Using spatial data to add value to official statistics on population: A case study on measuring resilience of urban development

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ABSTRACT

Resilience of urbanizing populations against threats to sustainable development have garnered increased attention from the official statistics community with adoption of the Sustainable Development Goals, particularly Goal 11 on sustainable cities and human settlements. Studies were organized by UNESCAP through a series of expert group processes on the use of spatial data, especially applications of satellite imagery, for assessing feasibility for enhanced utilization of censuses and household surveys in production and analysis of indicators for Sustainable Development Goal 11, especially for measurement of risk from disasters or from environmental degradation. The research also investigates some linkages between measurement of disaster risks with other components of the SDGs, such as accessibility of basic services, and monitoring against environmental degradation. This paper demonstrates examples of modern application of statistics from population and housing censuses in combination with satellite imagery for creating high geographic resolution analyses of location of population, their characteristics, and certain characteristics of infrastructure used in risk assessment. Utilizing satellite data provided by the German Aerospace Center (DLR) in combination with official population statistics from governments in Asia and Pacific, this study presents examples of multi-scale analyses of urban development based on publicly accessible data. Results of this study include documented methodologies that can be transferred for use by national statistics agencies. The methodologies are replicable, and adaptable, for assessing risks at multiple geographic scales and for strengthening an empirical-based understanding of the factors for resilience of populations in an increasingly urbanized world.

Keywords: Sustainable Development Goals, Urbanization, Population, Earth Observation Data, Exposure to Natural Hazards

1. BACKGROUND AND POLICY CONTEXT

1.1 URBANIZATION

Urban areas in the Asia and the Pacific region generate an estimated 80 per cent of regional economic output[1] and account for over fifty per cent of the region's population. The world's population in urban areas is projected to increase by another 2.5 billion people by 2050, with close to 90% of this increase taking place in Asia and Africa.[2] Trends vary across cities, but every Asia-Pacific sub-region is experiencing urban growth at higher rates than overall population growth.[3]

Urbanization—defined by population, economic, and physical growth of urban areas—can be a powerful tool for sustainable development when well-planned and managed. While the rapid pace of urbanization in Asia-Pacific presents many opportunities, a lack of planning and management, as well as environmental degradation and climate change, has increased risksfrom natural hazards, such as droughts, floods, heatwaves, and earthquakes. Many cases exist where the pace of urbanization is outgrowing the capacity of municipal governments and communities to provide or maintain reslient infrastructure and basic services (e.g., roads, water and wastewater management systems). [4] While many of the key challenges have been outlined as goals, targets, and indicators for monitoring in the UN Sustainable Development Goal 11 (Sustaianble Cities and Communities), monitoring of progress towards the targets is limited in many cases by lack of available data or methodologies for integrating the existing official datasets for analyses of urbanization trends and to identify and address potential high risk areas. This research aims to help address these challenges by developing replicable methodologies for integrating population census statitsics with earth observation data towards development of improved risk-monitoring and response systems based on official statitstics.

The challenges and risks associated with unplanned and unmanaged urbanization are especially pronounced in smaller cities and peri-urban areas. While considerable attention has been paid to megacities, comprehensive research on smaller cities, with populations below five million people, remains limited—even though they account for 60 per cent of the Asia-Pacific urban population.[5] These smaller cities may also be more vulnerable due to having less access to regional and global markets, constrained opportunities to generate revenue, and limited capacity to build and maintain infrastructure.

Development in peri-urban areas is characterized by widespread informal land use and development patterns, inadequate infrastructure and housing, and persons living in poverty; at times contrasted with a desire for a suburban lifestyle and access to urban centres. Peri-urban areas are expected to accommodate much of the region's urban growth by 2025; including 40 per cent in China, over 50 per cent in Bangkok, and 75 per cent in Jakarta.[6]

1.2 DISASTER RISK MEASUREMENT

The basic model for measurement of risk before a disaster is defined in the Disaster Related Statistics Framework (DRSF)[7] by the Asia-Pacific Expert Group on Disaster-related Statistics and is based on an extensive literature and collection of risk assessments by disaster risk management experts. The same model has been used in disaster risk assessment studies across the world and the basic concept is inscribed in the new United Nations definition for a disaster.[8] The model defines measurement of disaster risk (for a community or for a social-ecological system or spatial area) as a function of three main components: (i) exposure to hazards, (ii) vulnerability, and (iii) coping capacity.

Disaster risk is dynamic and incorporates some of the same basic data used in analysis of urbanization trends, e.g: demographic changes, population densities, poverty and inequality, structure of the economy, land management, and so on. Improved understanding, including through improved measurement, of

disaster risk is the priority number one in the Sendai Framework for Disaster Risk Reduction adopted at the Third World Conference on Disaster Risk Reduction in Sendai, Japan, and endorsed by the UN General Assembly on 23 June, 2015.[9]

A basic idea for this working paper was to experiment with applying the conceptual framework used for measurement of disaster risk and utilize inputs of official statitsics for analysing trends and potential risks associated with urbanization, not just from disasters but also from environmental degradataion and other sources of risk to sustainable development.

2. PILOT STUDIES IN ASIA AND THE PACIFIC

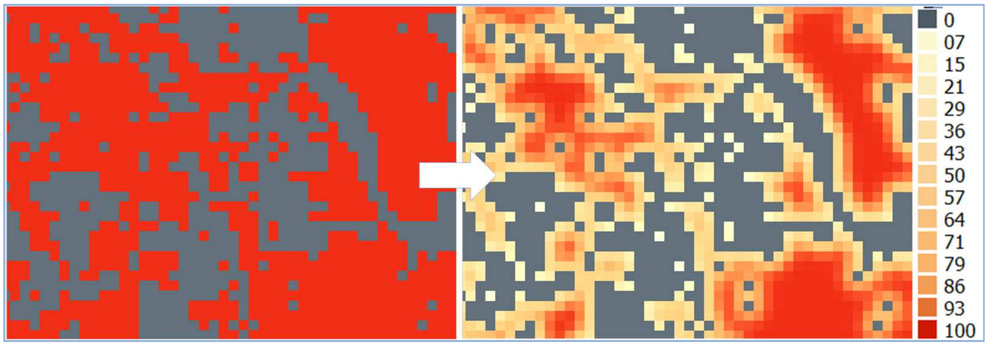
Assessing exposure to risks requires detailed and well geo-referenced data becausee hazard-prone areas are not evenly distributed over space, nor are the locations of populations, buildings, and other manmade or natural infrastructures.

During its development and national pilot testing of initial schemes for the DRSF, the Asia-Pacific Expert Group on Disaster-related statistics identified a lack of reliable data on exposure of population to natural hazards as a serious gap. There was a lack of transparent methodologies for spatial analyses of disaster risk that are replicable using datasets available to national disaster management agencies. Pilot tests were carried out with six countries of the region, focussing initially on population exposure to hazards, as one of the key baseline metrics for building broader systems of integrated statistics for risks assessments. The pilot studies utilized publicly accessible data on population combined with earth observation data, especially the global urban footprint (GUF) dataset, produced based on radar satellite imagery by the German Aerospace Center (DLR).[10]

The pilot studies were conducted utilizing population census data at multiple scales, depending on availability of official statistics from the official national sources. The methodology produces estimates for population densities with sufficiently geographic detail for reliable assessment of exposure of the population to hazards. It was developed as a tool for implementation by governing agencies and is applicable at different scales for analysis, e.g. local, subnational regions, national, and trans-boundary, and in relation to sub-national areas of interested, such as river basins, coastal zones and expected hazard areas.

The model adjusts average population density for each administrative division, based on the outputs from population and housing censuses, to the size of the agglomerations of built-up areas mapped with satellite images. The implicit assumption is that actual population density is higher inside large cities than in small ones and in villages. The methodology applies Gaussian distribution to svalues for a collection of cells in a GUF raster file (a grid of binary data indicating built-up and non-built up areas) to convert and assign coefficients as values between 0 and 100. Large clusters of pixels will keep a value close or equal to 100 while smoothing will dilute the value of smaller ones down to very low values for the isolated ones. The smoothed map of built-up areas in the grid is lastly multiplied by the average population of native GUF pixels for each administrative region (e.g. district) in the study. In the resulting map, population density is correlated to the smoothed values of urban conglomerations.

Figure 1: Effect of weighting the GUF map with smoothed pixel values



Source: German Aerospace Centre (DLR), Global Urban Footrptint (GUF), processed with SAGA GIS

Results of the Gaussian smoothing function depend on the size of the pixels, the size of the kernels of cells used for the smoothing (for the 5x5 kernel, the radius is 2) and the standard deviation (σ) selected for the distribution. Larger values for standard deviation produce a wider peak in the distribution and greater smoothing (or blurring) of the values. [11]

Figure 2: Illustration of Guassian Smoothing and Effect on the GIS raster Data

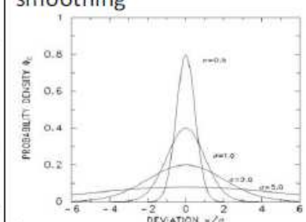
Original data

0	0	0	0	0
0	0	0	0	0
0	0	1.00	0	0
0	0	0	0	0
0	0	0	0	0

Smoothed data, σ =1

0.00	0.01	0.03	0.01	0.00
0.01	0.06	0.10	0.06	0.01
0.03	0.10	0.15	0.10	0.03
0.01	0.06	0.10	0.06	0.01
0.00	0.01	0.03	0.01	0.00

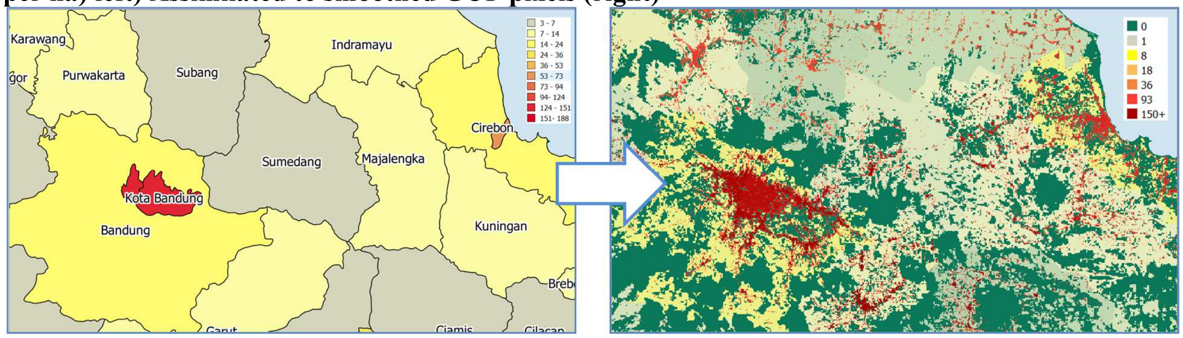
Effect of σ value on smoothing



Source:
http://www.asp.ucar.edu/colloquium/1992/notes/part1/node15.html

The methodology produces a much improved geospatial perspective on risks and priorities for addressing them as compared to the aggregated administrative region view. For example, the region of Bandung on the island of Java, Indonesia, has an average population density per hectare of 17, which corresponds to three different contexts: densely populatied urban areas, peri-urban areas, rural landscape and areas with no population. In the maps produced from pilot studies in Indonesia shown below, legends indicate population density per hectare. On the right map, dark green is for “no population” or negligible average density per hectare.

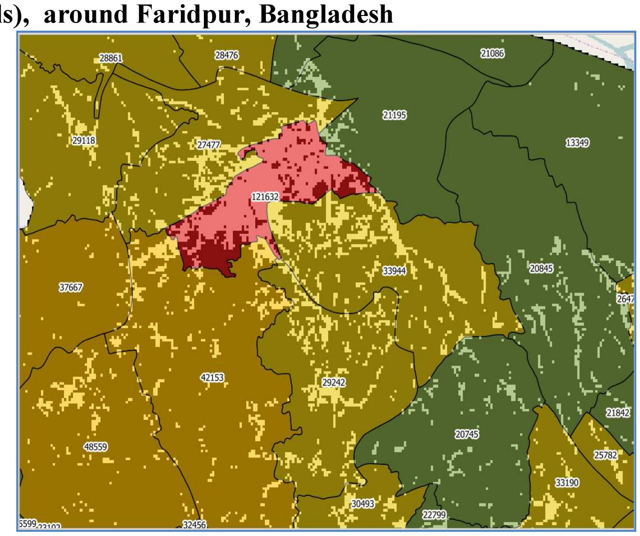
Figure 3: View of part of Java, Indonesia: Census data by Administrative Region (average density per ha) left) Assimilated to smoothed GUF pixels (right)



Sources: Population: Indonesia Central Bureau of Statistics; GUF: DLR, processing by the authors, using QGIS and SAGAGIS

Another example, from a pilot assessment in the Banglaedesh district of Faridpur, shows the potentially complex relationships between administrative zones and urbanization, which creates the need to integrate multiple data sources for a more geographically detailed (down-scaled) analysis of population and housing census data. Figure 4 below illustrates relationships between population by administrative boundaries (districts) and the actual (predicted) location of the population (in light colour) around Faridpur.

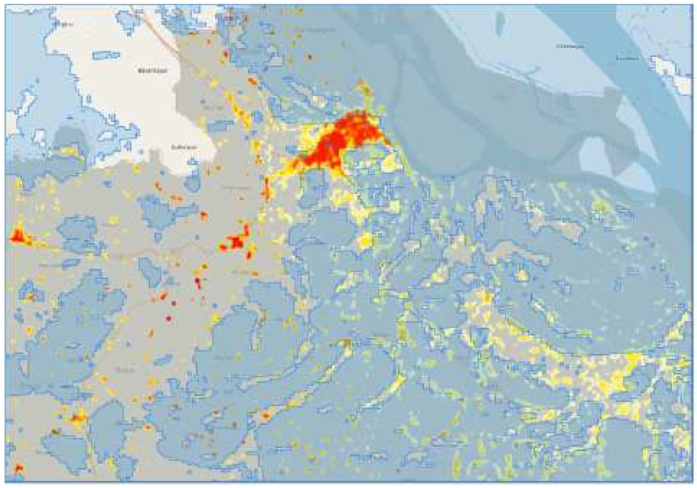
Figure 4: Overlay of 2011 population census data from municipalities to the GUF map in Bangladesh (light pixels), around Faridpur, Bangladesh



Sources: Population census: Bangladesh Bureau of Statistics; GUF: DLR

The implementation of the methodology in Bangladesh was tested considering flood hazard. Figure 6 shows that human settlements for a significant portion of the urban population in Faridpur are on the outer areas of urban conglomerations, which are alongside the river and beyond the risk perimeter (safe zones) according to the flood hazard map[12] used for this pilot study.

Figure 6: Sample overlap of population density estimations with predicted flood hazard zones (light blue area) for a region in Faridipur, Bangladesh

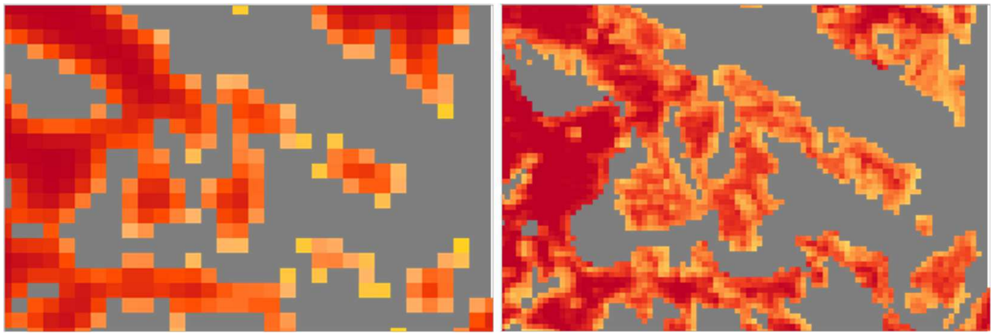


Sources: Population census: Bangladesh Bureau of Statistics; GUF: DLR;Flood risk map: UNEP-GRID; (processing and analysis by the authors, using QGIS and SAGAGIS)

This vew of the urban agglomeration of Faridpur suggest an effect of urban sprawl that includes an increase in population at risk from flood hazard (light blue areas). This urban sprawl effect of settlements on the periphery of towns and cities that overlapp with hazard areas is recurrent in many places across Asia and the Pacific.

The outputs of the basic model for down-scaling population data are similar to the outputs of several global scale products available from international websites, in particular WorldPop and the European Joint-Research Center's Global Human Settlements layer (GHSL) . Comparisons and validations checks were made with the other relevant global-scale products, and in relation to studies conducted by partnering agencies at the national level, particularly with the national disaster management agency (BNPM) of Indonesia.[13] Although results of the different approaches are not very different, there are differences and this GUF-based methodology has several advantages. The first and most important one is that it is a simple and fully transparent methodology[14], which can be replicated by national statitcal offices (or other official sources of relevant data).[15] Also, the fact that the model uses official population statistics as input means that final statistics are fully consistent and can be verified (if re-aggregated, the results of the model are precisely consistent with the orginal cenus outputs). Lastly, the same model can be implemented at different scales, allowing for the analyst to zoom-in for specific areas of interest, using high resolution data and statistics available for a specific project but without reinventing new methodologies. As an example, Figure 7 illustrates the possible informational gains for urban features location when shifting from 100m resolution to 12 m resolution.

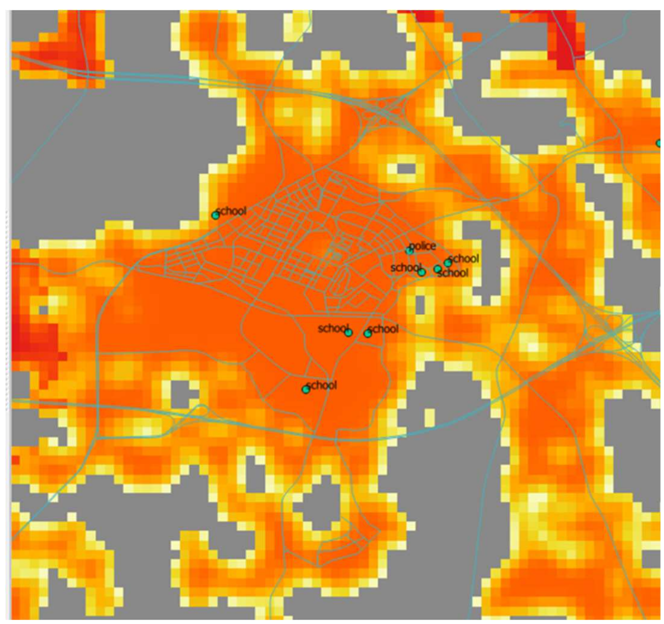
Figure 7: Illustration of urban features (smoothed) at 100m and 12 m resolution



Source: German Aerospace Centre (DLR), Global Urban Footrptint (GUF), processed with SAGA GIS

Maps, with metadata, of road networks and other important types of infrastructure types, like schools, are now available in GIS-compatible formats globally from open data sources like Open Street Maps (OSM), and governments will also have special access to official maps of infrastructures and associated metadata. The infrastructure layers can be utilized to help verify or to improve/calibrations to the accuracy of the population density estimates calculated based on the census and GUF data and for assessments of exposure of the infrastructure itself.

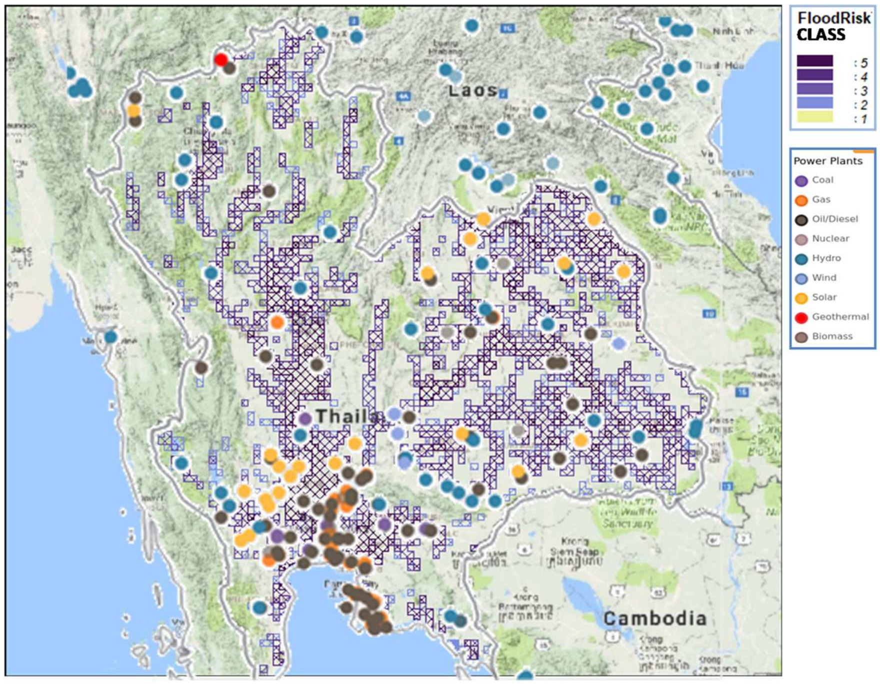
Figure 8: Sample of Output of Population to the GUF model, overlaid with Open Street Maps layer for roads and schools for an area near Seoul, Republic of Korea



Sources: DLR: GUF and OpenStreetMap (OSM) for roads and schools

Metrics for assessing exposure of buildings or critical infrastructure to potential hazards can be produced by layering locations of infrastructure (GPS coordinates or GIS vector files) with hazard maps. The hazard maps are calculated based on a probabilistic assessment of likelihoods for future hazards, e.g. mapped probabilities of 1-year, 5-year or 10-year return flood inundation areas. Hazard maps typically contain a range of probabilities for a particular hazard, which can be summarized as a range of discrete values (e.g 1-5 or low to high risk exposure) as in the below example comparing flood hazard areas with location of power plants in Thailand.

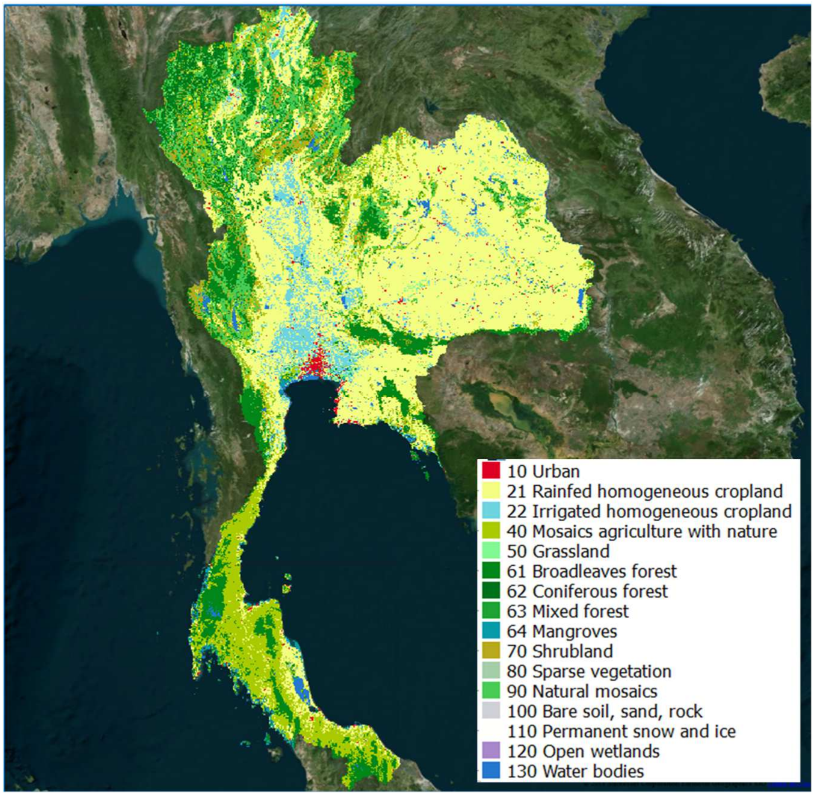
Figure 9 Location of power plants overlaid with flood hazard areas in Central, North, and Northeast Thailand



Source: Asia Pacific Energy Portal (asiapacificenergy.org) and UNEP GRID; processing and analysis by the authors using QGIS

In addition to locations of infrastructure, land cover maps are another crucial resource for risk assessments both for producing statistics on the types of land exposued to hazards and for modelling the exposure of the dispersed populations whose locations are more difficult to predict based on GUF. A major difficulty faced by all population spatial models relates to the assessment of dispersed and/or nomadic populations because their housing cannot be observed by satellites. In south and southeast Asia (as well as other parts of the world), it is common to have dispersed human settements in agriculture land including agro-forestry, with thatched roofs or other types of housing that cannot be detected by remote sensors. This also includes settlements in wooded areas, population living on boats, tents and other shelters of nomadic pastoralists. All these cases requires exogenous assessments.

Figure 10 Land Cover Map Used In Pilot Studies for Thailand



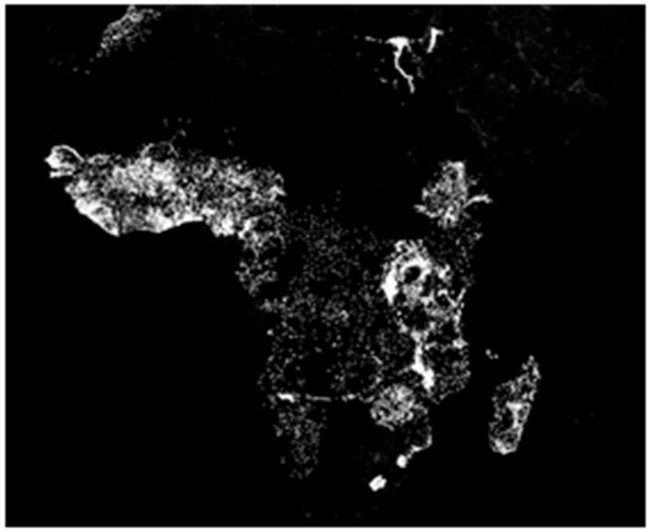
Source: European Space Agency Climate Change Initiative Land Cover Map, 2015 (SEEA-EA/ENCA-QSP legend)

3. VULNERABILITY AND COPING CAPACITY

Depending on the context and scale of the analysis, measurement of vulnerability of the populations or areas exposed to hazards may rely on a variety of variables. Generally, economic poverty is one of the powerful indicators for predicting vulnerability to external shocks. Increasingly, location and small areas disaggregation of statistics on poverty can be made available from statistics agencies from small area estimation techniques that establish links between census data and household income and expenditure or from use of new big data sources, like mobile phone use data or visible nightlights.

An example is the work of Jean, Burke et al. (2016)[16], which has utilized visible light at nights viewed from satellites and a deep learning algorithm to estimate location of poverty in Africa. The methodology, including the formulas and code used to run the machine learning algorithm have been shared by the authors and are available on ESCAP SDG Data Hub[17] for testing application of the same model for other countries, for example in Asia and the Pacific.

Figure 11: Night lights in Africa



Source: Neal, Burke et al. 2016

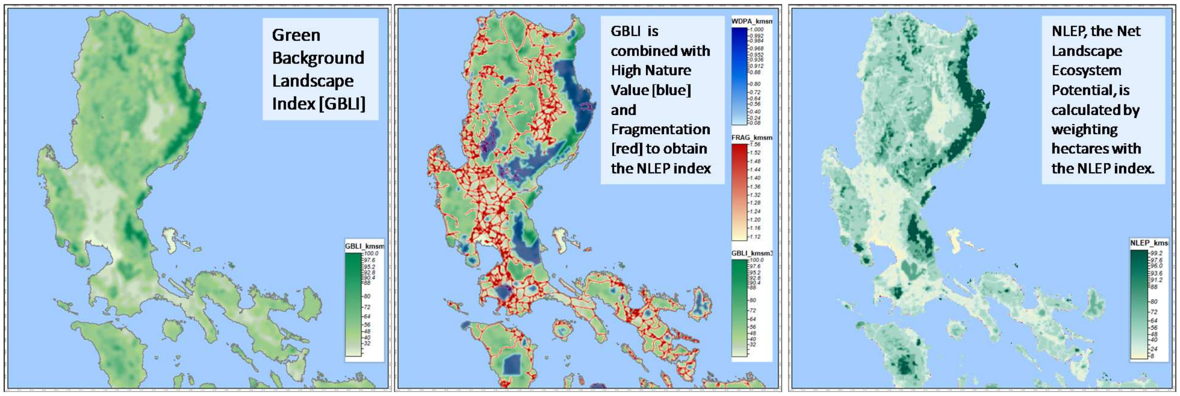
Coping capacity refers to the resilience of a household or community to absorb impacts from a disaster and quickly eliminate the new vulnerabilities created through recovery and by 'building back better'. In many cases, coping capacity will be correlated with the vulnerability assessments. For example, the same factors that cause vulnerabilities for slum communities, such as extreme poverty and unreliable or unsafe access to basic services, are also factors of coping capacity for those same communities. However, there are other measures, associated with local infrastructure and access to emergency services, which can be used to incorporate coping capacity metrics into the database and assessments. Information on the location, coverage, and functioning of disaster early warning systems, for example, can be easily incorporated as GIS vector files to complement the exposure and vulnerability assessments. Coverage of disaster early warning systems is already an indicator in the global Sendai Framework Monitoring System of the UN Office on Disaster Risk Reduction (UNISDR).[18]

4. ENVIRONMNTAL DEGRADATION RISK ASSESSMENT

Another important component for assessing vulnerability and coping capacities for disasters is information on the environmental systems, and particularly environmental degradation, which could contribute to the scale of impacts from a disaster (for example a polluted river during a flood). Environmental degradation is also, itself, a type of hazard, which sometimes leads to slowly evolving catastrophic risks of disasters to the communities that are directly or indirectly dependent on that environment.

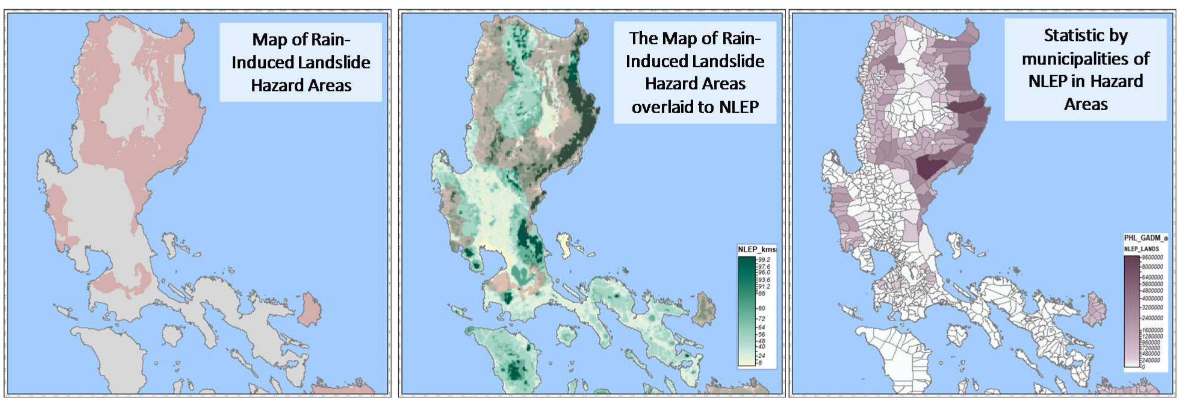
For the Asia and Pacific pilot studies, the outputs of the census-based population density estimations were compared with layers of pilot estimations of local environmental conditions, in particular a calculation of net landscape ecological potential (NLEP), which is an index of ecological condition for ecosystem accounting developed in Weber (2014).[19] The NLEP combines quantified information on the greenness and fragmentation of landscapes into a GIS layer (see example below for the Philippines).

Figure 13: Sample Calculation of net landscape ecological potential (NLEP) in Quezon, Philippines



Sources: Processed by the authors with SAGAGIS from land cover and roads data provided by the Philippines Statitsics Authority, the Cental Mapping Agency (NAMRIA), and the UNEP/WCMC WDPA World database of protected areas

Figure 14: Overlay of NLEP and Map of Rain-Induced Landslide Hazard Areas in Quezon, Philippines



Sources: Hazard: UNEP/GRID, Municipalities (ADM2) from the GDAM database, processed by the authors

The map and statistics of net landscape ecosystem potential by rain-induced landslide hazard areas can be interpreted in two ways: (i) the amount of landscape ecosystem potential at risk and (ii) regulation of water surface runoff by ecosystems for proximate human settlements, i.e. the ecosystem service provided to downstream populations.

In general, areas in good ecological condition will provide a greater resilience from natural or industrial hazards, for ecosystems and the populations living there. Ecosystems natural structures and functions buffer climate effects by storing water in soil and vegetation, protections from soil erosion, sinks for pollution and waste with autoepuration capacity. In these ways, the natural systems contribute to mitigating against stress from extreme events, such as floods. These functions are often reduced by urban expansion, in part because of the increase of impervious surfaces, i.e. "anthropogenic features through which water cannot infiltrate into the soil" (Hu and Weng 2011)[20], such as roads and buildings.

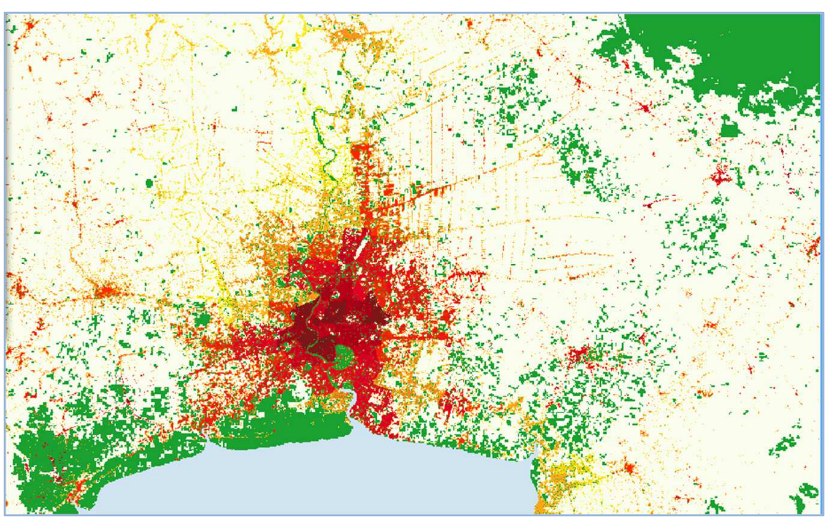
As methods for ecological accounting and integrating the relevant datasets in GIS become more common and more developed, ecological condition metrics will become more integrated with geo-referenced social and economic statistics and other relevant data for more comprehensive assessments of risks before the disasters happen.

5. NEXT STEPS & FURTHER RESEARCH

Building on the baseline localization estimates of population statistics, which could be calculated at virtually any scale or degree of resolution (limited only by available data and computing capacity), the next steps involve contining to integrate other geospatial datasets, including administrative data and geo-refernced information accessible by government agences that are important for analysing access to basic services by these populations and that could be used to produce statisics on the risk factors of people, land, and infrastructure. The second major recommendation for further development is to work on back-casting estimations to incorporate analysis of time series trends into the assessment.[21] Assessments of risk factors (exposure, vulnerability, coping capacities) need not be limited to disaster, but also could be developed from the perspective of the broader risk and opportunities associated with urbanization and the related environmental, demographic, social and economic changes happening over time.

There are significant differences in urban development across countries that affect how satellite imagery can be utilized for integration with official statistics and for modelling of risks and opportunities associated with urbanization. In the case of Thailand, for example, road infrastructures are broadly visible directly from the GUF and modelled estaimation of Population-to-GUF grid cells (figure 12), apparently a result of the way that urban development has followed the transportation networks in that country, especially in the areas surrounding metropolitan Bangkok. But, the spatial aspects of urbanization (e.g. urban sprawl) have evolved differently in different countries. Thus, one of the advantages of a transparent, adaptable and scalable methodology for down-scaling population statistics is to allow for national-specific (or regions-within countries-specific) calibrations to avoid bias and to account for differences or special contextual features of urban development and demographic changes.

Figure 15: Census to GUF estimation for an extracted metropolitan Bangkok region, Thailand



Sources: Thiland National Statitics Office Population and Housing Censu, GUF: DLR
Processing by Authors using QGIS and SAGA GIS

Satellite imagery can also be used for producing measurements of urban expansion in terms of spatial area (urban sprawl). Accurate, consistent, and timely data on urbanization trends and city growth will continue to develop for assessing current and future needs with respect to urban growth and for setting policy priorities to promote resilient urban and peri-urban development. The techniques for measuring the expansion of urban areas outlined in the below table may be tested as a complement to the methodologies described in this working paper and combined with hazard areas and geo-referenced stastisics on vulnerabilities.

Table 1 - Urban expansion indices[22]

Indices	Description
Land use transfer matrix (spawl)	May be used to evaluate the specific contribution of each land use type to urban land use. The matrix can quantitatively disclose the mutual conversion relationships among different land use types and can specifically and comprehensively describe the areas, structural characteristics and change trends for each land use type.
Urban gravity center	May be used to describe the changes in the urban land spatial distribution by following the weighted distance and direction of the center.
Urban expansion indices	Urban expansion process can be quantitatively analyzed by the speed and intensity of expansion. The speed of expansion is the degree of expansion relative to the total urban land in preceding year (udied year), whereas the expansion intensity is the average annual growth rate of urban expansion during a given study period. This indices supports comprehensive assessments on the degree of urban expansion in terms of speed, area, ratio, and intensity.
Urban spatial pattern indices	Compactness and fractal dimensions are widely used to quantitatively evaluate the urban spatial patterns and these indices can reveal the spatial shape, stability, and complexity of city boundaries. Compactness reflects the shape of a city and provides a characterization of the basic features of an urban space and land use efficiency. The fractal dimension value may be used to indicate the degree of complexity and stability of city boundaries. Based on calculated values of the fractal dimension, the morphological characteristics of a city's spatial expansion during different periods can be inferred.

Further research is also recommended on potential applications of the methodology for evaluating possible relationships between urbanization, urban sprawl and other types of changes to the ecological value of landscapes and the potential future risks for sustainability of a world in which over 60% of the population are in cities.

It is recommended that national institutions consider applying this methodology for validation testing and, subsequently, further improvements as they will have access to the best and most detailed data inputs for implementing and assessing calibrations to the model and the best local knowledge of the realities on the ground and the information requirements for policy-making.

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[8] "A serious disruption of the functioning of a community or a society at any scale due to hazardous events interacting with conditions of exposure, vulnerability and capacity, leading to one or more of the following: human, material, economic and environmental losses and impacts." (Definition for a Disaster, UN General Assembly, December, 2015)

[9] https://www.unisdr.org/we/inform/publications/43291

[10] Global Urban Footprint (GUF); DLR 2016, https://www.dlr.de/eoc/en/desktopdefault.aspx/tabid-9628/16557_read-40454/

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[15] The sequence of steps for this model has been fdocumented as a step-by-step manual, available from the website of the Asia-Pacific Expert Group on Disaster-related Statistics.

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[17] http://www.sdgdatahub.io/project/using-deep-learning-to-estimate-poverty-rates-from-satellite-features

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