Developing an Adaptive Global Exposure Model to Support the Generation of Country Disaster Risk Profiles

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1.0 Abstract

Corresponding to increased realization of the impacts of natural hazards in recent years and the need for quantification of disaster risk, there has been increasing demand from the public sector for openly available disaster risk profiles. Probabilistic disaster risk profiles provide risk assessments and estimates of potential damage to property caused by severe natural hazards. These profiles outline a holistic view of financial risk due to natural hazards, assisting governments in long-term planning and preparedness. A Country Disaster Risk Profile (CDRP) presents a probabilistic estimate of risk aggregated at the national level. A critical component of a CDRP is the development of consistent and robust exposure model to complement existing hazard and vulnerability models. Exposure is an integral part of any risk assessment model, capturing the attributes of all exposed elements grouped by classes of vulnerability to different hazards, and analyzed in terms of value, location and relative importance (e.g. critical facilities and infrastructure).
Using freely available (or available at minimum cost) datasets, we present a methodology for an exposure model to produce three independent geo-referenced databases to be used in national level disaster risk profiling for the public sector. These databases represent aggregated economic value at risk at 30 arc-second spatial resolution (approximately 1x1-km grid at the equator) using a top-down (or downscaling) approach. To produce these databases, the models used are: 1) a building inventory stock model which captures important attributes such as geographical location, urban/rural classification, type of occupancy (e.g. residential and non-residential), building typology (e.g. wood, concrete, masonry, etc.) and economic (replacement) value; 2) a non-building infrastructure density and value model that also corresponds to the fiscal infrastructure portion of the Gross Capital Stock (GCS) of a country; and 3) a spatially and sectorially disaggregated Gross Domestic Product (GDP) model that relates to the production (flow) of goods and services of a country. These models can be adapted to produce - independently or cohesively - a composite exposure database. Finally, we provide an example of the model’s use in economic loss estimation for the reoccurrence of the 1882 Mw 7.8 Panama earthquake.

2.0 Introduction and Objectives

With the end of the UN Hyogo Framework for Action (2005-2015) and beginning of the UN Sendai Framework for Disaster Risk Reduction (2015-2030) there is increased pressure on policy
makers to address risk quantification that assists disaster risk reduction (UNISDR, 2015; GFDRR 2014a). There is also increased sensitivity to the impacts of natural disasters in recent years and a corresponding increased demand from the public sector for openly available disaster risk profiles. Initiatives such as Hyogo and Sendai Frameworks and seminal publications such as the Global Assessment Report (UNISDR, 2015) and the World Bank’s Disaster Risk Financing and Insurance (DRFI) Strategy (Cummings and Mahul, 2008), advocate quantification of disaster risk at the national level. A Country Disaster Risk Profile (CDRP) presents this quantification of probabilistic risk at the national level.

Traditionally, sophisticated global building inventory exposure models for use in natural hazard risk assessment are held within the private sector, usually the reinsurance industry and catastrophe risk modeling agencies. However, these models, databases, and methods are proprietary and not freely or openly available to the public sector. They also concentrate on building stock and do not explicitly address the fiscal exposure of a government, which is important for the public sector to quantify its sovereign disaster risk.

While there has been a recent proliferation of openly available tools for the generation of disaster risk profiles (GFDRR 2014a; GFDRR, 2014b), there are only a few openly available, globally consistent, and robust exposure databases that can be used with other openly available tools to generate CDRPs. To address this issue, the exposure model presented here produces three exposure databases and is visualized as a methodology to assist in creating
future initiatives for open, adaptive, and compatible exposure databases for disaster risk modeling around the world. The exposure model may also offer other additional benefits such as providing a basis for modelling urban change, and could in addition be used as a reference basis for post disaster Damage and Loss Assessment (DaLA) reports (GFDRR, 2010).

In this paper exposure is defined in terms of economic value, not only of assets such as physical assets (buildings) and non-building infrastructure, but also in terms of spatially and sectorially disaggregated GDP. The objective of this paper is to propose a methodology that produces an open global exposure dataset based upon topological data such as population, country specific building construction type distribution, infrastructure assets and other economic indicators. This would consist of three independently produced geo-referenced databases of aggregated economic value at risk, at 30 arc-second resolution (approximately 1x1 km grid at the equator), using a top-down (or downscaling) approach to assist in national level disaster risk profiling for the public sector.

The three databases are 1) a building inventory (stock) database which captures important attributes such as geographical location, urban/rural classification, type of occupancy (e.g. residential and five types of non-residential use), structural typology (e.g. wood, concrete, masonry etc.) and economic (replacement) value; 2) a non-building infrastructure density and value database that also corresponds to the fiscal portion of the Gross Capital Stock (GCS) of a country; and 3) a spatially and sectorially disaggregated Gross Domestic Product (GDP)
database that relates to the production (flow) of goods and services of a country. We then integrate these three databases to derive a composite exposure database.

This methodology is primarily focused on the development of an exposure model for earthquake risk assessment; however, the model is also adaptable for other hazards such as windstorms and floods. This interdisciplinary exposure model draws heavily on methods used within geoscience, engineering, statistics and economics. Academic and public sector peer-reviewed articles were used to derive factual data to complement the proposed exposure model.

3.0 Literature Review

3.1 Structural building inventory exposure model

Recently there have been several initiatives to produce global building inventory exposure models such as UNISDR’s Global Assessment Report’s global exposure model GEG-2013 (De Bono and Mora, 2014), Global Earthquake Model’s GED4GEM (Gamba et al., 2012; Dell’Acqua et al., 2012), and USGS’ Prompt Assessment for Global Earthquake Response (PAGER; Wald et al., 2008; Jaiswal et al., 2010). Each has their strengths and weaknesses. In very generic terms, all three of these models follow key components of 1) disaggregating national or sub-national level information based on population as a proxy to a defined spatial grid resolution, 2)
assessing and applying building typology and vulnerability class distributions, and 3) applying a financial risk metric in terms of GDP, capital stock, or other socio-economic indicator(s).

The GEG-2013 global exposure model (De Bono and Mora, 2014) uses an innovative technique to assign building typologies per capita income level and settlement by size of population (Wyss et al., 2012). However, GEG-2013 is confined to urban areas and since almost 50% of the global population currently lives in rural areas (UNDESA, 2014), the method is not adequate for national level risk assessments as it underestimates the true exposure. The updated GEG-2015 (UNISDR, 2015) includes both urban and rural areas, but it is still limited to 5x5km grid cells, except for coastal areas. GED4GEM uses a more engineering-based approach in its building taxonomy classification and integrates both top-down and bottom-up approaches by producing exposure models at different scales (from coarse national level to individual buildings).

However, GED4GEM uses the Global Rural-Urban Mapping Project (GRUMP) database to delineate urban and rural areas and due to GRUMP’s main referral to coarse-level night-time lights satellite imagery for urban identification purposes, significantly overestimates the extent of urban areas (Schneider et al., 2012).

While other partially openly available models such as CATDAT Damaging Earthquakes Database simplify the exposure modelling approach and recalibrate by using socio-economic indicators such as global stocks and flow datasets (Daniell et al., 2012), the PAGER database relies on disaggregation of nominal GDP and its correlation to Produced Capital (PK) for exposure
disaggregation and loss estimation. As a fully open access model, PAGER (Wald et al., 2008) is a real-time loss assessment model which estimates loss of life and economic losses from earthquakes around the world. The model incorporates the detailed PAGER-STR taxonomy containing 106 different building construction types and proposing distributions in urban and rural areas for most countries and territories of the world mostly by judgment or reference to a neighboring country census. However, for economic valuation, it uses an exposure correction factor that is simply the ratio of per capita wealth (obtained from the World Bank, 2006a) to the per capita GDP of each country (Jaiswal and Wald, 2013) bypassing the requirement of detailed building inventories (Jaiswal et al., 2010). For spatial exposure disaggregation most of the exposure models use remote sensing to derive proxy information for identifying population and built-up areas and for building inventory region classification (e.g. urban, rural, etc.; Potere et al., 2009). Increasingly, remote sensing is seen as a quick, low cost, and relatively accurate tool to derive spatial exposure information and to determine enumeration of assets (buildings, roads, bridges, etc.; Adams and Huyck, 2006; Geiß and Taubenböck, 2013; Pittore and Wieland, 2013). To summarize, Table 1 reviews the global datasets that are publicly available (free or at little cost) and used in producing structural building inventory exposure models. The table is categorized in terms of datasets available for exposure disaggregation, building vulnerability classification, and asset value determination. Table 1 does not include all datasets used in this paper.
3.2 Non-building Infrastructure value distribution

Our effort to model non-building infrastructure value for the purpose of exposure modelling has two objectives: 1) to estimate the total value of physical assets and 2) to spatially disaggregate the asset values so that risks might be more precisely defined. Ideally, this would be achieved by assembling a database of replacement value of individual infrastructure features by type and size. This task grows quickly complex when the features of even a single economic sector are enumerated. In the power sector, for example, the list would include power generation by coal, gas, hydro, nuclear, wind, geothermal, and other sources of fuel, as well as transmission lines, substations, the distribution network, and service connections. Even when such an effort has been undertaken, broad ranges of unit costs were found, as well as significant effects of economies of scale for road projects in particular (World Bank, 2009a).

To achieve the first objective, some previous efforts have relied on the Perpetual Inventory Method (PIM) and annual capital formation data from national accounts (e.g. Berlemann and Wesselhöft, 2014). This method produces a monetary estimate of the current value of physical capital stocks based on investment over a long time-series using a fixed asset depreciation rate. It has been used in the World Bank Wealth of Nations reports to estimate the PK component of wealth (World Bank, 2006a; 2011). DeBono and Mora (2014) use a top-down exposure modelling approach, where PK represents the total asset value and is spatially disaggregated according to population density and urban typology (by the size of population).
Alternatively, products like the Global Human Influence Index (HII) Dataset (WCS and CIESIN, 2005) are created by combining spatial datasets into a weighted index of human impact on the environment. While not explicitly aimed at mapping infrastructure, the gridded product incorporates precise locations of many of the features of interest, such as railroads and highways, assets that would be expected in urban areas or areas of intense agriculture. The result, while lacking monetary valuation, is a measure of infrastructure density, mapped with somewhat greater spatial accuracy.

Finally, while infrastructure assets follow a spatial pattern similar to population distribution, they also have some unique characteristics. High-value assets, such as power plants and major inter-city highways, may exist in relatively remote and sparsely populated areas. Infrastructure networks also serve a connectivity function that is not fully captured in the asset value. Exploration of connectivity and the spatial dependencies it creates, however important, is not within the scope of this paper.

### 3.3 GDP disaggregation

Sub-national GDP data are increasingly used in socio-economic analyses. A brief review of some of the existing techniques and datasets for GDP modelling provides context to the approach used in this paper. A few models that estimate GDP at a sub-national level exist in the public
domain. These include the G-Econ model, which is a country level model at a spatial resolution of 1 degree longitude by 1 degree latitude that facilitates analysis between the spatially explicit environmental factors and economic activity (Nordhaus, 2006; Nordhaus, 2008). A GDP disaggregation model has also been produced by the World Bank and UNEP that was motivated by disaster risk analysis and based on observations from approximately 70 countries and territories at approximately 1x1 km (or 30 arc-seconds) grid resolution using over 2900 observations of sub-national GDP and population datasets (UNISDR, 2011). Gennaioli et al. (2013) compiled 1349 regional observations of GDP from 89 countries and an additional 220 regional observations from another 21 countries, using data including expenditure, income, and wages. Daniell et al. (2012) also compiled a GDP dataset for 110 countries, with 1569 sub-national observations for CATDAT Damaging Earthquakes Database. McKinsey Global Institute (2011) constructed a model to create city level GDP estimation. Other research and datasets leveraged the GDP spatial variation from satellite imagery of night-time lights products. These studies highlight the importance to socio-economic analysis in establishing a relationship between area of night-time lights and GDP economic activity (Doll et al., 2000; Elvidge et al. 2001; Ebener et al., 2005; Doll et al., 2006). Ghosh et al. (2010) provide a dataset that used night-time lights and sub-national observations to estimate GDP at approximately 1 km grid resolution.
4.0 The CDRP Exposure Model Methodology

4.1 Components of the model

Buildings are considered the most important asset category because from a financial perspective, most damage and loss that occur during earthquakes, floods, windstorms, etc. relate to building damage and associated loss (Neumayer and Barthel, 2011). For exposure modeling of buildings, the primary information attributes needed are the location of the buildings and their respective estimated replacement value in terms of their occupancy and construction types. For the CDRP exposure model, key types of datasets referenced were publicly available sources, remote sensing sources, on-site surveys of building stock, crowd sourcing, private and public make-up of built stock in each country and examining the definition and categorization of the stock.

Figure 1 presents a flow chart that summarizes the key steps involved in the production of the CDRP exposure model. The components of this flow chart are then detailed in the subsequent sections 4.2 – 4.4. The key components of the building inventory stock model (shown within the grey box in Figure 1) are exposure disaggregation, building typology and vulnerability distribution, and asset value determination. The key steps required to produce the spatially allocated non-building infrastructure model are shown in the red box. The key steps related to disaggregation of GDP to a 1 km² grid is shown in the brown box of Figure 1.
Within each of these components, the required datasets and spatial modeling steps needed and component inter-linkages for production of the composite exposure model are outlined. Required input datasets are in yellow parallelograms (datasets available at minimum cost are label in grey), model processing steps are in blue boxes, and intermediate and final outputs are shown in red and green ellipses respectively. Demographic, building typology, floor area and unit costs of construction information and sub national GDP datasets compiled and developed for each country are shown in orange colored folders.

4.2 Building stock exposure model

4.2.1 Exposure disaggregation

4.2.1.1 Step 1 – Identification of built up areas

For developing the building stock exposure model, we first carry out the steps in the exposure disaggregation component to spatially allocate the exposed value at risk into 30 arc-second grid cells (approx. 1km²) classified into 6 types of building inventory regions. These are 1) capital city residential, 2) urban residential areas other than the capital city, 3) rural residential, 4) mixed (residential and non-residential) in the capital city, 5) mixed (residential and non-residential) in the urban areas other than the capital city, and 6) mixed (residential and non-residential) in rural areas.
We use the level 1 Global Administrative Areas (GADM) boundary vector layer dataset (available at www.gadm.org) to define spatial boundaries. Then, we use the Global Urban Footprint (GUF) dataset (Esch et al., 2013) to delineate built up areas. The dataset is aggregated from the 75m binary (built up/non-built up) mask to the CDRP model output resolution of 1 km² preserving the inherent area information to illustrate the continuous degree of built-up (Figure 2a). Next, population information is integrated for the urban-rural characterization. The LandScan (Bhaduri et al., 2007) gridded population dataset was identified as best-suited dataset for this purpose. Other gridded population datasets such as Gridded Population of the World (GPW; Balk and Yetman, 2004) and GRUMP (Balk et al., 2010) were too coarse in resolution and in accuracy and WorldPop (Linard et al., 2012) is not yet available for all regions of the world (refer to Table 1 for more details).

### 4.2.1.2 Step 2 - Identification of urban and rural areas and application of built-up-adjusted population reallocation

Using population density as a proxy for housing density, and vice versa, is a common approach in dasymetric mapping (Aubrecht et al., 2013). LandScan (Bhaduri et al., 2007) adequately allocates urban population to built-up areas, but largely fails to do so in rural areas, i.e. widely (mal)distributing rural population outside of built-up areas (Aubrecht et al., 2015). To address this issue, a novel population reallocation approach developed by Aubrecht et al. (2015) that reassigns population in rural regions from outside to inside of built-up areas in a multi-stage, weighted manner was adopted. Since urban areas are considered to be well captured in the
gridded population data, to identify all urban areas, the largest and most populated contiguous gridded population data cells (which henceforth will be referred to as built-up patches) are classified as urban. This step is then repeated iteratively for the remaining largest and most populated contiguous gridded cells until the national-level urban population proportion, as reported in the UN’s World Urbanization Prospects (UNDESA 2014) is reached. For the remaining built-up patches that are now considered rural, population is reallocated according to size, relative population distribution within a patch, and its inherent density (Aubrecht et al., 2015). The newly derived population cell counts are then adjusted at province or national level (according to data availability) to match the latest available or projected census information (Figure 2b).

Capital city metropolitan areas were delineated differently as they are considered distinctly different in terms of population growth, building stock, construction prices, critical facilities and infrastructure relative to other urban areas in most developing countries. A seed-growth approach is implemented, clustering adjacent cells of high population density (Aubrecht et al., 2015). The most populated cell within the capital city administrative area is selected and subsequent high-density cells are added in iterative manner until a pre-identified overall metropolitan area population number is reached (Aubrecht et al., 2015).

**4.2.1.3 Step 3 - Determination of residential and mixed grid cells**
Having the population distribution information now fully allocated to within built-up areas, the above-identified urban and rural areas can be further reclassified to determine residential and mixed occupancy grid cells to allocate PAGER-STR (Jaiswal et al., 2010) vulnerability class taxonomy. Since the model operates at a spatial resolution of approximately 1 km², we assume in general at that spatial scale in areas of mixed land-use, that residential structures exist amongst non-residential structures, such as offices, commercial, and industrial buildings as well as mixed-occupancy buildings. For urban areas, Impervious Surface Area (ISA; Elvidge et al., 2007) data based on satellite-derived night-time lights are used to highlight cells of intense human activity, corresponding to mixed occupancies. This refers to the correlation of high artificial light intensity at night with urban non-residential areas such as commercial and industrial. The median light intensity value within an urban area is used as a threshold to separate the two occupancy types (Figure 2c). It has been tested with reference to local-level cadaster data for a case study in Ecuador (Aubrecht and León Torres, 2015).

In rural areas, road networks are often considered the main ‘arteries’ that attract human activities. In particular, regional-level road junctions are usually associated with commercial activities such as supermarkets, gas stations, etc. It is therefore assumed that within the pre-identified rural built-up areas, grid cells featuring mixed occupancies would include road junctions (as derived from the Global Roads Inventory Project GRIP vector data; Meijer, 2009). These assumptions allow the exposure model to classify the grid cells in rural areas as either residential or mixed occupancy (Figure 2c).
4.2.2 Step 4 – Apply building typology distribution by vulnerability class

The second key component within the building stock exposure model is to assess how the population in each type of grid cell defined in the exposure disaggregation component (section 4.2.1) is distributed into buildings of different vulnerability. With all natural hazards and earthquakes in particular, determining buildings’ vulnerability class by structural type (i.e. the type of load-bearing structure) is crucial, as vulnerability to ground shaking (the main earthquake hazard and consequent loss generator) varies greatly (Pomonis et al., 2014). Various international efforts have been made to classify buildings according to their load-bearing structure for earthquake risk modelling (Jaiswal et al., 2010), and other attributes such as roofs, external wall type, height and number of floors for other hazards such as windstorm and flooding.

In this methodology, information on the existing building stock in a given country was obtained from census data, particularly for the residential buildings. In most countries of the world, Population and Housing Census are carried-out simultaneously at regular intervals (UN Statistical Division, 2008). From the Housing Census, data extracted provided information on the following key attributes of the dwelling stock: a) Dwelling occupancy status (e.g. permanently occupied, seasonally occupied, collective, institutional, vacant, abandoned etc.); b) Dwelling type (e.g. dwellings in single-family buildings or apartments in multi-family buildings etc.); c) External Wall material (e.g. brick, stone, adobe, concrete panels etc.); d) Roof cover
material (e.g. concrete slab, tiled roof, thatched roof etc.); and e) Floor type material (e.g. concrete floor, earthen floor, wooden floor, etc.).

The data is usually extracted by administrative unit (e.g. department, district, municipality etc.) and (or) by type of inventory region (e.g. urban and rural areas). For residential buildings, the existing dwelling stock’s distribution (expressed in number of dwelling units and (or) the respective resident population) into structural typologies for each inventory region (capital city, other urban and rural) is estimated by reference to the external wall and roof cover type information.

The size of dwellings (i.e. their floor area) and the number of people per dwelling unit in different vulnerability classes is then used to derive the structure type-specific existing dwelling floor area distribution per grid cell. Information on dwelling size is obtained or estimated from respective Housing Census where usually the number of rooms and (or) bedrooms and sometimes the actual floor areas are reported. Additional literature research about the housing policy and related socio-economic issues is also often necessary (e.g. Angel, 2000 and Angel, 2001).

For non-residential buildings, as data cannot be derived from population and housing census, the existing built floor area is estimated using employment statistics by economic sector in the
urban versus rural environment of each examined region, in conjunction with information on
the likely floor area per employee for the different economic sectors. The estimated non-
residential built floor area exposure is then disaggregated to the inventory regions at grid cell
level using inventory-region-specific population distribution patterns as weights (i.e. a cell’s
share of the inventory region’s total population serving as proxy). As data are sparse, we
attribute the non-residential built floor area into five broad use-types (i.e. commercial-retail,
critical buildings (educational, health, other public buildings), office and other services buildings
(hotels, restaurants, recreation etc.), warehouses and industrial) and then to corresponding
structural vulnerability classes, using expert judgment.

4.2.3 Step 5 - Asset value determination

For the asset value determination in the residential sector, unit costs of construction that
depend on the type of building (structural vulnerability class) were derived. The World Housing
Encyclopedia (http://www.world-housing.net/) reviews such information for many countries
affected by earthquakes worldwide; in addition there are the standard unit value tables for the
issuance of building permits in several countries. Globally, international estate agency reports
also provide unit cost values for the higher-end of housing and non-residential sectors.
Standardized cost estimates for all countries of the World were derived from the World Bank’s
annual Doing Business reports that refer to the cost of getting a permit and building to
completion a two-storied warehouse of total floor area of 1300.6 m² in the capital city
Table 2 shows unit costs of construction for several structural typologies in Argentina from the respective World Housing Encyclopedia reports.

Subsequently, integration of residential structure type-specific unit costs of construction for the building inventory regions enables calculation of the residential asset replacement value for each grid cell. For non-residential buildings, after estimating built floor area in the capital city, other urban areas, and rural areas, appropriate unit cost values referred from aforementioned sources were applied.

To derive a final combined asset replacement value, the residential and non-residential values are summarized at cell-level, i.e. all cells having a residential value and for the identified cells of mixed occupancy, adding the non-residential value. This combined value is evaluated against the private portion of GCS which represents the full replacement cost of all assets currently to the standard of new stock (see section 4.3.2 and 4.3.5 for more details). The comparison of these values gives a “top-down” and “bottom-up” approach to asset replacement values. Where these values differed by greater than 15%, a detailed check of service lives and Gross Fixed Capital Formation (GFCF) for the capital approach (top-down) or asset costs and area (bottom-up) was conducted and the model readjusted.
4.3 Non-building infrastructure exposure model

4.3.1 Background

This section refers to the non-building infrastructure model component of Figure 1. We use a hybrid approach to model the distribution of non-building infrastructure value at approximately 1 km² resolution (at 30 arc-second) grid. First, a top-down approach is used in the estimation of total asset value (capital model) and allocation across infrastructure sectors. Sectors considered are road transport, air transport, ports, energy, telecommunications, and water and sanitation. For total asset value we use the public portion of GCS, assuming most non-building infrastructure is government-owned, acknowledging that this is not the case equally across sectors. We then employ a feature-based proportional approach to map values at grid cell level, in order to increase the spatial precision of exposure estimates.

4.3.2 Step 6 - Capital model calculation

For the capital model, we investigated the feasibility of using sub-national estimates of government expenditure by sector from compiled sources such as the World Bank Open Budgets Portal (World Bank, 2014c). While this is a promising source of information both in terms of the spatial disaggregation and sector allocation, the time-series are not long enough to estimate total physical stock using the PIM method (Berlemann and Wesselhöft, 2014), and data is currently available only for a limited number of countries. Due to these constraints, we
must rely on national accounts and annual investment in capital formation (GFCF) as a percentage of GDP.

All infrastructure, buildings and other capital (machinery, equipment etc.) has a service life associated with it (the service life of a particular bit of infrastructure being the average time in years that the building is expected to withstand). The Perpetual Inventory Method (Berlemann and Wesselhöft, 2014) is one of the simplest methods which for GCS assumes that the total value will remain until the service life of infrastructure is finished and then changes from 100 to 0. The survival function of the stock can be classified by the service life of an asset being \( S(t) \) which shows the amount of investment that has survived as a function of time to year \( t \) (100).

\[
S(t) = 1 - F(t) \quad \text{Eq. 1}
\]

Through this calculation of capital stock, the GCS at each year \( t \) is calculated. For most countries, at least 40-50 years of GFCF data are required before a stable calculation can be made. The GCS is calculated with a variable retirement of stock between the indicated service lives of the different groupings of structures.

Data was collected from national accounts as to annual investment in different portions of the economy (structures, machinery + equipment etc.); service life data for buildings and infrastructure were collected for each nation. Time series of investment generally exceeding
the mean service life of components can be examined in most countries from 1960 onwards. The GCS is then calculated with the service life when looking at the GCS at the end of the year \( t \), and looking at the investment from starting year \( i \) by

\[
GCS_t = \sum_{i=1}^{t} P\text{index}_{t-i,t} \times GFCF_t \times S(t + 1 - i)
\]

Eq. 2

Where

- \( GCS_t \) = gross capital stock (fixed assets) in year \( t \) in prices of year \( t \)
- \( GFCF_t \) = gross fixed capital formation in year \( t \) in current prices
- \( P\text{index}_{t-i,t} \) = price index of year \( t \) with base year \( t-i \) (generally GFCF, GDP deflator, Consumer Price index (CPI))
- \( S \) = expected service life remaining at time \( t \) (100% in PIM until end of service life)

The next step is to differentiate GCS between buildings (which were quantified in the building exposure model), and other non-building infrastructure. In many cases, this investment information is available and a PIM (Berlemann and Wesselhöft, 2014) approach to capital stock creation is undertaken for multiple assets mainly by discretizing construction versus machinery and equipment. GFCF data is then collected through time of investments in construction versus machinery/equipment in national accounts. The separation of private and public investment in each year has also been collated from economic ministries and other government sources. In some cases, this is also available as distributed GFCF. The rates are assumed to be the same for service lives from private and public infrastructure (where designated). Where spatially disaggregated detailed infrastructure asset data are not readily available, we assume that non-building infrastructure is largely publicly financed and used the time-series of public contribution to capital formation as a proxy.
As noted above, the components of capital formation data from national accounts are construction (houses, other buildings and infrastructure) and capital (machinery and other equipment, transportation equipment). However, in order to take advantage of specific types of infrastructure features in the GIS database (roads, ports, airports, power plants), the model requires allocation of GCS across sectors. This poses a significant challenge to implementation. To address this data constraint, we rely on information compiled in regional reports, supplemented by data from OECD (OECD, 2011). A summary of the available data on spending per sector used in this analysis is presented in Table 3. Although, the model uses the fiscal (public) portion of GCS, total investment is also used in the proportional allocation as ownership of some infrastructure features include both public and private interests.

Assuming a direct relationship between spending and total infrastructure quantity, an “infrastructure unit value” is estimated using a sector-specific size variable from the World Development Indicators (WDI; World Bank, 2014b) and other secondary sources. The average infrastructure unit value for each sector is then multiplied by the size variable for a given country and rescaled to a range of 0-1, to arrive at a sector share of the country estimated fiscal portion of GCS.
4.3.4 Step 8 - Spatial disaggregation of non-building infrastructure

The final step of the non-building infrastructure exposure model is the spatial disaggregation to cell-level. This uses spatial features representing inland (road and rail), air (airport) and maritime (port) transport infrastructure, energy production (power plants), with a quantitative attribute that captures relative size. For the most part, the feature size attributes used are identical to the WDI indicators used in sector allocation of GCS.

We calculate a sector value for each cell that represents the proportion of sector-specific infrastructure units located within the cell, based on the presence of features in the cell. The cell-level sector value is then calculated by multiplying the proportion by the sector specific fiscal portion of GCS. The final cell value is the sum of sector values. Infrastructure features and the underlying spatial datasets used are (Figure 3):

1. Major roads – GRIP v3 (Meijer, 2009) road density in km per 5 arc minute cell, of type 1 (Highway and Motorway) and type 2 (Primary). Total road spending is allocated to major and other roads using a ratio of 10:1, based on average project spending as documented in the World Bank ROCKS (Road Cost Knowledge Systems) database (World Bank, 2006b).

2. Other roads – GRIP v3 (Meijer, 2009) road density in km per 5 arc minute cell, of types 3 (Secondary), 4 (tertiary), and 5 (local/urban). Total road spending is allocated to major
and other roads using a ratio of 10:1, based on average project spending as documented in the ROCKS database.


5. Power plants – Using PLATT’s World electric power plant database with total installed electricity production capacity in MW for plants with status of operating or under construction in 2009, georeferenced using Enipedia.


4.4 GDP Disaggregation Model

4.4.1 Background

To disaggregate GDP, we use a model of economic activity that considers the different structure of urban and rural economies as well as agricultural and non-agricultural contributions to GDP. Agriculture has a notable contribution to many countries’ GDP and a distinct spatial structure.
Globally, the percentage contribution from agriculture to GDP varies by income group from 1 to 2% in high-income countries, to approximately 28% in low-income countries, based on 2005-2011 World Development Indicators (World Bank, 2014a). Due to the spatial structure of agricultural land use, data from satellites can be used to derive land cover classifications that include agricultural activity. In a Geographic Information System (GIS), we construct a derivative variable that is the total area of agricultural land within a cell, which is derived from the area of each cell and its proportion of agriculture within the same cell.

4.4.2 Step 9 – Gross Regional Product calculation

Gross Regional Product (GRP) data - which is subnational GDP data - come from many sources. These data are usually provided with administrative names and in local currency. We constructed the GRP dataset from shares of the total GRP per administrative area in order to be consistent with the respective country’s GDP provided by the World Bank World Development Indicators (2012 version) in 2005-constant-USD, as well as the economic sector contribution to GDP from WDI (2012).

For calculation of GRP, we define the extents of urban areas based purely on population density from LandScan (Bhaduri et al., 2007). The two derived variables from the spatial analysis of population density are urban extents and rural (non-urban) classifications. As an alternative to
Section 4.2.1 above, the grid of urban extents is derived using a population density threshold of 500 people per km². Further processing steps include the use of a 3x3 majority filter to eliminate isolated cells (noise). Rural classification is defined as all areas with a population density estimate above zero that is not urban. Since rural population in the model is dispersed, the spatial delineation of urban and rural is less robust (than the built-up-based approach in Section 4.2.1). However, this impact of spatial delineation on GDP disaggregation is relatively minor.

Given the total agricultural GDP and total agricultural land area, we allocate the total agricultural GDP proportionally across the total agricultural area by country again at approximately 1 km² spatial resolution using the constructed variable derived from Fritz et al. (2011). We acknowledge that we do not account explicitly for spatial variation in agricultural productivity; however the agricultural density captures some of this variation. For example, low shares of agricultural area are likely correlated with low productivity or subsistence agriculture, and in the model, these areas are allocated a small share of the production value. Thus, it follows that the high-density agricultural areas are allocated a larger share of the production value.

The non-agricultural country-level GDP is allocated proportionally to each national and sub-national unit according to the most current reference year GDP provided for each country dataset. We allocate the non-agricultural GDP to urban areas according to a ratio and to rural
cells (per hectare). Using the urban and rural typologies, we constructed a ratio that provides an estimate of an urban-rural designation of GDP. We used urban level GDP and population data (http://citymayors.com) to construct this ratio that is defined as the urban level GDP per capita divided by the country-level GDP per capita.

From a regression analysis of per capita GDP and production data for selected cities, we used this model to estimate the GDP contribution from the urban areas with regards to the total for every country (i.e. an urban-rural ratio). In the regression analysis, urban-rural ratios, which are greater than 3.25, were excluded (considered as outliers). These ratios ranged from approximately 0.98 (Qatar) to 3.00 (Democratic Republic of Congo). The results of the regression analysis are shown in Table 4.

The non-agricultural spatial allocation of GRP is based on a per capita distribution from the population dataset. To allocate the level of GRP across the urban and rural classifications, we used the following equations:

\[
GRP_u = \left( P_u \cdot q \right) \cdot \frac{GRP}{\left( P_u \cdot q + P_r \right)}
\]

Eq. 3

\[
GRP_r = \frac{P_r \cdot GRP}{\left( P_u \cdot q + P_r \right)}
\]

Eq. 4
Where $\text{GRP}_u$ and $\text{GRP}_r$ = Gross regional product in the state for urban and rural population respectively; $P_u$ is urban population; $q$ = urban/rural GRP ratio: $\text{GRP}_u / \text{GRP}_r$; $\text{GRP}$ = Gross regional product in the state and $P_r$ is rural population. By combining both the agricultural and non-agricultural sector of GDP, the result is an estimate of cell-level GDP, at approximately 1 km² resolution. Values sum to input unit totals (regional or national).

4.5 Step 10 - Combination of building stock, GDP and infrastructure databases

To combine building stock, non-building infrastructure and GDP databases, we assume joint time paths of capital stock (i.e. GCS), GDP, and depreciation and consumption along an overlapping-generations structure (OLG) as per Wälde (2012). Capital stock and GDP are generally two parameters that are not mixed, with one representing the stocks of an economy and the other representing the flows of the economy. There is interaction between capital stock and GDP in the construction and other investment components of GDP. GFCF is an expenditure component of GDP looking at the invested value of new or existing fixed assets in the economy minus the disposal of fixed assets. GFCF is also a flow value, but is related to capital stock using the PIM approach (Berlemann and Wesselhöft, 2014).

GFCF is looked at as a percentage of GDP, through the analysis of Qin et al. (2005), where GDP is composed of real consumption (both public and private), net exports, GFCF and inventories.
For each grid cell, the building and infrastructure stock are quantified as one component of capital stock, machinery and equipment (inventories) are quantified as the other component of capital stock. The service lives of these two components differ significantly with the service lives of machinery and equipment generally being 3-5 times lower than that of buildings and other infrastructure. Using the PIM approach (Berlemann and Wesselhöft, 2014), capital stock is quantified through time to present day value for the service lives.

It should be noted that it is difficult to have a standard valuation for all assets, so various methods and depreciation rates are investigated such as CATDAT Damaging Earthquakes Database (Daniell et al., 2012) to check the approximate quality of the capital stock estimate. The back calculation from replacement cost also validates GCS. Using the disaggregated GDP value at each location for that year, the GFCF is removed from the GDP value in that year to approximate the removal of the stock portion of GDP to avoid overlap and double counting in a single cell. Care must be taken to analyze the GDP and capital stock portions separately and long-term interactions are taken into account. This jointly yields time paths of aggregate consumption, capital stock, and GDP for each cell along simplified assumptions.

5.0 Results and Discussion
5.1 Results

This section briefly details some of the key results of the exposure model. First, for the building stock model, we present our results by way of an example of the exposure model for Panama (Figure 4). The three inventory regions in Panama City metropolitan area (Panamá and San Miguelito districts), other urban areas, and rural areas, are further categorized as single and multi-family residential areas as shown in Table 5. For these areas, significantly different vulnerability class distribution (according to the PAGER-STR taxonomy) have been identified (Table 5). It is shown that in the metropolitan area nearly 20% of the people live in multi-family buildings and 53% of this population live in reinforced concrete structures (C3) while in the country’s rural areas more than 99% of the population live in single-family houses made out of different types of masonry or wood frame construction (Table 5). The reinforced concrete buildings have been assumed to be non-ductile as the earthquake design-code requirements were first introduced in 2003. For the full residential exposure database (at the grid cell level) the floor area of the dwellings and the number of people per dwelling unit were estimated and the unit cost of construction of the dwellings per vulnerability class (both discussed in section 4.2.3) was adopted.

To determine the non-building infrastructure values by class for Panama, GFCF was differentiated using national accounts (World Bank, 2011). A hybrid service life estimate for each asset was made from Panama tax law data (NCG 13) and other infrastructure service life data. The final service life estimated were: residential buildings 40 years, other buildings 55
years, construction and infrastructure 28 years, machinery/equipment 14 years and transportation/equipment 9 years.

The final estimated GCS values by public and private splits and their respective sector allocation is shown in Figure 5. The total non-building infrastructure of GCS is estimated at USD 117.8 billion. However, a significant proportion of this amount relates to the exposure of the Panama Canal. Similarly, the total replacement value of the building stock in Panama is estimated at USD 45.8 billion (28% of GCS) and GDP of USD 46.2 billion. Masonry structures are the most prevalent building types in Panama. Single-family, residential houses constructed with unreinforced fire brick masonry and unreinforced concrete block are the buildings most vulnerable to earthquakes. The total replacement value of single- and multi-family residential building stock in Panama is approximately USD 25.4 billion. To assess the earthquake loss on the building stock, we consider the reoccurrence of the 1882 Mw 7.8 offshore earthquake that occurred at an estimated depth of 20 km. The results show that if the earthquake occurred in present time the total economic direct loss to property could be USD 810 million which is approximately 1.8% of Panama’s GDP and Total Exposed Value (TEV) or replacement value of buildings. The direct economic loss distribution show economic losses are highest in Panama City and then in urban areas of Colón. Significant losses are also concentrated along the arterial road between the two cities (Figure 6).
5.2 Discussion

5.2.1 Spatial distribution of population and associated assets

Province-level Census information on proportions of urban and rural population from several countries in Central America show that global population datasets (such as LandScan and WorldPop 2012) allocate urban population relatively well within built-up areas while rural population is significantly mis-allocated outside of built-up areas (Aubrecht et al., 2015). The main reason is that to date there has been no global-level processed land cover data available to accurately detect small-size rural settlements. While this is going to change substantially in the future with datasets such as GUF and GHSL becoming available as potential input, it is likely a higher margin of error in population distribution of rural areas will still remain due to high anisotropy and differing approaches in weight determination of variables used in these models.

5.2.2 Structural distribution

In theory, the more detailed a structural vulnerability class, the more homogeneous the group of assets, and the smaller the variation in loss potential. However, in practice, narrowly defined classes often result in small sample sizes. A careful balance is therefore needed (Wieland et al., 2012). Accordingly, various international efforts have been made to classify buildings based on their load-bearing structure and other key attributes as well as the PAGER program (Jaiswal et al., 2010), the Global Earthquake Model (GEM) Taxonomy system (Brzev et al., 2013) and the
GEM Earthquake Consequences Database (So et al., 2012). In addition, efforts have been made to insert social conditions into the taxonomy process; e.g. in the context of India’s cities, socio-economic clustering has been considered by Prasad et al. (2009) to capture the different building class distributions in zones of different socio-economic profile (e.g. in areas of informal sector housing as opposed to historic town centers etc.).

5.2.3 Asset value distribution

Earthquakes and other natural hazards cause tremendous and often crippling economic losses, especially in the countries of the developing world, with damage to buildings being a primary cause of these losses. Daniell et al. (2011) estimated that in the period 1900-April 2011, worldwide economic losses (direct and indirect) associated with the occurrence of over 7,000 damaging earthquakes (of which 1996 caused loss of life) reached 2.1 trillion US$ (in 2010 values). Bird and Bommer (2004) in a thorough review of 50 important earthquakes occurring in the period 1989-2003, reported total losses of over 250 billion US$ (in 2003 values) and that the overwhelming majority of these losses were related to building failures due to ground shaking; financially, the losses due to damage in transportation and lifeline infrastructure being less significant. However damage to buildings due to other induced earthquake hazards can also be significant, as painfully experienced, for example during the 2004 Sumatra and 2011 Tohoku tsunami events that destroyed 365,000 and 130,000 houses respectively. Similarly, tremendous
losses to building properties occur due to meteorological hazards (particularly windstorms and flooding events).

It is therefore clear that capturing the value of building properties is an important and integral part of any risk assessment modeling effort. In the disaster loss estimation field, the term “building replacement value” is being used, which is the amount that will be needed to rebuild a property exactly as it was prior to its destruction regardless of any depreciation due to its age.

In reality however, the costs to rebuild buildings can be higher because destroyed properties (which often tend to be old and depreciated) may be replaced by new, safer, and often better fitted structures (e.g. an old adobe house replaced by a new confined masonry house). The new structures thus may have a higher unit cost of construction (i.e. the construction cost excluding the cost of land, per square meter). In addition, demand surge (i.e. an economic process in which the cost to repair damage to buildings and other infrastructure in large natural disasters is significantly greater than the cost to repair the same damage in a smaller disaster) may further inflate costs by up to 20% depending on the scale of a disaster, geographic context, and other factors, due a surge in needs for materials and labor (Olsen and Porter, 2010).

5.2.4 Non-building infrastructure distribution

Regarding non-building infrastructure, the sector allocation method described in this paper ignores some important factors, such as trends in infrastructure class spending over time and...
the non-smooth nature of such time-series. Furthermore, one potential source of error is due
to omission of features in the GIS datasets. Efforts were made to assess the completeness of
GIS data by comparing summary statistics to other sources (WDI total road length, EIA total
electricity generation installed capacity, WDI port throughput and number of air passengers
and departures).

5.3 What is innovative about this method?

The exposure modeling methodology presented not only builds upon previous and existing
efforts to quantify different categories of exposure but also combines and provides original
perspectives to assess exposed elements at risk with low cost or free-public domain data.
Within the building inventory (or stock) model, the exposure disaggregation using novel
techniques for urban/rural classification and assumption of mixed occupancy of residential and
non-residential typology provides a more representative picture of exposure distribution in
developing countries. The building typology distribution and update to USGS PAGER
distribution, while keeping the same PAGER-STR taxonomy, helps assess consistency in
structural vulnerability classification across countries and territories. Updates in unit cost of
construction information and use of private portion of GCS also helped to validate the total
replacement value determined by floor area and unit costs of construction for the different
building typologies.
Another innovative feature of this model is not only the identification of non-building infrastructure sub-classes, but also understanding their spatial distribution and density. The application of the non-building infrastructure dataset to development of sectorial risk profiles integral for public sector disaster risk reduction and mitigation, is also a new contribution. The updated disaggregated GDP between agricultural and non-agricultural sectors is another innovative feature of the exposure model. Building on the delineation of agricultural area by Fritz et al. (2011), we allocate the total agricultural GDP proportionally across the total agricultural area of a country. This would also be useful when considering agricultural drought disaster risk profiles.

6.0 Conclusions

We have outlined a methodology to produce three different economic perspectives of exposure that is adaptive and integral to produce a disaster risk profile for a particular country. The building inventory and non-building infrastructure databases complement each other well to provide information on the fixed assets (stock) at risk from a total economic and a sovereign disaster loss perspective. The disaggregated GDP that relates to the production (flow) of goods and services of a country provides a macro-economic loss perspective.
The datasets produced by this exposure model methodology also have other multiple applications that are beneficial to both private and public stakeholders. Urban and development planners can also utilize the exposure model to best identify new development areas, evaluate the impact of natural hazards on development, and consequently assess whether the costs of risk mitigation implementations are justified. Further, the exposure model with its products of building stock, GDP and GCS distribution, is also useful for poverty mapping analysis. As a secondary measure, the contribution of the exposure model to the development of disaster risk profiles can help inform disaster risk financing and insurance solutions, and ex-ante budget planning, in terms of how best to improve the financial resilience of countries against natural disasters without compromising their fiscal balance. Therefore, it is important that the input data used remains open as well as transparent in its approaches and limitations.

Holistically, the risk information produced is extremely helpful in supporting more carefully targeted intervention in community-based disaster risk management, territorial planning, and climate change adaptation action. When a natural disaster occurs, these datasets would be instrumental in providing key baseline data and information so that post-disaster damage assessments can be conducted and quantified more swiftly and efficiently.

7.0 References


World Bank. 2006b. Road Costs Knowledge System (ROCKS) v2.3. Roads and Highways Thematic Group, World Bank, Washington DC.


2014.
8.0 Acknowledgements

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The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the International Bank for Reconstruction and Development/World Bank and its affiliated organizations, or those of its Executive Directors or the governments they represent. The Global Urban Footprint product used in this study represents a preliminary raw version (status 08/14) which has not yet been subject to any systematic quality assessment and improvement.
Tables

Table 1: Global datasets that are publicly available (free or at little cost) and used in producing structural building inventory models. The table is categorized in terms of datasets available for exposure disaggregation, Building vulnerability typology classification and asset value determination.

Table 2: World Housing Encyclopedia unit cost of construction by structural typology in Argentina.

Table 3: Total Investment in Infrastructure as % of GDP, 2001-2006 (Source: Adapted from Infrastructure in Latin America (Calderón and Servén, 2010), and OECD Stats-ITF)

Table 4: Regression results where *** represents p<0.01.

Table 5. Panama’s estimated population distribution in terms of PAGER-STR seismic vulnerability classes for single and multi-family occupancy and by inventory region (capital city – other urban – rural) and associated building replacement value.
Figures

Figure 1: Schematic flow chart outlining the components and steps in creating the composite exposure model. Required input datasets are in yellow parallelograms, model processing steps are in blue boxes, and intermediate and final outputs are shown in red and green ellipses respectively. Demographic, building typology, floor area and unit costs of construction information and sub national GDP datasets compiled and developed for each country are shown in orange colored folders.

Figure 2: Panama City and surrounding region exposure disaggregation. (a) GUF built up area distribution rescaled to a 1km grid, (b) population distribution after reallocation of LandScan to GUF built up areas and (c) building inventory region classification.

Figure 3: An example of Infrastructure class distribution spatial allocation.

<table>
<thead>
<tr>
<th>Major roads (top left)</th>
<th>road density in km per 5 arc minute cell, of type 1 (Highway and Motorway) and type 2 (Primary)</th>
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<td>Other roads (top right)</td>
<td>road density in km per 5 arc minute cell, of types 3 (Secondary), 4 (tertiary), and 5 (local/urban)</td>
</tr>
<tr>
<td>Airports (middle left)</td>
<td>total passengers</td>
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<tr>
<td>Ports (middle right)</td>
<td>annual container throughput</td>
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<td>Power plants (bottom left)</td>
<td>total installed electricity production capacity in MW</td>
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<tr>
<td>Other urban (bottom right)</td>
<td>DN from radiance-calibrated night-time lights 2010</td>
</tr>
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</table>

Figure 4: (a) refined building inventory region classification (b) asset exposure residential and non-residential building stock (c) infrastructure value distribution as a percentage based fiscal portion of gross capital stock (d) disaggregated GDP value distribution in Panama.

Figure 5: Estimated GCS for Panama broken down by Public and private splits and their respective sector allocations in USD M.

Figure 6: Distribution of potential direct economic losses in USD from a repeat of the 1882 Mw 7.8 offshore Panama earthquake (epicenter shown as a red dot) in present time.
<table>
<thead>
<tr>
<th>Dataset</th>
<th>Reference with latest release date</th>
<th>Use</th>
<th>Scope/description</th>
<th>Advantages</th>
<th>Disadvantages</th>
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<td>Grided Population Of the World (GPWv3)</td>
<td>Balk and Yetman (2004)</td>
<td>Population allocation</td>
<td>Continuous measure of population distribution</td>
<td>Free and global availability; Population distribution at admin1 level accurate; Model re-traceability</td>
<td>Resolution at 5x5 km grid level; no consideration of sub-admin-level variations</td>
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<tr>
<td>LandScan</td>
<td>Bhaduri et al., 2007</td>
<td>Population allocation</td>
<td>Continuous measure of population</td>
<td>Global availability at 1km grid-level; It captures urban population distribution well</td>
<td>Information on input population data and weights used for distribution is proprietary and not accessible</td>
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<tr>
<td>WorldPop</td>
<td>Linard et al. 2012</td>
<td>Population allocation</td>
<td>Continuous measure of population</td>
<td>Free availability; Model output is at 100 m spatial resolution and provides urban change masks</td>
<td>Currently not globally available; Constant 100m output evades real resolution and accuracy (varying input data)</td>
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<td>Impervious Surface Area (ISA)</td>
<td>Elvidge et al., 2007</td>
<td>Provides degree of imperviousness of land</td>
<td>Continuous measure of imperviousness</td>
<td>Free and global availability at 1km grid-level; Useful in identifying high human activity concentration areas</td>
<td>Hard to delineate built up areas; evade urban-rural distinguishing at global scale due to lighting variations</td>
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<td>Globecover</td>
<td>Arino et al., 2012</td>
<td>Global Land cover</td>
<td>RS based land cover categories</td>
<td>Provides agriculture based classification</td>
<td>Characterisation of built up areas poor</td>
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<td>Global Rural-</td>
<td>Balk et al., 2010</td>
<td>Population allocation</td>
<td>Classifying urban/rural</td>
<td>Free and global availability at</td>
<td>Significantly overestimates extent</td>
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<td>areas and respective continuous measure of population</td>
<td>1km grid-level; Quick and global use</td>
<td>of urban areas</td>
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<td>Modis-500</td>
<td>Schneider et al., 2012</td>
<td>Built up area delineation</td>
<td>Based on optical satellite imagery and modelled built up area extent layer</td>
<td>Higher spatial resolution and accuracy than predecessors</td>
<td>Identifies built up as urban and fails to identify smaller rural settlements</td>
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<tr>
<td>Built-up Reference Layer (BuREF)</td>
<td>Pesaresi et al., 2013</td>
<td>Built up area delineation</td>
<td>Combines Landscan and Modis-500</td>
<td>Globally available with population and built up areas</td>
<td>Model results in rural areas are limited and heavily dependent on Landscan</td>
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<tr>
<td>Global Urban Footprint (GUF)</td>
<td>Esch et al., 2013</td>
<td>Built up area delineation</td>
<td>Radar based product</td>
<td>Global availability; Aggregated model operates at 75 m resolution; Radar basis enables good separation of roads from buildings</td>
<td>Sensitive to misidentification in high relief areas</td>
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<td>Global Human Settlement Layer (GHSL)</td>
<td>Pesaresi et al. 2013</td>
<td>Built up area delineation</td>
<td>Built up area delineation at high resolution; based on optical satellite imagery</td>
<td>Widely tested and adopted in European context at very high resolution (meter-level); Alpha version produced at global level at high resolution (deca-meter-level)</td>
<td>Global dataset not yet fully tested and calibrated; difficulties at global level with Landsat imagery as basis</td>
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1045

1046
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<td>1</td>
<td>May 2002</td>
<td>250</td>
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<td>Traditional Adobe House with Reinforcement</td>
<td>2</td>
<td>Jun 2002</td>
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<td>Solid brick masonry house with composite hollow clay tile and concrete joist</td>
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<td>Roof slabs</td>
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<tr>
<td>Traditional adobe house without seismic features</td>
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<td>March 2003</td>
<td>350</td>
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<td>Base Isolation of Confined Masonry</td>
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<td>November 2008</td>
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<td>Country</td>
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<td>Argentina</td>
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### Table 4

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<td>Ln(pc GDP)</td>
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<td>Stud. Breusch-Pagan</td>
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<td>(on 1 DF)</td>
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### Table 5

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<th>Material Description</th>
<th>PAGER-STR</th>
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<th>Other Urban</th>
<th>Rural</th>
<th>Total Replacement Value</th>
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<td>M-F</td>
<td>S-F</td>
<td>M-F</td>
<td>S-F</td>
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<td>UCB (Concrete block unreinforced masonry with lime or cement mortar)</td>
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<td>31.99%</td>
<td>33.45%</td>
<td>70.87%</td>
<td>17.23%</td>
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<tr>
<td>UFB (Unreinforced fired brick masonry)</td>
<td>36.27%</td>
<td>11.63%</td>
<td>37.16%</td>
<td>15.12%</td>
<td>24.99%</td>
</tr>
<tr>
<td>DS (Rectangular cut-stone masonry block)</td>
<td>16.92%</td>
<td>0.00%</td>
<td>20.90%</td>
<td>0.00%</td>
<td>0.00%</td>
</tr>
<tr>
<td>RS (Rubble stone (field stone) masonry)</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>16.17%</td>
</tr>
<tr>
<td>C3 (Non-ductile reinforced concrete frame with masonry infill walls)</td>
<td>4.84%</td>
<td>53.32%</td>
<td>1.39%</td>
<td>8.50%</td>
<td>0.41%</td>
</tr>
<tr>
<td>W1 (Wood stud-wall frame with plywood/gypsum board sheathing)</td>
<td>3.21%</td>
<td>3.05%</td>
<td>6.46%</td>
<td>5.51%</td>
<td>24.42%</td>
</tr>
<tr>
<td>W4 (Wood panel or log construction)</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>10.69%</td>
</tr>
<tr>
<td>A5 (Adobe block, mud mortar, with bamboo or rope reinforcement)</td>
<td>0.05%</td>
<td>0.00%</td>
<td>0.29%</td>
<td>0.00%</td>
<td>2.04%</td>
</tr>
<tr>
<td>A1 (Adobe block, mud mortar, wood roof and floors)</td>
<td>0.02%</td>
<td>0.00%</td>
<td>0.29%</td>
<td>0.00%</td>
<td>3.78%</td>
</tr>
<tr>
<td>Informal-Squatter Housing</td>
<td>0.01%</td>
<td>0.00%</td>
<td>0.05%</td>
<td>0.00%</td>
<td>0.28%</td>
</tr>
<tr>
<td><strong>Population distribution (S-F, M-F)</strong></td>
<td><strong>80.4%</strong></td>
<td><strong>19.6%</strong></td>
<td><strong>92.4%</strong></td>
<td><strong>7.6%</strong></td>
<td><strong>99.3%</strong></td>
</tr>
</tbody>
</table>
Figure 2

(a)

(b)

(c)
Figure 3
Figure 4

(a) Inventory regions

(b) Building replacement value in USD millions per sq. km:

(c) Panama does GDP Value

(d) Panama does GDP Value
Figure 5
Figure 6