https://doi.org/10.5194/essd-2019-189
Preprint. Discussion started: 29 October 2019

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Exposure data for global physical risk assessment

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Abstract. One of the challenges in the globally consistent assessment of physical climate risks is that exposure data are either unavailable or restricted to single countries or regions. Here, we introduce "lit population" (LitPop), a globally consistent methodology to estimate spatially explicit exposure data proportional to a combination of nightlight intensity and geographical population data. By multiplying nightlight and population data, unwanted artefacts such as blooming, saturation, and lack of resolution are mitigated. Thus, the combination of both data types improves the spatial distribution of macroeconomic indicators. To evaluate the predictive skill of the downscaling approach, GDP distributed proportional to LitPop to subnational administrative regions is compared to reference values. The results for 14 countries show that the predictive skill of LitPop is higher than using nightlights or population data alone. The advantages of this approach are: high predictive skill, global consistency, scalability, openness, replicability, and low entry threshold. The flexibility of the open-source LitPop exposure data and methodology offers value for manifold use cases for economic disaster risk assessments and climate change adaptation studies. Code is published on GitHub as part of the open-source software CLIMADA (CLIMate ADAptation) and archived in the ETH Data Archive with link: http://doi.org/10.5905/ethz-1007-226 (Bresch et al., 2019b). The resulting exposure dataset for 227 countries is archived in the ETH Research Repository with link: https://doi.org/10.3929/ethz-b-000331316 (Eberenz et al., 2019).

1 Introduction

The modelling of climate risks on a global scale requires globally consistent data representing hazard, vulnerability, and exposure, as defined by the Intergovernmental Panel on Climate Change (IPCC, 2012, 2014) among others. While natural hazard data can be derived from general circulation models, there is a lack of consistent exposure data on a global scale. Exposure data is frequently defined as an inventory of elements at risk from natural hazards (Cardona et al., 2012; UNISDR, 2009). For the modelling of direct economic impacts of disasters, exposure should specifically represent the spatial distribution of physical assets, i.e. buildings and machinery. While aggregate estimates of asset values are available at country level, open data on the spatial distribution of asset values are scarce. Exposure data owned by insurance companies are usually not publicly available.

Due to the lack of comprehensive asset inventories, large scale exposure maps are often estimated top-down, using downscaling techniques (De Bono and Mora, 2014; Murakami and Yamagata, 2016). Estimates of total physical asset values can be derived from socio-economic flow measures, such as GDP, since the two indicators exhibit strong correlations (Kuhn and Ríos-Rull, 2016). Annual values of socio-economic flow variables, particularly GDP, are often more readily available than physical asset values. Assuming that human presence and activity are proxies of economic output, downscaling of gross domestic product (GDP) has been based on population combined with land-use, road networks, and locations of airports (Murakami and Yamagata, 2016). While high resolution yearly GDP maps based on this approach were created for academic use (Frieler et al., 2017), there is no recent global high-resolution exposure dataset available for unrestricted use known to us.

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A global exposure data base was produced for the Global Assessment Report 2013 of the United Nations Office for Disaster Risk Reduction (UNISDR), following a downscaling approach (De Bono and Mora, 2014). However, the data base's use beyond the scope of Global Assessment Report is limited, because the data represents urban areas only and was produced from a variety of sources to represent the best estimate of a global exposure data base in 2013. For future quantitative risk assessments, more recent exposure data would be desirable. Reproducing De Bono and Mora's methodology is beyond the scope of most climate impact studies.

In recent years, the use of nightlight satellite imagery has seen a marked increase in usage in science in general and especially for the estimation of socio-economic indicators (Elvidge et al., 2012; Ghosh et al., 2013; Mellander et al., 2015; Pinkovskiy, 2014). With global satellite images being publicly available and updated regularly, it has been proven to be an useful source of information and is commonly used in scientific contexts for the estimation of unavailable GDP or growth data (Henderson et al., 2012). However, there are some technical limits to the usage of nightlight satellite imagery (Han et al., 2018), especially saturation and blooming. As luminosity can only be distinguished up to a certain brightness, saturation may lead to very bright spots being underrepresented. In the NASA dataset "Earth at Night" (NASA Earth Observatory, 2017), there are 256 shades of brightness, from the minimum zero (no light emission) to the maximum 255. Any pixel brighter than what would entail a value of 255 will also appear at this value (Elvidge et al., 2007).

Brightness can exude from bright pixels to neighboring pixels, causing the brightness in the latter to be overestimated, leading to blooming. This issue occurs especially in large urban areas and on specific surfaces, such as sand and water (Elvidge et al., 2004; Small et al., 2005). These shortcomings can be mitigated by combining nightlights with other data types: Zhao et al. (2017) enhanced nightlight intensity values with population data to get a more accurate estimation of spatial economic activity in China. They showed that "lit population" (LitPop), the product of nightlight intensity and gridded population count, is a better indicator for economic activity in China than nightlight intensity alone.

Applying the LitPop approach to spatially explicit exposure estimation on a global level, the present paper documents a globally consistent methodology for the distribution of asset values at high spatial resolution. A LitPop exposure dataset for 227 countries is made available online at the ETH Research Repository (Eberenz et al., 2019). It is suitable to provide the globally consistent exposure base for modelling direct economic disaster impacts. The methodology is published on GitHub as part of the open-source event-based probabilistic impact model CLIMADA (CLIMate ADAptation) (Aznar-Siguan and Bresch, 2019; Bresch et al., 2019a) and archived in the ETH Data Archive (Bresch et al., 2019b).

Information on input data, methodology, and validation are provided in Section 2. Subsequently, the resulting global LitPop exposure data is shown for selected metropolitan areas (Section 3.1), is validated on country level (Section 3.2), and local shortcomings are portrayed in a detailed case study for Mexico City (Section 3.3). The advantages and limitations of the approach are discussed in Sections 4 and 6. Please refer to section 5 for data and code availability.

2 Data & Methods

2.1 Overview

The core functionality of the LitPop exposure approach is to estimate spatially explicit asset values, i.e. the total value of produced capital per geographic grid cell. The work flow of the exposure data modelling is shown in Figure 1: Gridded nightlight data (Section 2.2) and gridded population data (Section 2.3) are combined to compute "lit population" (LitPop) at pixel level (Section 2.5). LitPop is then used to obtain gridded physical asset values by distributing national produced capital (Section 2.4.1) proportional to the LitPop-value per pixel (Section 2.6). Likewise, gross domestic product (GDP, Section 2.4.2) or gross regional product (GRP, Section 2.4.3) can be distributed to obtain pixel-based GDP. Because of a lack of sub-national

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produced capital data, GDP and GRP are used for validation of the underlying downscaling approach as described in Section 2.7.

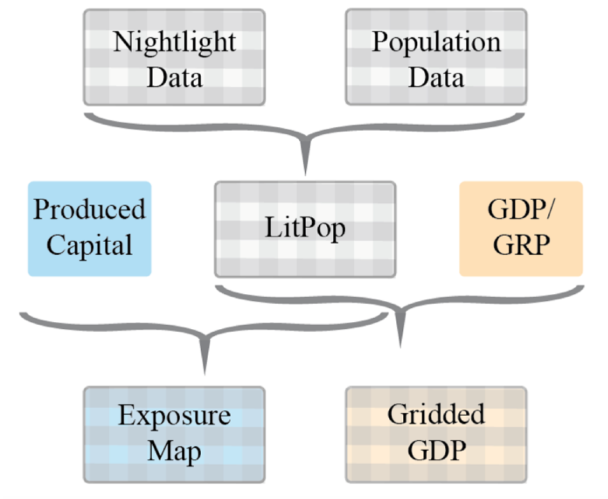

Figure 1: Work flow of the downscaling methodology: Gridded nightlights and population datasets are combined as LitPop. This is used for the downscaling of produced capital or GDP to estimate gridded exposed assets or gridded GDP respectively.

2.2 Satellite nightlight data

NASA nightlight satellite images (NASA Earth Observatory, 2017) are processed datasets of luminosity by human activity, as recorded by the Satellite Suomi NPP's Visible Infrared Imaging Radiometer Suite (VIIRS). VIIRS marks an distinct improvement over previous technologies, allowing for a greater range of light to be recorded (Carlowicz, 2012). The sun-synchronous satellite passes each place on Earth twice a day, at approximately 1.30 am and pm local time. Nightlight intensity on a scale from 0 to 255 is calculated from the raw measurements, taking into account cloud cover, lunar activity and even the environmental context to isolate luminosity of stable lights (Carlowicz, 2017). The data is provided for 2012 and 2016 at a resolution of 15 arcsec, which corresponds to around 500m at the equator. The open-source code developed here can be adapted easily to use other versions and sources of nightlight data. This could be of interest for near-time applications in the future, as NASA aims to eventually provide daily images (Carlowicz, 2017).

2.3 Gridded population data

The Gridded Population of the World (GPW) dataset is a spatially explicit representation of the world's population. It is based on two sets of inputs: non-spatial population data and cartography data. Using census data or population figures by the official national statistics offices, it uniformly distributes the numbers at the smallest available administrative unit to the corresponding cartographic shape, without taking into account any ancillary sources (Doxsey-Whitfield et al., 2015). The data quality for each country strongly depends on the underlying level of availability of population data. For example, for Canada, population data is available down to the fifth subnational administrative unit, of which 493'185 exist. The information there is hence a lot more fine-grained than in Jamaica or Uzbekistan, where population numbers are only recorded at the first subnational administrative unit (Socioeconomic Data and Applications Center (SEDAC), 2017). While modelling is kept at a minimum in

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the GPW dataset, values are inflated or deflated from the latest year with data available to 2000, 2005, 2010, 2015, and 2020 (Center for International Earth Science Information Network (CIESIN), 2017).

GPW was selected for this application, because unlike other spatial population datasets, it does not incorporate nightlight satellite data or other auxiliary data sources (Leyk et al., 2019). This allows us to enhance nightlight data with a completely independent dataset. Moreover, it is released under the creative commons license. From GPW, the Population Count v4.10 data at the highest available resolution, 30 arcsec, is used, because it is the closest to NASA's nightlight dataset, in terms of both spatial and temporal resolution.

2.4 Socioeconomic indicators

2.4.1 Produced capital stock

The World Bank's produced capital stock (World Bank, 2018) is one of the most comprehensive global estimate of the value of manufactured or built assets per country. It has been used as an indicator of exposure to natural disaster in the UNISDR's Global Assessment Report 2013 (De Bono and Mora, 2014) and produced capital accounts for machinery, equipment, and physical structures (World Bank, 2018). It also includes a fixed scale-up of 24% to account for the value of built-up land.

Produced capital values are currently available for 141 countries and 5 time steps: 1995, 2000, 2005, 2010, and 2014 from the World Bank Wealth Accounting (World Bank, 2019a). For target years between 1995 and 2014, produced capital is interpolated linearly. For years outside that range, produced capital is scaled proportionally to the country's change in GDP. Per default, the scale-up for built-up land is subtracted, assuming that there is no direct damage to the value of the land itself in the case of disaster.

2.4.2 Gross domestic product GDP

GDP is a well-established indicator of macroeconomic output. For most countries in the world, annual values are available dating back several decades. National GDP data is retrieved from the World Bank Open Data portal (World Bank, 2019b).

While GDP is not a direct measure of physical asset values, it is used here both to scale asset values in time to fill data gaps and for validation of the downscaling. The underlying assumption is that within a country, GDP and wealth are correlated, i.e. a higher GDP value is equivalent to higher asset values. This correlation has been established in empirical studies (Kuhn and Ríos-Rull, 2016).

2.4.3 Gross regional product GRP

The subnational equivalent to GDP is often referred to as GRP. GRP can be used to improve the downscaling of GDP, especially for countries with considerable regional differences. As described below in Section 2.7, we use GRP data from 14 countries to evaluate the LitPop-model's skill to predict GRP from national GDP. As there is no unified data source for GRP, it was gathered manually from government sources and OECD.Stat (Organisation for Economic Co-operation and Development, 2019). The countries used for validation are Australia, Brazil, Canada, Switzerland, China, Germany, France, Indonesia, India, Japan, Mexico, Turkey, USA, and South Africa. The aim of the selection was to include countries from a wide range of income groups and world regions. Since the selection of countries was limited by the availability of GRP data, the selection has a bias towards developed and emerging economies with eight countries from the high-income group, four countries from the upper-middle-income group, two countries from the lower-middle-income, and no countries from the low-income group. The income groups and data sources are listed in Table A1 in the Appendix.

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2.5 Computation of gridded LitPop

The computation of gridded LitPop is central to the exposure downscaling approach presented here. The method is closely adapted from the work of Zhao et al. (Naizhuo Zhao et al., 2017). In their paper, historic GDP is downscaled proportionally to a function of nightlights and population with the aim to make spatial GDP predictions for China. The underlying idea is to enhance brightness values with spatial population data to get a more accurate estimation of spatial economic activity. While the absolute value of LitPop in itself does not bear any interpretable meaning, its relative value in comparison to the national or subnational sum determines how much of a macroeconomic indicator each pixel receives.

In a first step, the two datasets are interpolated linearly to the same resolution of 30 arcsec, or coarser resolution if desired. Then, the combination of the two aforementioned datasets is conducted for each pixel:

$$Lit^n Pop^m{}_{pix} = \left(NL_{pix} + \delta\right)^n \cdot Pop_{pix}{}^m \qquad (1)$$

Where the LitPop-value $Lit^n Pop^m{}_{pix}$ is computed from the nightlight luminosity $NL_{pix} \in [0, 255]$, and population count $Pop_{pix} \in \mathbb{R}^+$. The exponents $n, m \in \mathbb{N}$ can be adjusted to change the weight of the two input variables (default $n = m = 1$). For all $m > 0$, the added δ is equal to 1 to ensure that non-illuminated but populated pixels do not get assigned zero value. In the case that nightlight data is used on its own without population data ($m = 0$), δ is set to 0.

2.6 Downscaling of socioeconomic indicators to LitPop

The LitPop dataset is used to linearly distribute any known socioeconomic indicator of an administrative unit (i.e. country or state) to a geographical grid:

$$I_{pix} = I_{tot} \cdot \frac{Lit^n Pop^m{}_{pix}}{\sum_i^N \left(Lit^n Pop^m{}_{pix}\right)} \qquad (2)$$

Where I denotes the socioeconomic indicator. The given indicator's total value for the administrative unit I_{tot} is distributed to each pixel I_{pix} proportionally to the LitPop-share of the pixel. N denotes the total number of pixels inside the boundaries of the administrative unit.

The socioeconomic indicator I can represent GDP as in the study of Zhao et al. (2017) and as used here for the validation of the methodology in Section 2.7. For physical risk assessments, an estimation of physical asset value like the World Bank's produced capital stock is distributed.

2.7 Validation of the Downscaling

Gridded population and nightlight intensity can both be used as proxies for the spatial distribution of economic activity and wealth. Both proxies have limitations: an asset-distribution proportional to population density assumes that physical wealth is distributed equally among the population and that assets are located exactly where people live. As already mentioned in Section 2.3, for many developing countries, gridded population data has a coarse resolution. Nightlight-based models, on the other hand, are mainly limited by saturation and blooming as described in the Introduction. By using LitPop, the product of nightlight

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intensity and population count, we expect to combine their skills while reducing the limitations mentioned above. To validate the performance of the LitPop exposure downscaling, we evaluate its ability to predict the share of subnational administrative units. Due to a lack of data on subnational asset values against which it could be tested, this is done for GDP only. Here, we use gross regional product (GRP) data from 14 countries to evaluate the model's ability to distribute national GDP to subnational regions.

To ensure comparability of the scores between different countries, GRP is normalized:

$$nGRP_i = \frac{GRP_i}{GDP} \tag{3}$$

Where $nGRP_i$ [5] denotes the normalized GRP of subnational region i. Given that $GDP = \sum_i^N (GRP_i)$, it follows that $\sum_i^N (nGRP_i) = 1$. Here, N is the set of all subnational units in the country.

To assess the model performance per country, two simple skill scores are computed from $nGRP$: The Pearson correlation coefficient ρ is computed to measure the linear correlation between the modelled normalized gross regional product $nGRP_{mod}$ and the reference value $nGRP_{ref}$. ρ is computed from the covariance (cov) and the standard deviations $\sigma_{mod} = \sigma(nGRP_{mod})$ and $\sigma_{ref} = \sigma(nGRP_{ref})$: $\rho = cov(nGRP_{i,mod}, nGRP_{i,ref})/(\sigma_{mod} \cdot \sigma_{ref})$.

The correlation coefficient ρ is a widely used score and straight forward to interpret and communicate: A value of 1 means a perfect positive linear correlation between the two variables while a value of 0 means no linear correlation. However, ρ is no direct measure of the deviations of $nGRP_{mod}$ from $nGRP_{ref}$ and yields no information regarding the slope of the linear relationship. Therefore, it needs to be evaluated in combination with a measure of the slope. The slope of the linear regression $\beta = \rho \cdot \sigma_{mod}/\sigma_{ref}$ is calculated to complement the analysis: β larger (lower) than 1 implies an overestimation (underestimation) of the GRP of economically strong regions and an underestimation (overestimation) of economically small regions in the downscaling. Together, ρ and β allow for an evaluation of the linear fit between modelled and reference data.

Complementarily, the root-mean-squared fraction (RMSF[6]) weights the relative deviation for each region equally, independently of the absolute values. The RMSF (Equation 5) thus puts equal weight to all subnational administrative units in a country, even if their GRP and thus absolute difference between prediction and reference are small. A RMSF of 1 indicates perfect fit.

$$RMSF = exp\left(\sqrt{\frac{1}{N}\sum_i^N \left[\log\left(\frac{nGRP_{i,mod}}{nGRP_{i,ref}}\right)\right]^2}\right) \tag{5}$$

This analysis is applied using varying combinations of nightlight and population data as base for the GDP-downscaling: gridded population density (Pop^n), nightlight intensity (Lit^m), and $Lit^m Pop^n$. The resulting skill scores are compared for each combination and country.

3 Results

In this section, the skill of the LitPop exposure downscaling is examined both qualitatively and quantitively. Since most exposed values are concentrated in urban areas (De Bono and Mora, 2014), exposure maps of two metropolitan areas are

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discussed with a focus on saturation, blooming, and resolution in Section 3.1. The results of the quantitative validation introduced in Section 2.7 are presented in Section 3.2. Finally, limitations of the LitPop-methodology are discussed by the example of Mexico.

3.1 Metropolitan areas

Saturation and blooming in nightlight intensity data cause exposure maps based on nightlights alone to misrepresent actual value distribution, especially in urban areas. This can be seen in Figure 2, showing maps based on nightlight intensity (a), population count (b) and LitPop (c), which is the product of the first two datasets. London (top row) and Mumbai (bottom), two large metropolitan areas, were chosen as examples. Comparable maps for Mexico City and New York are shown in Figure A1 in the Appendix.

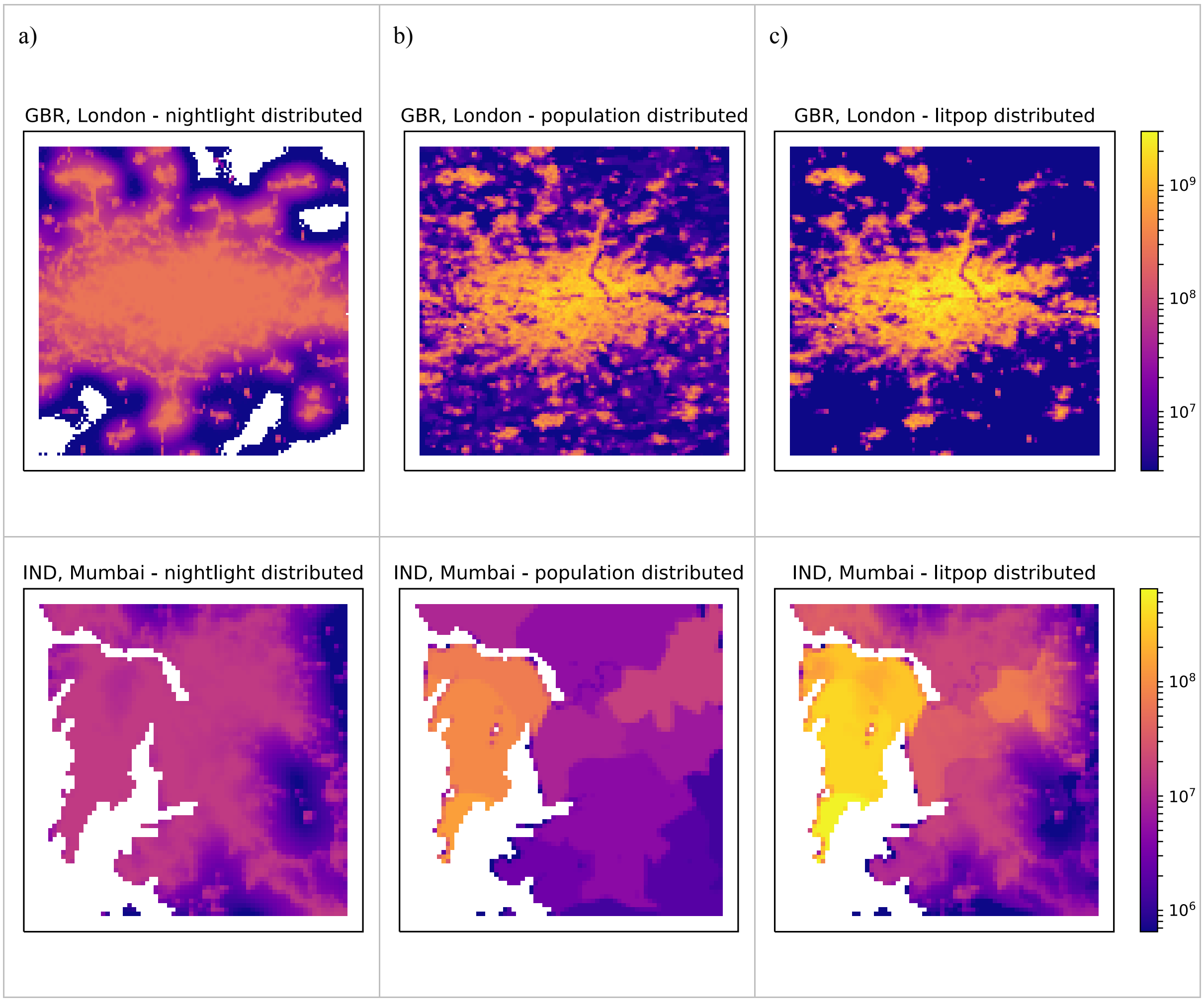

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Figure 2: National produced capital as of 2014. Values are spatially distributed proportional to nightlight intensity of 2016 (a), population count as of 2015 (b), and the product of both (LitPop, c) for the United Kingdom (GBR) and India (IND). The maps are restricted to the wider metropolitan areas of London (0.6°W-0.4°E; 51-52°N) and Mumbai (72-73.35°E; 18.8-19.4°N) respectively. The log-normal colorbar shows exposure values in USD per pixel of approximately 1 km².

The value distribution based on nightlight intensity (Fig. 2a) does not show many details within the urban area. This effect is partially caused by saturation: the light radiation in the depicted areas is of such high intensity, that the nightlight data does not offer any way to distinguish different levels of human activity. We can also observe the blooming effect, with the luminosity of bright parts crowding out to neighboring pixels, causing them to appear brighter than their underlying light sources would warrant. This latter effect can be particularly illustrated over the Thames river and Bow Creek in the northeastern part of London: The unpopulated river area is resolved in the population data (Fig. 2b top) but not by the nightlights (Fig. 2a top). By taking population density into account, the LitPop dataset enhances contrast and detail in urban areas (Fig. 2b, c). In addition, bright objects can be over-represented by nightlight intensity: In Figure 2a (top), the M25 London Orbital Motorway around London clearly stands out, with some pixels even at the same value as in central London.

As seen in the case of Mumbai, the LitPop-based exposure map of the metropolitan area in Figure 2c (top) shows much higher total values than those based on nightlights or population alone. This means that for LitPop, a larger proportion of the national produced capital of India is attributed to the metropolitan area of Mumbai. Whether the subnational distribution of values is more accurate for LitPop than for the other two datasets, is evaluated in Section 3.2.

3.2 Validation

The downscaling within countries is validated by comparing the downscaled and reported subnational GDP with three quantitative methods. The Pearson correlation coefficient ρ, linear slope parameter β, and root-mean-squared fraction RMSF per country are shown in Tables A2. To compare the overall performance of the different methods, median and spread of the scores are compared in Figure 3 and Table A3. As for the linear regression, $LitPop$ shows the highest overall median correlation coefficient of 0.94 with the lowest interquartile range (IQR[7]) of 0.09. The same holds for the slope parameter of $LitPop$ $(median\ =\ 1.03,\ IQR = 0.12)$. In contrast, the slope parameter is on average well below 1 for all exponents of Lit. A slope below 1 indicates an underestimation of the GRP of economically larger regions compared and an overestimation of smaller regions. This can possibly be attributed to the saturation problem of nightlight intensity data, given that economically large regions usually accommodate more metropolitan areas where saturation occurs the most. This interpretation is supported by the relatively low values attributed to London and Mumbai metropolitan areas as observed in Figure 2a. For population-based methods, we found a median slope below 1 for Pop and well above 1 for Pop^2. This suggests that population-based distribution underestimates the asset values in urban agglomerations, while it is overestimated by Pop^2.

Figure 3c shows the RMSF. RMSF is the average multiplicative error between two datasets, giving the same weight to all data point independently of absolute value. A RMSF-value of 2 means that on average, the modelled GRP deviates by a multiplicative factor of 2 from the reference value. For this score, Pop $(median\ =\ 1.37,\ IQR = 0.37)$ and Lit^4 $(median\ =\ 1.64,\ IQR = 0.36)$ perform best, while $LitPop$ has a median RMSF of 1.67 and an IQR of 1.29.

Based on these results, we conclude that $LitPop$ is the most an adequate combination of Lit and Pop for the subnational downscaling of GDP.

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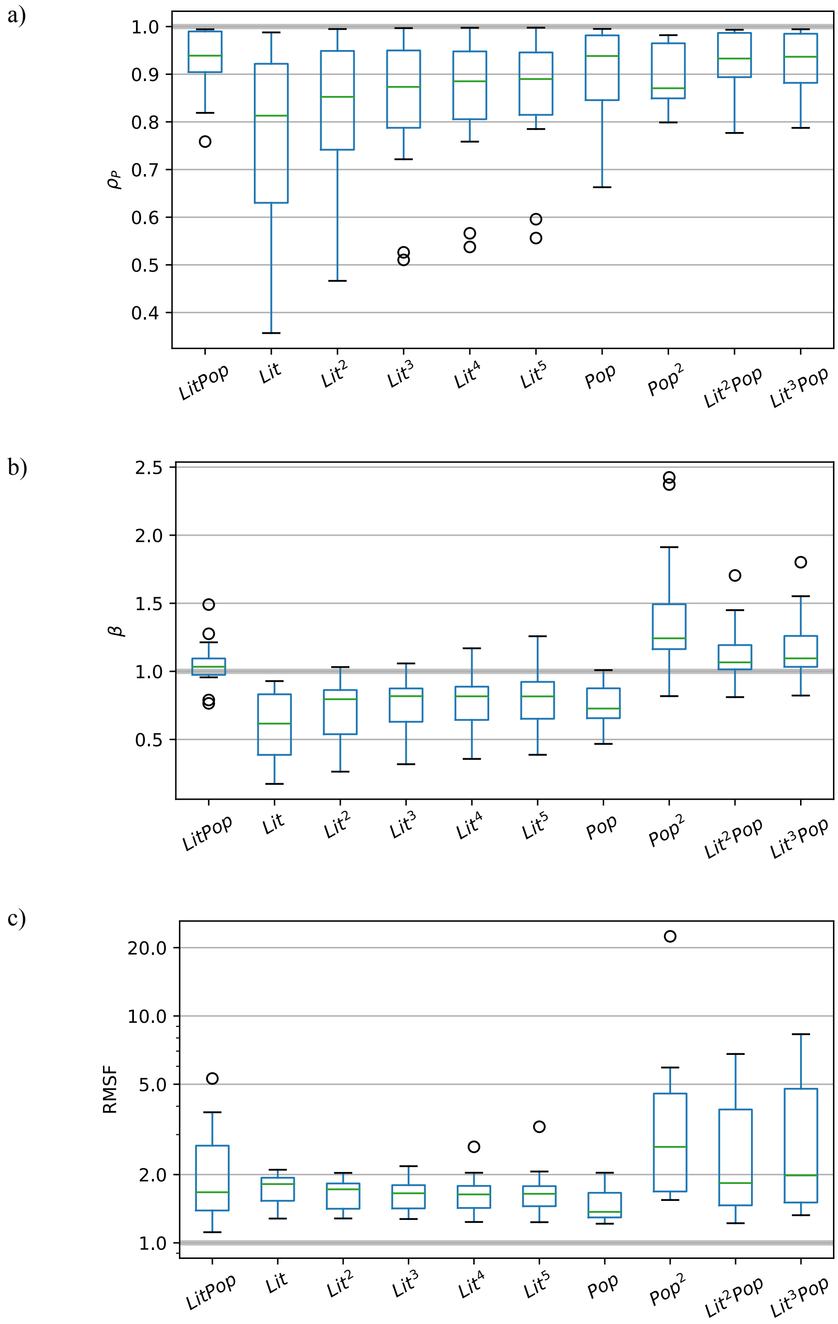

Figure 3: Box plots showing the Pearson correlation coefficient ρ (a), linear regression slope β (b), and root mean squared fraction RMSF (c) for variations of Lit^nPop^m. The best score of 1 is demarcated by the solid grey line. The plots are based on data from 14 countries and show the 1st, 2nd and 3rd quartile (box), 1.5*interquartile range (black whiskers), and outliers (black circles). RMSF is plotted on a logarithmic scale. Numbers are shown in Table A3.

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3.3 Example Mexico

In the validation in Section 3.2, Mexico shows low correlation ρ compared to most other countries. Figure 4 shows the modelled and reference normalized gross regional product (*nGRP*) for all 32 districts of Mexico. The corresponding plot data can be found in Table S.1 as supplementary material. While LitPop-methodology works well for most of the smaller districts, it fails to reproduce the *nGRP* for the main (capital) metropolitan region with the districts México and Mexico City. Exposure maps of the metropolitan region are shown in Figure A1 in the Appendix.

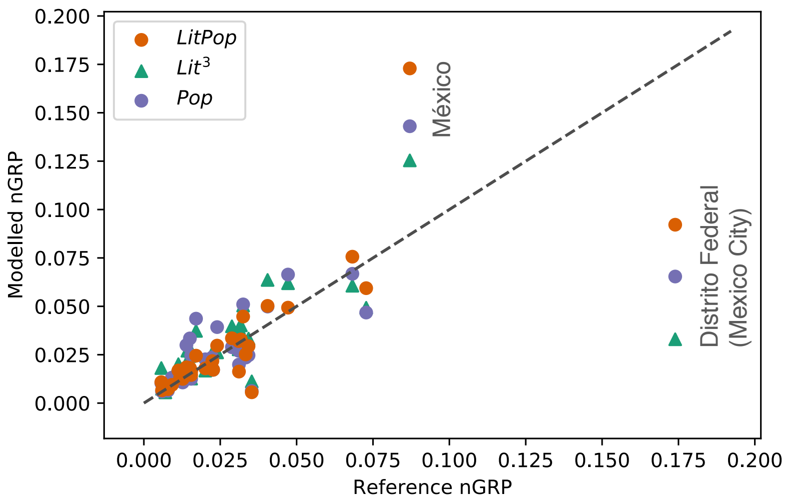

Figure 4: Normalized gross regional product (nGRP) for the 32 districts of Mexico. Reference values are shown on the horizontal axis and modelled values on the vertical axis.

The two economically largest districts of the highly centralized country are Distrito Federal (Mexico City) with a reported *nGRP* of 17.4% and the surrounding México (8.7%). The LitPop-based downscaling of GDP underestimates *nGRP* for Mexico City while overestimating the value for México (Fig. 4). The overestimation of México's GRP for all combinations of Lit and Pop indicates that the district has a high nightlight luminosity and population density compared to a relatively low economic output. This phenomenon could be an artefact of Mexico City's urban sprawl (de la Luz Hernández-Flores et al., 2017): There is probably a lot of housing and infrastructure in suburban México that is used by a population that works in the city and thus contributes to the GRP of Mexico City. Following this speculative interpretation, downscaling with LitPop might be more appropriate for physical assets (i.e. produced capital) than for GDP. Since no subnational breakdown of produced capital stock is available, we cannot test this hypothesis.

Using reference GRP as an intermediate downscaling layer in the case of Mexico would increase the estimated exposure in the Mexico City and decrease the exposure in the surrounding district of México. While this would obviously improve the downscaling for GDP, it might not be adequate for the distribution of physical assets. Further studies could use subnational asset values to examine whether the correlation between GDP and asset values is stronger than the correlation between LitPop and asset value. Where subnational asset values exist, they can be used as intermediate downscaling layers for physical assets.

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4 Discussion

The LitPop methodology allows for the creation of globally consistent and spatially highly resolved estimates of gridded physical asset value. According to Pittore et al. (2017), efforts towards improving exposure data should aim at global consistency, continuous integration of new data and methods, and a careful validation of models and data. Here, we will discuss the advantages and limitations of the LitPop methodology with regard to the following key criteria: Global consistency, predictive skill, scalability and flexibility, openness, replicability and reproducibility, and low entry threshold:

Global consistency. Based on global input data, the LitPop methodology performs well across countries from different continents and income groups without any customization. Therefore, LitPop-based exposure data can be used as a basis for globally comparable economic risk assessments. In order to improve downscaling for countries with large regional differences, a subnational breakdown of GDP in the form of GRP data can be used as an intermediate downscaling layer wherever available. As the case of Mexico City (Section 3.3) suggests, the link between LitPop and asset value might be stronger than the link between LitPop and GDP. It should be noted that due to lack of data we were not able to evaluate the method's performance for countries in income group 1. Another caveat to global consistency is the fact that the quality and resolution of the underlying population dataset varies between countries. This is discussed below.

Predictive skill. LitPop shows high skill in predicting subnational economic output based on the downscaling of national GDP in the 14 countries analyzed in detail. Although the skill of downscaling exposure cannot be validated directly, the high skill of LitPop for GDP downscaling recommends this method also for exposure downscaling. The evaluation of correlation coefficients and linear regression slope showed that LitPop distributes GDP better than other multiplicative combinations of nightlight and population data. In most of the evaluated countries, there is a large number of economically relatively small regions compared to few large ones. While the linear regression parameters are more sensitive to outliers (i.e. how good the fit is for regions with a large GRP), a low value of RMSF indicates that the smaller regions' GRPs were reproduced well by the model. For RMSF, pure population data performs best on average. Depending on the application, population data could be considered as an alternative basis for downscaling. However, the resolution of population data varies between countries. For high resolution risk assessments, the exact distribution of light sources as highlighted by nightlight data allows for an increase in spatial precision. Based on our results, we recommend LitPop for physical risk assessment because it combines the advantages of both input data types and mitigates their disadvantages, i.e. resolution, saturation and blooming. For countries without a high-resolution distribution of population in the gridded dataset, an exposure map based on $Lit^n Pop^m$ is equivalent to one based on Lit^n alone. For more locally refined risk assessments, in countries with coarsely resolved population information, we advise to use a higher exponent of nightlights instead, i.e. $n \geq 3$. Additionally, LitPop could be combined or masked with other auxiliary data, such as road networks, land cover (Murakami and Yamagata, 2016), or mobile phone cell antenna density (Brönnimann and Wintzer, 2018).

Scalability and flexibility. Subject to data availability, the LitPop exposure model can be used to estimate the distribution of physical asset values for any target year at a wide range of resolutions. Our used data sources cater for resolutions up to 30 arcsec. While the GPW dataset provides population data for the previous two decades, the NASA nightlight images are currently only available for 2012 and 2016. The methodology includes a scaling of exposure data proportional to current GDP for years without any data available. The model can be adapted to a variety of applications by an appropriate choice of the macroeconomic indicator: The World Bank's produced capital data is set as the default total asset value per country. Alternatively, GDP can be used as an estimator of economic output. GDP multiplied by a factor derived from the country specific income group can also be used to estimate asset values (Aznar-Siguan and Bresch, 2019). Since the CLIMADA repository is open-source, the LitPop-methodology can easily be amended to include alternative data sources and versions of both gridded nightlight, population, asset base or other socioeconomic indicators to expand the repertory of the top-down exposure data model. The LitPop methodology was developed to provide a globally consistent exposure base for large-scale disaster risk modelling. While it could be used for other applications as well, the limitations of its scope should be noted: The top-down approach implemented here does not account for differences in infrastructure types and vulnerability. In addition, gridded data may cause poor scoping of areas most vulnerable to risk, or those with more exposed population. Thus, the

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applicability for local-based applications and detailed socio-economic risk assessments is limited by the top-down nature of our methodology. Especially for risk assessments with a local focus as well as in countries with low resolution of population data, we would advise to use more local-based approaches and bottom-up methods for identifying and analyzing the vulnerability component.

Openness, replicability, and low entry threshold. The LitPop methodology was developed in the programming language Python 3 and published on the code hosting service GitHub as well as in a permanent repository (c.f. Section 5). The CLIMADA repository is developed open-source and makes use of open-access data to enable unrestricted use for applications also beyond academia. The LitPop-module can be used both to apply the exposure data directly in event-based risk assessment with CLIMADA or to export gridded exposure data to standard formats for use in other applications. While $LitPop$ is the default, any multiplicative combination of Lit and Pop can be chosen as a downscaling function. The documentation of CLIMADA is hosted on Read the Docs (https://climada-python.readthedocs.io/en/stable/). It includes an interactive tutorial of CLIMADA and the LitPop module (https://climada-python.readthedocs.io/en/stable/tutorial/climada_entity_LitPop.html), with guidance on how to compute and export LitPop exposure data.

5 Data and code availability

LitPop exposure data at a resolution of 30 arcsec for 227 countries, and normalized Lit and Pop for the 14 countries highlighted in this study is archived in the ETH Research Repository with link: https://doi.org/10.3929/ethz-b-000331316 (Eberenz et al., 2019). The LitPop methodology is openly available as a module of CLIMADA (Bresch et al., 2019a) at GitHub under the GNU GPL license (GNU Operating System, 2007). CLIMADA v1.2.0 was used for this publication, which is permanently available at the ETH Data Archive with link: http://doi.org/10.5905/ethz-1007-226 (Bresch et al., 2019b). The scripts reproducing the published dataset, as well as all figures in the present publication and the main results are published in the CLIMADA-papers repository on GitHub with link: https://github.com/CLIMADA-project (Aznar-Siguan et al., 2019).

6 Conclusion

The open-source LitPop exposure methodology was developed to provide a geographical distribution of physical asset values that can be used to model first-order economic impacts of climate and weather events. It integrates publicly available data sources to calculate area-based economical exposure estimates. The global consistency, flexibility and openness and the integration in the CLIMADA repository offers value for manifold use cases for top-down economic disaster risk modelling and climate change adaptation studies. Future research and development could focus on the integration of higher resolved population data and other ancillary data sources as they get available globally, and validation of the top-down downscaling against bottom-up data.

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Appendix A

Country	Regions	Income Group	Data Source
Australia	8	4	Australian Bureau of Statistics, http://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/5220.02016-17?OpenDocument
Brazil	27	3	OECD.Stat, https://stats.oecd.org/
Canada	14	4	OECD.Stat, https://stats.oecd.org/
Switzerland	26	4	Swiss Federal Statistical Office, https://www.bfs.admin.ch/bfs/en/home/statistics/national-economy/national-accounts/gross-domestic-product-canton.assetdetail.6369918.html
China	31	3	National Bureau of Statistics China, http://data.stats.gov.cn/english/easyquery.htm?cn=E0103
Germany	16	4	Statistische Ämter des Bundes und der Länder, https://web.archive.org/web/20110717065817/http://www.statistik-portal.de/Statistik-Portal/en/en_jb27_jahrtab65.asp
France	101	4	Eurostat, http://ec.europa.eu/eurostat/web/regions/data/database
Indonesia	33	2	OECD.Stat, https://stats.oecd.org/
India	30	2	Open Government Data Platform India, https://data.gov.in/catalog/capita-state-domestic-product-current-prices#web_catalog_tabs_block_10
Japan	47	4	Cabinet Office Government of Japan, http://www.esri.cao.go.jp/jp/sna/data/data_list/kenmin/files/contents/main_h26.html
Mexico	32	3	National Institute of Statistics and Geography of Mexico, https://www.inegi.org.mx/sistemas/bie/?idserPadre=10200070#D10200070
Turkey	81	3	OECD.Stat, https://stats.oecd.org/
USA	52	4	US Bureau of Economic Analysis, https://www.bea.gov/data/gdp/gdp-state
South Africa	9	3	OECD.Stat, https://stats.oecd.org/

Table A1: List of countries used for validation with the number of regions on the administrative level 1, the World Bank income group 2016, and gross regional product (GRP) data source with URLs as accessed in January 2019. The income groups are: low income (1), lower middle income (2), upper middle income (3) and high income (4).

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ρ	AUS	BRA	CAN	CHE	CHN	DEU	FRA	IDN	IND	JPN	MEX	TUR	USA	ZAF
$LitPop$	0.99	0.98	0.99	0.94	0.93	0.90	0.92	0.90	0.82	0.93	0.76	0.99	0.98	0.99
Lit	0.92	0.92	0.99	0.81	0.95	0.96	0.37	0.75	0.81	0.59	0.36	0.53	0.76	0.85
Lit^2	0.93	0.96	0.99	0.89	0.96	0.94	0.47	0.79	0.82	0.73	0.47	0.66	0.78	0.95
Lit^3	0.94	0.96	1.00	0.91	0.95	0.93	0.51	0.83	0.83	0.79	0.53	0.72	0.79	0.97
Lit^4	0.94	0.97	1.00	0.93	0.95	0.92	0.54	0.85	0.84	0.82	0.57	0.76	0.80	0.97
Lit^5	0.94	0.97	1.00	0.93	0.95	0.91	0.56	0.87	0.84	0.84	0.60	0.79	0.81	0.97
Pop	0.99	0.96	1.00	0.97	0.85	0.98	0.84	0.80	0.79	0.92	0.66	0.98	0.98	0.92
Pop^2	0.97	0.97	0.98	0.81	0.82	0.88	0.86	0.86	0.80	0.96	0.85	0.96	0.86	0.97
Lit^2Pop	0.99	0.99	0.99	0.89	0.90	0.86	0.92	0.90	0.87	0.94	0.78	0.99	0.98	0.99
Lit^3Pop	0.99	0.99	0.99	0.86	0.89	0.84	0.93	0.89	0.88	0.95	0.79	0.99	0.98	0.98

Table A2a: Pearson correlation coefficient ρ for 14 countries: Australia (AUS), Brazil (BRA), Canada (CAN), Switzerland (CHE), China (CHN), Germany (DEU), France (FRA), Indonesia (IDN), India (IND), Japan (JPN), Mexico (MEX), Turkey (TUR), United States of America (USA), and South Africa (ZAF). Best fit would mean $\rho = 1$. Linear correlation is statistically significant with a p-value lower than 0.05 for all shown countries and combinations.

β	AUS	BRA	CAN	CHE	CHN	DEU	FRA	IDN	IND	JPN	MEX	TUR	USA	ZAF
$LitPop$	1.02	0.79	1.10	1.07	1.05	1.01	0.96	1.21	0.96	1.28	0.76	1.49	1.01	1.07
Lit	0.82	0.55	0.90	0.67	0.93	0.89	0.22	0.76	0.84	0.33	0.22	0.17	0.57	0.54
Lit^2	0.82	0.61	0.96	0.77	1.03	0.89	0.32	0.83	0.82	0.52	0.32	0.26	0.62	0.87
Lit^3	0.82	0.63	0.99	0.84	1.06	0.88	0.38	0.86	0.82	0.64	0.38	0.32	0.65	1.05
Lit^4	0.82	0.64	1.01	0.89	1.07	0.86	0.41	0.88	0.81	0.73	0.42	0.36	0.66	1.17
Lit^5	0.82	0.64	1.02	0.93	1.07	0.85	0.44	0.90	0.81	0.80	0.45	0.39	0.67	1.26
Pop	1.01	0.66	1.01	0.87	0.68	0.92	0.47	0.77	0.84	0.66	0.55	0.61	0.88	0.65
Pop^2	1.23	0.97	1.21	1.16	0.82	1.01	2.42	1.40	1.19	1.91	1.26	2.37	1.52	1.40
Lit^2Pop	1.03	0.81	1.12	1.12	1.04	0.99	1.09	1.26	1.01	1.45	0.82	1.70	1.04	1.22
Lit^3Pop	1.03	0.82	1.13	1.15	1.03	0.96	1.16	1.29	1.04	1.55	0.86	1.80	1.06	1.32

Table A2b: Linear slope β for 14 countries: Australia (AUS), Brazil (BRA), Canada (CAN), Switzerland (CHE), China (CHN), Germany (DEU), France (FRA), Indonesia (IDN), India (IND), Japan (JPN), Mexico (MEX), Turkey (TUR), United States of America (USA), and South Africa (ZAF). Best fit would mean $\beta = 1$. Linear correlation is statistically significant with a p-value lower than 0.05 for all shown countries and combinations.

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RMSF	AUS	BRA	CAN	CHE	CHN	DEU	FRA	IDN	IND	JPN	MEX	TUR	USA	ZAF
$LitPop$	1.31	1.54	1.80	2.70	1.37	1.44	1.93	5.30	2.61	2.86	1.55	3.76	1.37	1.11
Lit	1.28	1.93	1.69	1.74	1.50	1.44	1.89	2.00	2.10	1.52	1.93	2.03	1.94	1.58
Lit^2	1.28	1.83	1.51	1.85	1.42	1.36	1.68	1.86	2.03	1.41	1.77	1.77	1.81	1.37
Lit^3	1.32	1.80	1.48	2.18	1.40	1.38	1.63	1.81	2.02	1.47	1.69	1.68	1.77	1.27
Lit^4	1.34	1.79	1.49	2.65	1.40	1.40	1.63	1.79	2.04	1.58	1.64	1.64	1.77	1.24
Lit^5	1.37	1.78	1.53	3.25	1.40	1.42	1.66	1.79	2.06	1.70	1.60	1.63	1.77	1.23
Pop	1.27	1.72	1.29	1.36	1.48	1.32	1.38	2.04	1.73	1.21	1.69	1.59	1.32	1.28
Pop^2	1.67	1.73	3.50	3.18	1.61	1.64	4.73	5.93	4.01	5.34	1.81	22.4	2.12	1.54
Lit^2Pop	1.37	1.53	2.07	4.18	1.40	1.60	2.41	6.80	3.00	4.16	1.53	6.36	1.44	1.22
Lit^3Pop	1.41	1.53	2.27	5.74	1.41	1.69	2.75	7.64	3.23	5.29	1.52	8.31	1.50	1.32

Table A2c: Root-mean-squared fraction RMSF for 14 countries: Australia (AUS), Brazil (BRA), Canada (CAN), Switzerland (CHE), China (CHN), Germany (DEU), France (FRA), Indonesia (IDN), India (IND), Japan (JPN), Mexico (MEX), Turkey (TUR), United States of America (USA), and South Africa (ZAF). Best fit would mean RMSF = 1.

	$\boldsymbol{\rho}$		$\boldsymbol{\beta}$		**RMSF**	
	Median	IQR	Median	IQR	Median	IQR
$LitPop$	0.94	0.09	1.03	0.12	1.67	1.29
Lit	0.81	0.29	0.62	0.44	1.82	0.40
Lit^2	0.85	0.21	0.80	0.32	1.72	0.41
Lit^3	0.87	0.16	0.82	0.24	1.65	0.38
Lit^4	0.89	0.14	0.82	0.24	1.64	0.36
Lit^5	0.89	0.13	0.82	0.27	1.65	0.33
Pop	0.94	0.14	0.73	0.22	1.37	0.37
Pop^2	0.87	0.12	1.24	0.33	2.65	2.87
Lit^2Pop	0.93	0.09	1.07	0.18	1.83	2.41
Lit^3Pop	0.94	0.10	1.10	0.23	1.98	3.27

Table A3: Comparison of three skill scores measuring the fit between modelled and reference normalized gross regional products. Median and interquartile range (IQR) over 14 countries are computed from the data in Tables A2a-c. The scores are Pearson correlation coefficient ρ, slope β, and the root-mean-squared fraction RMSF. Perfect fit would mean a value of one for each score.

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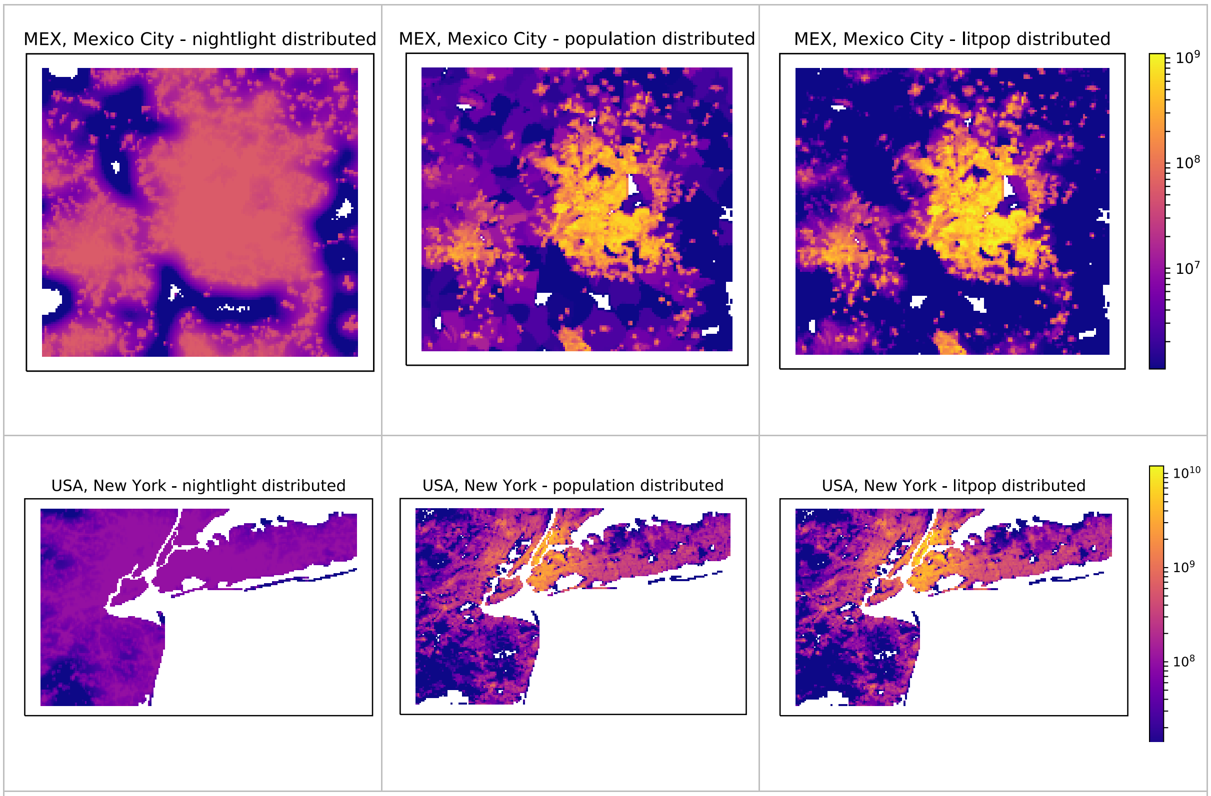

Figure A1: National produced capital distributed proportional to nightlight intensity (left column), population count (middle), and LitPop (right) for the Mexico (MEX) and USA. The maps are restricted to the wider metropolitan areas of Mexico City (99.8-98.6°W; 18.9-20°N) and New York (74.6- 73°W; 40- 41°N) respectively. The log-normal colorbar shows exposure values in USD for 2014.

Author contributions

DS, SE, and DNB developed the method collaboratively. The programming code was written by DS, TR, and SE. Validation and visualization was done by TR and SE. SE prepared the manuscript with contributions from all co-authors.

Competing interests

The authors declare that they have no conflict of interest.

Acknowledgements

We would like to thank: Lea Müller for her initial implementation of gridded nightlight as a proxy for global exposure, Gabriela Aznar-Siguan for her input regarding the platform CLIMADA and all members of the Weather and Climate Risks Group at ETH Zurich for their inputs and discussions shaping this publication.

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