Bono and Mora, 2014)). Among the different tools for collecting information on exposure, Earth observation represents an invaluable source of up-to-date information on the extent and nature of the built-up environments, ranging from the city level (using very high spatial resolution data) to the global level (using global coverage of satellite data) (Deichmann et al., 2011; Dell’Acqua et al., 2013; Ehrlich and Tenerelli, 2013). Besides, change-detection techniques based on satellite images can provide timely information about changes to the built-up environment (Bouziani et al., 2010). The choice of the approach determines the resolution (spatial detail) and the extent (spatial coverage) of the collected exposure data. It also influences the quality of the collected information.

Despite the general conceptual and theoretical understanding of disaster exposure and the drivers for its dynamic variability, few countries have developed multihazard exposure databases to support policy formulation and disaster risk-reduction research. Existing exposure databases are often hazard specific (earthquakes, floods and cyclones), sector specific (infrastructure and economic) or target specific (social, ecosystems and cultural) (Basher et al., 2015). They are often static, offering one-time views of the baseline situation, and cannot be easily integrated with vulnerability analysis.

This chapter reviews the current initiatives for defining and mapping exposure at the EU and global levels. It places emphasis on remote sensing-based products developed for physical and population exposure mapping. Innovative approaches based on probabilistic models for generating dynamic exposure databases are also presented together with a number of concrete recommendations for priority areas in exposure research. The broader aspects of exposure, including environment (e.g. ecosystem services) and agriculture (e.g. crops, supply chains and infrastructures), deserve to be addressed in a dedicated future chapter and will not be covered by the current review.

### 2.2.2 Why do we need exposure?

There is a high demand for exposure data by the communities that address disaster risk reduction (DRR). National governments and local authorities need to implement DRR programmes; the insurance community needs to set premiums and manage their aggregate exposures; civil society and the aid community need to identify the regions of the world that most urgently require DRR measures (Ehrlich and Tenerelli, 2013). Effective adaptation and disaster risk management (DRM) strategies and practices depend on a rigorous understanding of the dimensions of exposure (i.e. physical and economic) as well as a proper assessment of changes and uncertainties in those dimensions (Cardona et al., 2012).

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Both the scope and the scale of the natural hazard impact assessment determine the type of exposure data to be collected.

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Risk models require detailed exposure data (e.g. with information on buildings, roads and other public assets) to produce as outputs risk metrics such as the annual expected loss and the probable maximum loss (see Chapter 2.4). For instance, catastrophe models commonly used by the insurance industry include an exposure module, which represents either a building of specific interest, a dwelling representative of the average construction type in a given area or an entire portfolio of buildings with different characteristics.
(e.g. an entire city). The characteristics may include physical characteristics like building height, occupancy rate, usage (private, public like commercial, industrial, etc.), construction type (e.g. wood or concrete) and age, and also non-physical characteristics like the replacement cost which is needed for calculating the loss at a certain location (Michel-Kerjan et al., 2013). Besides, insurance companies need to assess and model the business interruption that represents a major part of the total economic loss. To quantify loss due to business interruption, exposure databases need to include information on building contents and business information for different types of properties (Rose and Huyck 2016). These industry exposure databases are often proprietary and use heterogeneous taxonomies and classification systems which hinder efforts of merging independently developed datasets (GFDRR, 2014). However, the Oasis (OASIS, 2016) community and the recently established Insurance Development Forum are dedicating special efforts to exposure data harmonisation, sourcing, structuring and maintenance at the global levels. Moreover, an initiative lead by Perils is offering de facto standard industry exposure databases for property across Europe at an aggregated spatial level (PERILS, 2016).

If the aim is to know whether a particular feature is likely to be affected or not by a certain level of hazard, then it is enough to simply identify the location of that feature (e.g. building location and building footprint) or group of features (e.g. building stock). Whereas if the purpose is to understand the potential economic impacts or human loss, then other attributes of the feature or group of features need to described (e.g. the type of construction materials, population density and the replacement value). Exposure databases detailed to single building units are seldom available for disaster modellers. Instead, the exposure data are more often available in an 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 (Ehrlich and Tenerelli, 2013). For optimal results the choice of the attribute and its granularity should be aligned with the scale and the purpose of the risk assessment. To a certain extent, the requirements in terms of granularity also depend on the peril being modelled: e.g. flood models require detailed information on the location and building type. By contrast, windstorm models arguably need to be less precise. Detailed gust speeds will not be known at a precise location level but rather estimated on a broader spatial scale. There are clearly many attributes that can be attached to exposure data. Developing such databases requires a multidisciplinary team of construction engineers, economists, demographers and statisticians.

In recent years, several exposure datasets with regional or global coverage have attempted to generate detailed building inventories and compile exposure data despite the challenges related to the heterogeneous mapping schemas, the different typologies and the varying resolutions. In the following sections, we review the existing initiatives at EU and global levels that have made a first step in overcoming these obstacles either i) by using exposure proxies such as land-use and land-cover products, ii) by using Earth observation technologies for mapping human settlements and population or iii) by integrating existing information from different acquisition techniques, scales and accuracies for characterising the assets at risk and for describing the building stock. We purposely limit the review here to large-scale exposure datasets that have a spatial component (i.e. associated with a geographic location) and that are open, hence ensuring replicability and a better understanding of risk (World Bank, 2014).

### 2.2.3 Land-cover and land-use products as proxies to exposure

These products outline areas with different uses, including ‘industrial’, ‘commercial’ and ‘residential’ classes, as well as non-impervious areas (e.g. green spaces).

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**Land-use and land-cover (LU/LC) information products that are usually derived from remote sensing data may provide information on buildings and thus on exposure.**
Some products may also describe the building density. LU/LC maps provide valuable information on infrastructure such as roads. The spatial characteristics of LU/LC maps are influenced by the minimum mapping units, which refer to the smallest size area entity to be mapped.

2.2.3.1 European land-use and land-cover (LU/LC) products

The currently available EU-wide and global LU/LC products have minimum mapping units ranging between 0.01 ha (e.g. the European Settlement Map (ESM)) to 100 ha (e.g. MODIS land cover). At the EU level, the Corine Land Cover is the only harmonised European land cover data available since 1990. It comprises 44 thematic classes with units of 25 ha and 5 ha for changes, respectively. From 1990 until 2012, four of such inventories were produced and completed by change layers, and it has been used for several applications like indicator development, LU/LC change analysis (Manakos and Braun, 2014) and flood risk assessment within the EU context (Lugeri et al., 2010). However, its limitations in terms of spatial resolution do not allow the conversion of land-cover classes into accurate, physical exposure maps. To complement LU/LC maps, detailed inventories of infrastructures are essential for assessing risks to infrastructures as well as for managing emergency situations. In 2015, a geographical

FIGURE 2.7

European Settlement Map – 10 m resolution – Genova
Source: European Commission (JRC)
The Urban Atlas is another pan-European LU/LC product describing, in a consistent way, all major European cities’ agglomerations with more than 100,000 inhabitants. The current specifications of the Urban Atlas fulfil the condition of a minimum mapping unit of 0.25 ha, allowing the capture of urban, built-up areas in sufficient thematic and geographic detail (Montero et al., 2014). The Urban Atlas cities are mapped in 20 classes, of which 17 are urban classes. It is a major initiative dealing with the monitoring of urban sprawl in Europe, designed to capture urban land use, including low-density urban fabric, and in this way it offers a far more accurate picture of exposure in urban landscapes than the Corine Land Cover does. Despite its accuracy and relevance for risk modelling, the main limitation of this product is its spatial coverage, as it is restricted to large urban zones and their surroundings (more than 100,000 inhabitants).

Currently, the continental map of built-up areas with the highest resolution so far produced is the ESM (Florczyk et al., 2016). The ESM is distributed as a building density product at both 10 metre x 10 metre and 100 metre x 100 metre resolutions, each supporting specific types of applications. For a pan-European risk assessment (Haque et al., 2016), the coarser (100 metre) resolution is sufficient, whereas the 10 metre product would be necessary for local to regional risk assessment.

### 2.2.3.2 Global land-use and land-cover products

A number of global land-cover products covering different time periods and different spatial resolutions have been created from remote sensing, e.g. MODIS (Friedl et al., 2010), Africover, GLC-SHARE of 2014 (Latham et al., 2014), GLC2000 (Fritz et al., 2010), IGBP (Loveland et al., 2000) and GlobCover (Arino et al., 2012). Many of these products are based on coarse resolution sensors, e.g. GLC2000 is at 1 km, MODIS is at 500 metre and GlobCover is at 300 metre resolution, which hampers the potential to provide accurate exposure data that can directly feed into risk assessment models.

The first high-resolution (30 metres) global land-cover product is the GlobeLand30, which comprises 10 types of land cover including artificial surfaces for years 2000 and 2010 (Chen et al., 2015). However, the ‘artificial surfaces’ class consists of urban areas, roads, rural cottages and mines impeding the straightforward conversion of the data into physical exposure maps.

The Global Urban Footprint describing built-up areas is being developed by the German Aerospace Centre and is based on the analysis of radar and optical satellite data. The project intends to cover the extent of the large urbanised areas of megacities for four time slices: 1975, 1990, 2000 and 2010 at a spatial resolution of 12 metre x 12 metre (Esch et al., 2012). Once available, this dataset will allow effective comparative analyses of urban risks and their dynamics among different regions of the world.

The global human settlement layer (GHSL) is the first global, fine-scale, multitemporal, open data on the physical characteristics of human settlements. It was produced in the framework of the GHSL project, which is supported by the European Commission. The data have been released on the JRC open data catalogue (Global Human Settlement Layer, 2016). The main product, GHS Built-up, is a multitemporal built-up grid (built-up classes: 1975, 1990, 2000 and 2014), which has been produced at high resolution (approximately 38 metre x 38 metre). The GHS Built-up grid was obtained from the processing of the global Landsat archived data in the last 40 years in order to understand global human settlement evolution. The target information collected by the GHSL project is the built-up structure or building aggregated in built-up areas and then settlements according to explicit spatial composition laws. They are the primary sign and empirical evidences of human presence on the global surface that are observable by current remote sensing platforms. As opposed to standard remote sensing practices based on urban land cover or impervious surface notions, the GHSL semantic
approach is continuously quantitative and centred around the presence of buildings and their spatial patterns (Pesaresi et al., 2015; Pesaresi et al., 2013). This makes the GHSL perfectly suitable for describing the physical exposure and its changes over time at a fine spatial resolution (Pesaresi et al., 2016).

2.2.4 Status of population exposure at the EU and global levels

The static component relates to the number of inhabitants per mapping unit and their characteristics, whereas the dynamic component refers to their demography and their activity patterns that highlight the movement of population through space and time. Population distribution can be expressed as either the absolute number of people per mapping unit or as population density. Census data are commonly used for enumerating population and for making projections concerning population growth. Census data may also contain other relevant characteristics that are used in risk assessment, such as information on age, gender, income, education and migration.

For large-scale analysis, census data are costly and seldom available in large parts of the world or are even outdated or unreliable. Remote sensing, combined with dasymetric mapping, represents an interesting alternative for large-scale mapping of human exposure. Dasymetric mapping consists in disaggregating population figures reported at coarse source zones into a finer set of zones using ancillary geographical data like LU/LC.

2.2.4.1 European-wide population grids

At the EU level, a European population grid with a spatial resolution of 100 metres x 100 metres was produced (Batista e Silva et al., 2013). The method involved dasymetric mapping techniques with a resident population reported at the commune level for the year 2011 and a refined version of the Corine Land Cover as the main input sources. The data are publically distributed on the geographic information system of the Commission following the standardised 1 km x 1 km grid net and the Inspire specifications. A new population grid at 10 me-
tres has recently been produced for the whole European territory, which builds on the ESM at 10 metres as a proxy of the distribution of residential population and 2011 census data (Freire et al., 2015a). The layer has been produced upon request of the European Commission and will soon be made freely available and downloadable online. Figure 2.8 shows an example of potential uses of the 10-metre-resolution, EU-wide ESM map for modelling day and night population distribution in volcanic risk assessment.

2.2.4.2 Global human exposure

Global distribution of population in terms of counts or density per unit area is considered as the primary source of information for exposure assessment (Pittore et al., 2016). Global population data are available from the LandScan Global Population Database (Dobson et al., 2000), which provides information on the average population over 24 hours and in a 1 km resolution grid.

The LandScan data have annual updates and are widely used despite being a commercial product. Although LandScan is reproduced annually and the methods are constantly revised, the annual improvements made to the model and the underlying spatial variables advise against any comparison of versions.

Other global human exposure datasets include the Gridded Population of the World (GPWv4) available at a resolution of approximately 5 km at the equator. It is developed by SEDAC and provides population data estimates at a spatial resolution of approximately 1 km at the equator. For GPWv4, population input data are collected at the most detailed spatial resolution available from the results of the 2010 round of censuses, which occurred between 2005 and 2014. The input data are extrapolated...

The open WorldPop is another initiative providing estimated population counts at a spatial resolution of 100 metres x 100 metres through the integration of census surveys, high-resolution maps and satellite data (Lloyd et al., 2017). Within the WorldPop project, population counts and densities are being produced for 2000-2020; the available data currently essentially cover America, Asia and Africa.

People present the most important elements-at-risk with a static and dynamic component.

Recently, within the framework of the GHSL, an improved global layer called GHS-POP, which maps the distribution of the population with unprecedented spatio-temporal coverage and detail, has been released. The data have been produced from the best available global built-up layer (GHS-BU) and from census geospatial data derived from GPWv4. The population grids correspond to residential-based population estimates in built-up areas and not ‘residential population’ or ‘population in their place of residence’, for which consideration of land use would be required (Freire et al., 2015b).

The multitemporal data are available free of charge at a spatial resolution of 250 metres x 250 metres for 1975, 1990, 2000 and 2015. It has already successfully been used in the context of global risk assessment for the analysis of the increase in population exposure to coastal hazards over the last 40 years (Pesaresi et al., 2016).

### 2.2.5 Exposure data describing the building stock

Several exposure databases attempt to characterise the assets at risk by including physical exposure information. The latter is often derived from the integration of a large variety of possible exposure information sources using different modelling approaches. We review here the existing initiatives that describe the building stock through a variety of attributes (e.g. height, construction material and replacement value).

#### 2.2.5.1 EU-wide building inventory databases

The European Union’s seventh framework programme for research and technological development (FP7) project, the NERA (Network of European Research Infrastructure for Earthquake Risk Assessment and Mitigation) initiated the development of a European building inventory database to feed into the Global Exposure Database (GED) (see Chapter 2.2.5.2). The database builds upon the outcomes of NERIES project (Network of Research Infrastructures for European Seismology) to compile building inventory data for many European countries and Turkey (Erdik et al., 2010). The European building inventory is a database that describes the number and area of different European building typologies within each cell of a grid, with a resolution of at least 30 arc seconds (approximately 1 km² at the equator) for use in the seismic risk assessment of European buildings (Crowley et al., 2012). The database includes building/dwelling counts and a number of attributes that are compatible with the Global earthquake model’s basic building taxonomy (i.e. material, lateral load, number of storeys, date of construction, structural irregularity, occupancy class, etc.). This inventory contains useful information for the assessment of risk assessment and for the estimation of economic loss at the EU level.

#### 2.2.5.2 Global building inventory databases

The prompt assessment of global earthquakes for response (PAGER) (Jaiswal et al., 2010), the GED for GAR 2013 (GEG-2013) and the GED for the Global earthquake model (GED4GEM) are examples of global exposure databases that specifically include physical exposure information.

On a country-by-country level, the PAGER (Jaiswal et al., 2010) contains estimates of the distribution of building types categorised by material, lateral force resisting system and occupancy type (residential or non-residential, urban or rural). The database draws on and harmonises numerous sources: (1) United Nations statistics, (2) the United Nations habitat’s demographic and health survey database, (3) national housing censuses,
(4) the world housing encyclopaedia project and (5) other literature. PAGER provides a powerful basis for inferring structural types globally. The database is freely available for public use, subject to peer review, scrutiny and open enhancement.

The GEC-2013 (De Bono and Chatenoux, 2015) is a global exposure dataset at 5 km spatial resolution which integrates population and country-specific building typology, use and value. It has been developed for the global risk assessment 2013 with the primary aim of assessing the risk of economic loss as a consequence of natural hazards at a global scale. The development of GEG-2013 is based on a top-down or ‘downscaling’ approach, where information including socioeconomic, building type and capital stock at a national scale are transposed onto a regular grid, using geographic population and gross domestic product distribution models as proxies. GEG-2013 is limited in some important ways: i) it was fundamentally constructed using national indicators that were successively disaggregated onto a 5 × 5 km grid; and ii) the capital stock in each cell is distributed on the basis of the number of persons living in that cell and does not take into account the real value of the assets of the cell. The data can be downloaded from the GAR risk data platform.

The GED4GEM is a spatial inventory of exposed assets for the purposes of catastrophe modelling and loss estimation (Dell’Acqua et al., 2013, Gamba et al., 2012). It provides information about two main assets at risk: residential population and residential buildings. Potentially, it can also include information about non-residential population and buildings, although the amount of information for these two additional assets is currently quite limited. In general, the GED is divided into four different levels, which are populated from different data sources and use different techniques. Each level has a different geographical scale as for the statistical consistency of the data it contains as well as a different level of completeness. Each level is thus appropriate for a different use:

- Level 0 — A representation of the population and buildings on a 30-arc seconds grid with information about the buildings coming from statistics available at the country level. The building distribution is thus the same for each element of the grid belonging to a given country, with a binary difference between ‘rural’ and ‘urban’ areas.
- Level 1 — A representation of population and buildings on a 30-arc seconds grid with information about the buildings that is available using the subnational statistics (e.g. for regions, states, provinces or municipalities according to the different countries).
- Level 2 — A representation where each element of the same 30-arc seconds grid includes enough information to be consistent by itself, and no distribution on a bigger geographical scale is used. This case corresponds to the situation when all building counts are actually obtained, not by means of a disaggregation of a distribution available on a wider area on the elements of the grid but by aggregating building -level data, possibly available for the area of interest.
- Level 3 — A representation at the single building level, including all the possible information about each building, such as structural, occupancy and economic variables.

The first version of the GED contains aggregate information on population and the number/built area/reconstruction cost of residential and non-residential buildings at a 1 km resolution. Detailed datasets on single buildings are available for a selected number of areas and will increase over time.

### 2.2.6 Future trends in exposure mapping: towards a dynamic exposure modelling

The review of existing initiatives for defining and mapping exposure shows that there is a clear trend towards the use of satellite data in combination with statistical modelling (top-down and bottom-up approaches) for building exposure data: remotely sensed data sourcing for exposure is particularly useful in low-income and emerging economies which lack well-established data collection resources, frameworks and agencies. These economies are often also undergoing rapid urbanisation with dramatically changing exposure concentrations over short periods of time.

In parallel, over the last 5 years, the field of risk assessment has been increasingly driven by open data and open-source modelling, as highlighted in the report Understanding risk in an evolving world (GFDRR, 2014).
Open data initiatives such as the Humanitarian OpenStreetMap Team has contributed significantly to the collection of exposure data in vulnerable countries: in a little over a year, more than 160,000 individual buildings were mapped through crowdsourcing and in situ surveys.

At present, one of the most challenging aspects of exposure modelling is to implement multihazard exposure models through dynamic, scalable frameworks. The dynamic nature of such frameworks in this context reflects the need to explicitly account for both the time variability of the exposed assets and the constant evolution of their representation in the model, which is seldom complete and exhaustive.

Remote sensing, combined with dynamic exposure modelling and bottom-up approaches such as citizen mapping initiatives, can be an effective way to build large exposure databases.

In a dynamic, multiresolution exposure model, two basic types of entities should therefore coexist: atomic data and statistical (aggregated) models. Atomic data refer to physical structures such as buildings or bridges that have been analysed individually and possibly not fully enumerated. Statistical models are aggregated descriptions defined over specific geographic boundaries and possibly influenced by atomic data. Atomic data and statistical models are closely related and mutually interactive, with both having geometric properties and attributes. Compound models accommodating both atomic data and statistical models would be able to optimally exploit direct, in situ information obtained from specialised surveys, even if not complete and exhaustive, by constraining a set of statistical distributions describing the assets’ attributes at the atomic level (e.g., material properties for a single building) or at the aggregation boundary level (for instance the expected number of storeys of different building types based on empirical observations in a city district). At atomic level, this can be obtained for instance by modelling the (in)dependence relationships among different assets’ attributes and with external covariates (e.g., geographical location, altitude, terrain slope, etc.).

An example for a probabilistic information integration approach is given in Pittore and Wieland (2013), where Bayesian networks are proposed for their sound treatment of uncertainties and for the possibility of seamless merging of different data sources, including legacy data, expert judgement and data mining-based inferences. Due to the increasingly large variety of possible exposure information sources including sparse and incomplete data available at small-scale resolution, the issue of the need for the flexible integration of existing information at different scales and accuracies in order not to discard available information needs to be confronted.

To exploit the full capabilities of the available information in combined spatio-temporal approaches, a database is needed that allows one to model and query complex data types composed of multiple spatial and temporal dimensions. Information extracted from a satellite image or manually sampled in situ show different degrees of quality in terms of reliability and accuracy. Therefore, a probabilistic framework for information integration, updating and refinement is required, as exemplified in Pittore and Wieland (2013). During monitoring activities, the resulting information model continuously evolves and a dynamic exposure database should be able to track an object’s evolution over space and time while accounting for its identity which is the lifespan of an object. To this regard, Pittore et al. (2015) propose a novel approach to prioritise exposure data collection based on available information and additional constraints. They utilise the concept of focus maps (Pittore, 2015), which combine different information layers into a single raster representing the probability of the point being selected for surveying, conditional on the sampling probability of each of the other layers. Based on a focus map, a set of sampling points is generated and suitably routed on the existing road network. This allows one to realise a further optimisation of the overall data collection by including additional survey constraints in the routing algorithm and which drives the in situ data collection phase. Iteratively repeating this process allows for an efficient model updating which can be optimised to fit the available time and resources.
2.2.7 Conclusions and key messages

The increasing availability of detailed and harmonised hazard datasets is calling for parallel efforts in the production of standardised multihazard exposure information for disaster risk models. GEDs can be a possible solution for harmonisation and for moving beyond single-hazard databases. Several recommendations can be distilled from this overview and are provided here to develop a roadmap towards the effective implementation of global, dynamic exposure databases. Finally, exposure data collection should be regarded as a continuous process sustaining a continuous re-evaluation of risks to enable an effective DRR.

Partnership
Authoritative and non-authoritative sources should be integrated in order to ensure quality standards and compliance with the disaster risk-reduction purposes. Within this context, it becomes important to harvest data from crowd-sourced information and exploit volunteered geographic information to augment authoritative sources and involve communities and experts, especially in data-poor countries.

Knowledge
The need for quality assessment and an analysis of the uncertainty in the exposure data to avoid error propagation. Quantification of exposure data uncertainty is useful for anatomising the structure of the total uncertainty in the risk assessment into individual uncertainties associated with the risk components (exposure uncertainty compared to that of hazard and vulnerability). In addition, the communication of uncertainty to the users of the exposure databases is also essential to ensure local understanding and trust in the data.

Innovation
Data and (statistical) models have to coexist in a statistically sound framework in order to overcome the impracticality of having a complete and fully enumerated global dynamic exposure database. Flexible integration of existing information at different scales and accuracies in order not to discard available information needs to be confronted. To this regard, rapid, large-scale data collection based on remote sensing should be fully exploited and be complemented whenever possible by information collected in situ using suitable sampling methodologies.
2.1. Qualitative and quantitative approaches to risk assessment


Gowland, R., 2012. The work of the european process safety centre (EPSC) technical Steering committee working group: ‘atypical scenarios’. Hazards XXIII, symposium series No 158, Institute of Chemical Engineers.


2.2. Current and innovative methods to define exposure


2.3. The most recent view of vulnerability


IPCC, 2012b. Summary for policymakers - Special report on managing the risk of extreme events and disasters to advance climate change adaptation (SREX). Intergovernmental Panel on Climate Change.


CHAPTER 2 UNDERSTANDING DISASTER RISK: RISK ASSESSMENT METHODOLOGIES AND EXAMPLES


2.4. Recording disaster losses for improving risk modelling


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2.5. Where are we with multihazards and multirisks assessment capacities?


El Adlouni, S., Ouarda, T., Zhang, X., Roy, R., Bobée, B. 2007. Generalised maximum likelihood estimators for the nonstationary gen-
eralized extreme value model. Water Resources Research 43(3), 410.


sessing the vulnerability of communities to landslides. Natural Hazards and Earth System Sciences 7, 765-779.

Pescaroli, G., Alexander, D., 2015. A definition of cascading disasters and cascading effects: going beyond the ‘toppling dominos’ metaphor. Planet@Risk 3(1), 58.


