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A global historical data set of tropical cyclone exposure (TCE-DAT)

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Abstract. Tropical cyclones pose a major risk to societies worldwide with about 22 million directly-affected people and damages of $29 billion on average per year over the last 20 years. While data on observed cyclones tracks (location of the center) and wind speeds is publically available these data sets do not contain information about the spatial extent of the storm and people or assets exposed. Here, we apply a simplified wind field model to estimate the areas exposed to wind speeds above 34, 64, and 96 knots. Based on available spatially-explicit data on population densities and Gross Domestic Product (GDP) we estimate 1) the number of people and 2) the sum of assets exposed to wind speeds above these thresholds accounting for temporal changes in historical distribution of population and assets (TCE-hist) and assuming fixed 2015 patterns (TCE-2015). The associated country-event level exposure data (TCE-DAT) covers the period 1950 to 2015 and is freely available at http://doi.org/10.5880/pik.2017.005. It is considered key information to 1) assess the contribution of climatological versus socio-economic drivers of changes in exposure to tropical cyclones, 2) estimate changes in vulnerability from the difference in exposure and reported damages and calibrate associated damage functions, and 3) build improved exposure-based predictors to estimate higher-level societal impacts such as long-term effects on GDP, employment, or migration.

We validate the adequateness of our methodology by comparing our exposure estimate to estimated exposure obtained from reported wind fields available since 1988 for the United States.

We expect that the free availability of the underlying model and TCE-DAT will make research on tropical cyclone risks more accessible to non-experts and stakeholders.

1 Introduction

Tropical cyclones (TCs) belong to the most harmful natural disasters worldwide with $29 billion of direct damages and 22 million people affected on average each year [*Guha-Sapir*, 2017]. In addition to these direct damages tropical cyclones have the potential to exercise influence on long-term development such as dampening of economic output [*Hsiang*, 2010; *Hsiang and Jina*, 2014], e.g. by reduced education achievements, mortality, and displacement.

Direct economic losses from TCs show a positive trend over time [*MunichRe*, 2015] whose attribution to increasing exposure, changing vulnerability, and more extreme hazards is heavily debated [*Pielke et al.*, 2008; *Estrada et al.*, 2015]. The attribution is particularly relevant for future projections of TC impacts given expected changes in population numbers and patterns [*Jones and O'Neill*, 2016], potential increases in hazards under unchecked climate change [*Emanuel*, 2013], and the future evolution of vulnerabilities [*Bakkensen and Mendelsohn*, 2016; *Geiger et al.*, 2016]. Options to gain a better understanding of TC induced societal risks strongly depend on high-quality observational TC and socio-economic records. However, availability of data strongly varies over time and space and data sets can be subject to various reporting biases [*Guha-Sapir and Below*, 2002; *Wirtz et al.*, 2014]. Working with these issues can be tedious and even beyond the scope of a researchers' expertise. Moreover, standardized methods of data selection and preparation facilitate the reproducibility and comparability of research results.

To overcome current limitations, we here provide a globally-consistent data set of TC exposure, named TCE-DAT. Exposure in TCE-DAT is defined per TC event as the number of potentially affected people and the sum of potentially affected assets. TCE-DAT covers the period from 1950 to 2015 and provides estimates of exposed population and exposed assets by 2713 individual landfalling TCs with at least 34 knots (kn) 1-min sustained wind speed above land documented by the International Best Track Archive for Climate Stewardship (IBTrACS) [*Knapp et al.*, 2010]. The data set is created using only publicly available data sources and running the open-source economics of climate adaptation (ECA) tool climada [*Bresch*, 2014; *Gettelman et al.*, 2017].

To allow for an assessment of purely physically driven changes in exposure we also provide estimates of the number of people and the sum of assets exposed given fixed 2015 distributions of population and assets. In this regard TCE-DAT extends and complements estimates from the Global Assessment Report on Disaster Risk Reduction (GAR 2015) [*UNISDR*, 2015], that provides a statistical assessment of exposure given fixed socio-economic conditions.

In combination with reported damages and number of people affected from other sources, e.g. EM-DAT [*Guha-Sapir*, 2017] and NATCAT [*MunichRe*, 2015], TCE-DAT allows for a convenient assessment of historical vulnerabilities finally translating hazard (wind intensities) and exposure into damages or people affected as indicators of societal risks.

In the following we describe the input data sets and our methodology used to create TCE-DAT. We then validate our findings based on exposed population estimates for the United States. We conclude by discussing potential applications of TCE-DAT and comment on its limitations and sources of uncertainty.

2 Data & Methods

2.1 climada - risk modeling

TCE-DAT builds on various TC and socio-economic data sets that are merged and analyzed using climada, an open-source probabilistic natural catastrophe risk assessment model [*Bresch*, 2014]. For the definition of natural hazard risk, we follow the definition by the IPCC [*IPCC*, 2014] where risk is defined as a function of hazard, exposure and vulnerability, i.e.

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$$\text{risk} = f(\text{hazard}, \text{exposure}, \text{vulnerability}) = \text{probability of hazard} \times f(\text{intensity of hazard}, \text{exposure}, \text{vulnerability})$$

where the latter three elements constitute severity of the impact. Hazard describes weather events such as storms, floods, drought, or heatwaves both in terms of probability of occurrence as well as physical intensity (see section 2.3 below). Exposure describes the geographical distribution of people, livelihoods and assets or infrastructure, generally speaking of all items potentially exposed to hazards, including ecosystems and their services. In the present case, exposure is determined for each TC separately based on the storm's wind field (see section 2.2 below). Vulnerability describes how specific exposure will be affected by a specific hazard, i.e. relates the intensity of a given hazard with its impact, such as wind damage to buildings as a function of wind speed or the effect of a flood on a local community and its livelihoods. The damage function hence expresses the specific vulnerability for a given kind of assets.

While climada allows for the implementation of different damage functions translating the intensity of the hazard, exposure, and vulnerabilities into damages and people affected [*Gettelman et al.*, 2017] we only use part of its functionality to solely estimate exposure by using a step-like vulnerability function that is zero below a certain wind speed threshold and unity above. The climada module ISIMIP v1.0 used to generate TCE-DAT can be found at: https://github.com/davidnbresch/climada_module_isimip/releases/tag/v1.0

2.2 Socio-economic data

We use socio-economic data on the grid level with 0.1° x 0.1° resolution. For the attribution of exposed population and assets to different countries we use a country mask with equal resolution.

2.2.1 Spatially-explicit population data

Affected population is determined based on the History Database of the Global Environment (HYDE, version 3.2) that is developed under the authority of the Netherlands Environmental Assessment Agency and provides (gridded) time series of population and land use for the last 12,000 years [*Klein Goldewijk et al.*, 2010, 2011] . HYDE provides population data with an original resolution of 5 arcmin (0.083°), decennially up to 2000 and annually up to 2015. Where required we linearly interpolate the data to derive annual distributions, and finally aggregate the numbers to 0.1° resolution.

2.2.2 Spatially-explicit assets data

The spatially-explicit assets data set is created based on spatially-explicit GDP data (in 2005 PPP $), available decennially between 1850 and 2100 [*Frieler et al.*, 2016; *Geiger and Frieler*, 2017; *Murakami, D. and Yamagata*, 2017]. Data from 2010 onwards is based on national GDP time series according to the Shared Socioeconomic Pathways (SSP2) [*Frieler et al.*, 2016; *Dellink et al.*, 2017]. Grid-level GDP is downscaled from national GDP estimates, using spatially-explicit population estimates and multiple other predictors, e.g. distance to cities and to the coast, road network densities, and others [*Murakami,* *D. and Yamagata*, 2017]. GDP data, provided with an original resolution of 5 arcmin (0.083°), is linearly interpolated to derive annual distributions for the years from 1950 to 2015. Finally data is aggregated to 0.1° resolution in the same way as the population data.

To estimate assets distributions from the GDP data we use the Global Wealth Databook 2016 assembled by Credit Suisse [*CreditSuisse*, 2016] to derive national Assets/GDP ratios for the year 2016 for 181 countries. Ratios for missing countries are approximated based on geographically close countries with similar GDP per capita values. Due to a lack of reported asset distributions for other years we assume national Assets/GDP ratios to be constant over the considered time period (1950-2015).

2.3 Hazard data and wind field modeling

2.3.1 Hazard data

IBTrACS provides the most comprehensive global data set of historical tropical cyclone activity [*Knapp et al.*, 2010]. We rely on the latest version (v03r09) that includes tropical cyclones records up to the end of 2015. IBTrACS combines TC data from various Regional Specialized Meteorological Centers (RSMC). However, historical TC records from the National Hurricane Center (NHC) of the United States (known as HURDAT), available for the North Atlantic and Eastern Pacific, and the Joint Typhoon Warning Center (JTWC), available for the remainder of the world, are regarded most accurate [*Holland and Bruyère*, 2014]. Whenever possible, we sub-select HURDAT and JTWC data from IBTrACS data, relying on other providers for otherwise missing events only (see Table 1).

The IBTrACS archive originally contains 7019 entries between 1950-2015 (3662 between 1980-2015). We select 5719 TCs between 1950-2015 (3577 TCs between 1980-2015) where all information required to estimate the associated wind fields is available (see Table 2 for the list of required variables) to subsequently filter 2713 events with landfall. Note that most incomplete data entries occur prior to 1980, and in particular for very weak events mostly without landfall.

provider	North Atlantic	South Atlantic	East Pacific	West Pacific	South Pacific	North Indian	South Indian
HURDAT	1	-	1	-	-	-	-
JTWC	-	-	3	1	1	1	1
ATCF	2	1	2	-	-	-	-
BOM	-	-	-	-	-	-	2
newdehli	-	-	-	-	-	2	-
CMA	-	-	-	2	-	-	-
remainder	3	2	4	3	2	3	3

Table 1: List of consulted data providers within the IBTrACS archive broken down by ocean basin. Numbers indicate order of priority. The row "remainder" has lowest priority for all basins and data from this source is only used in very few cases to provide estimates for otherwise missing data. Abbreviations are the following: HURDAT: Hurricane Databases of the National Hurricane Center, JTWC: Joint Typhoon Warning Center (available for various basins), ATCF: Automated Tropical Cyclone Forecast, BOM: Bureau of Meteorology (Australia), newdehli: Regional Specialized Meteorological Center New Dehli, India, CMA: China Meteorological Administration - Shanghai Typhoon Institute, remainder: [VARIABLE_NAME]_for_mapping variables in IBTrACS data.

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2.3.2 Wind field modeling

The IBTrACS archive only contains TC center coordinates and other physical variables on a 6-hour snapshot basis. A wind field model is required to generate continuous wind fields that - based on IBTrACS variables - provides realistic distributions of surface winds around the TC center. The spatial extent of a TC is usually described as the sum of the following components: 1) a static circular wind field for each track coordinate, and 2) the translational wind speed component that arises from the TC movement. To estimate the first component several models have been proposed, see e.g. [*Holland*, 1980, 2008; *Holland et al.*, 2010; *Chavas et al.*, 2015]. Here, we apply the improved wind field model by Holland et al. [*Holland*, 2008] (named Holland08 in the following), that has been successfully applied in other studies, e.g. [*Peduzzi et al.*, 2012]. The second component is added to the first one by quantifying the mean TC's translational wind speed between two consecutive track coordinates (via an optimized Haversine formula) and vectorial addition of both wind speed components. We incorporate that the effect of the translational wind speed decreases with distance from the TC center by multiplying the translational component with an attenuation factor given as the ratio between the distance to center and rmax, c.f. also [*Peduzzi et al.*, 2012].

Our implementation of the Holland08 model (including the translational TC movement) is freely available within the climada ISIMIP module (https://github.com/davidnbresch/climada_module_isimip/releases/tag/v1.0) that has been used to generate the provided data set. The input variables required to run the Holland08 model are summarized in Table 2.

variable short name	variable long name	further details
cgps	current TC center lat/lon-coordinates	-
ngps	TC center lat/lon-coordinate at next timestep	-
tint	time between time steps	usually 6 hours
pcen	minimum central pressure	in mbar
prepcen	minimum central pressure at previous timestep	required to calculate pressure gradient
vmax	1-min maximum sustained wind speed	only used if pcen not given
penv	environmental pressure at outer closed isobar	if unavailable set to 1010 mbar
rmax	radius of maximum winds	extrapolated from pcen if not given; based on cubic fit of IBTrACS data

Table 2: Input variables for Holland08 wind field model as implemented in climada.

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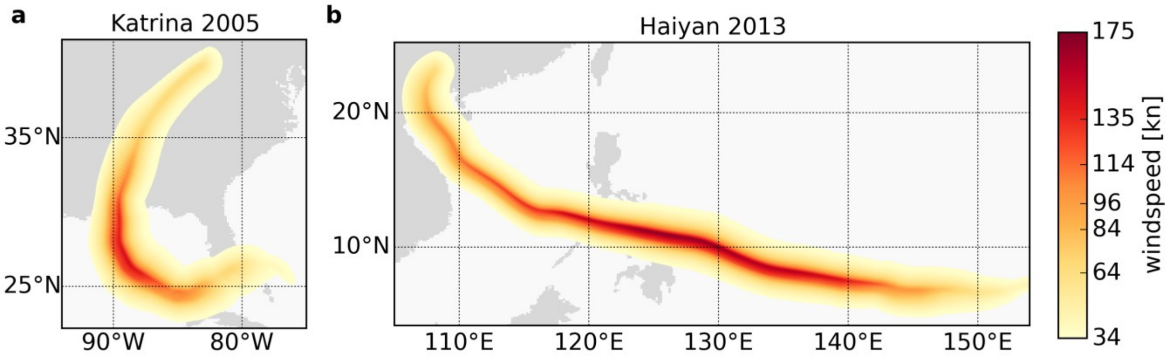

Figure 1: Exemplary wind fields for Hurricane Katrina affecting the United States in 2005 (a) and Typhoon Haiyan affecting the Philippines in 2013 (b) as generated using the Holland08 wind field model. The colorbar ticks highlight the relevant wind speed thresholds from the Saffir-Simpson scale in kn.

The Holland08 model works best in the tropics; for TCs with sub-tropical transition that potentially enter the westerlies of the mid-latitudes we limit the translational wind speed component to 30 kn, thereby removing fast-moving storms that lack TC characteristics.

The present implementation of the Holland08 wind field model generates a complete wind profile for each TC by saving its lifetime's maximum wind speed at each spatial location; 1-min sustained wind speeds below 34 kn (17.5 m/s) are discarded (see Fig. 1).

2.4. The global TC exposure data set (TCE-DAT)

2.4.1. Overview of TCE-DAT

The final TCE-DAT is freely available at http://doi.org/10.5880/pik.2017.005. It is created by overlaying the estimated winds fields and the distributions of assets and population and subsequent aggregation of all non-zero country- and TC-specific exposure values. Two data sets are included in TCE-DAT: 1) TCE-hist where socio-economic information matches the year of landfall, and 2) TCE-2015 where socio-economic patterns are fixed at 2015 values. TCE-DAT provides estimates of exposed population and exposed assets by event and by country for 34, 64, and 96 kn wind speed thresholds, corresponding to the Saffir-Simpson hurricane scale classification of tropical storm, hurricane, and major hurricane, respectively. Note that TCE-2015 contains 23 additional entries compared to TCE-hist. This is due to the fact that population and assets distributions have advanced over time and would have been exposed if all historical TCs were to make landfall in 2015 (as assumed in TCE-2015), while they were not exposed historically.

Due to technological innovations the reporting of TCs in the IBTrACS data base has improved significantly over time, reaching comprehensive global coverage by 1980 (see also Fig. 2). Compared to basin-wide TC activity, the number of landfalling TCs is smaller and shows greater variability due to underlying climate variability, e.g. driven by the El Nino Southern Oscillation (ENSO). When using TCE-DAT to analyze trends in TC risk (see Fig. 3), one should be aware of the underreporting in IBTrACS for earlier periods as this can be one reason for trends.

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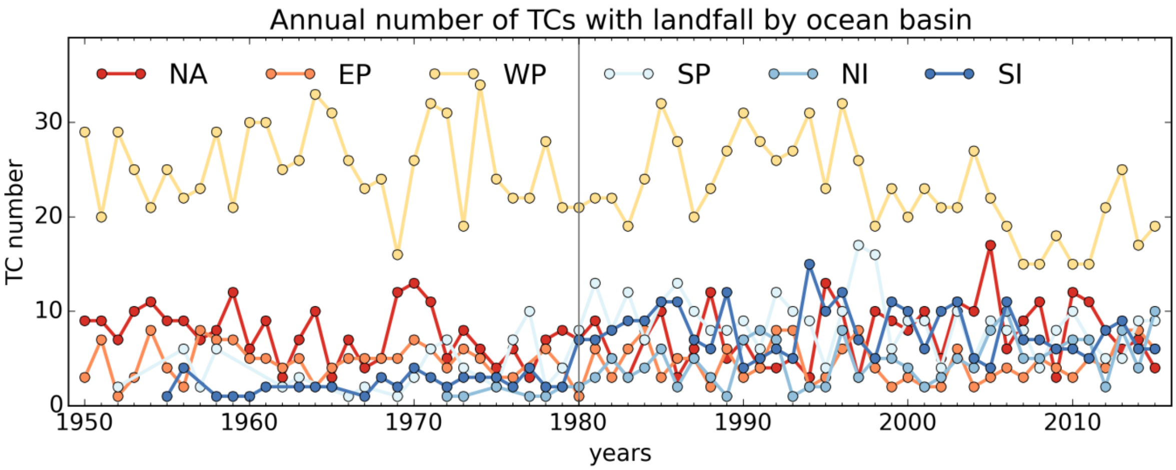

Figure 2: Annual numbers of TC landfalls by ocean basin. The number of TC landfalls varies greatly due to the stochastic occurrence of landfalls, natural variability, and reporting biases (prior to 1980, indicated by vertical gray line). Ocean basin abbreviations are as follows: NA=North Atlantic (red), EP=East Pacific (orange), WP=West Pacific (yellow), SP=South Pacific (light blue), NI=North Indian (blue), SI= South Indian (dark blue). South Atlantic is excluded (2 TCs).

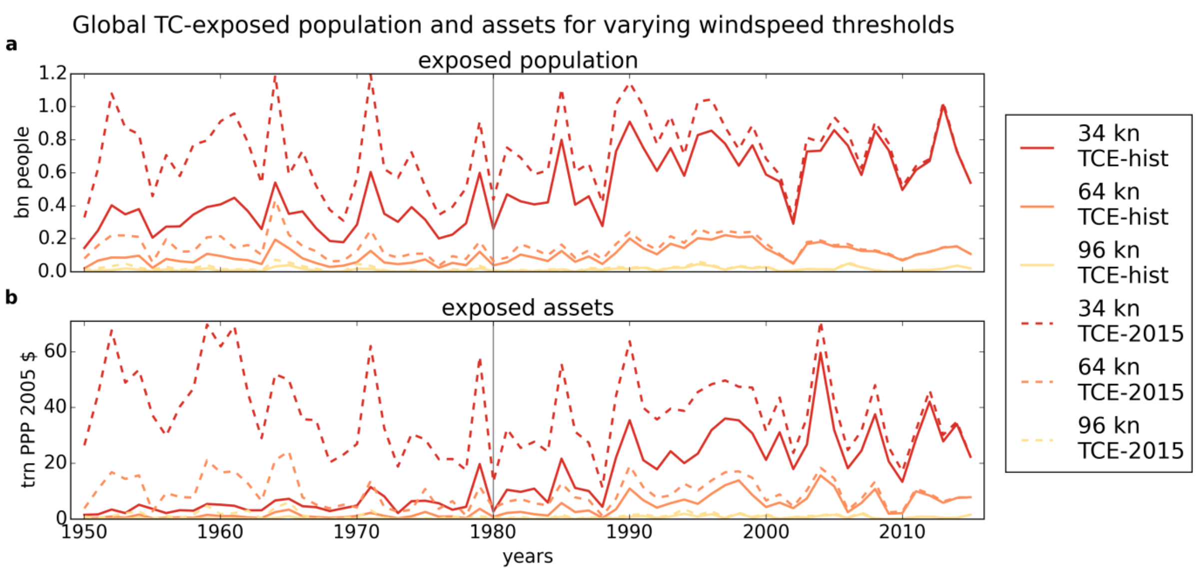

Figure 3: Annual global TC exposure for different thresholds of wind speed (34 kn red; 64 kn orange; 96 kn yellow). Dashed lines: estimates based on fixed 2015 patterns of population and assets (TCE-2015); solid lines: estimates based on the historical evolution of population and assets patterns (TCE-hist).

2.4.2. Limitations of TCE-DAT

We ask each user to consult the list of limitations of TCE-DAT before working with the data.

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The IBTrACS archive is the most comprehensive data set of TC activity today. However, before the invention of remote sensing technologies TC coverage in IBTrACS data is incomplete (see Fig. 2). In particular the Indian Ocean and the Southern Pacific Ocean should be treated with care for all events before 1980.

The Holland08 wind field model (as well as other available wind field models) provide a rather generic setup to derive wind fields based on statistical properties of observed TCs. The wind field generated by the model represents a gross approximation of the actually realized wind field. Wind fields of "standard" TCs are more accurately captured by wind field models than TCs with very unusual properties, e.g. Superstorm Sandy in 2012 whose extension was unusually huge despite its rather weak winds. Therefore, one should be aware of outliers when analyzing single storm properties from TCE-DAT. Furthermore, our methodology defines exposure solely using the storm's wind field. We do not account for additional people and assets in regions that might still be exposed to e.g. severe precipitation and/or storm surges. This is particular relevant for TCs that cause damage but whose wind field never touches land directly. The same is true for offshore activities (e.g. oil platforms, ships) whose assets remain unresolved by our methodology.

The socio-economic data has been carefully assembled but still gives rise to uncertainties, e.g. caused by linear interpolation between decennial timesteps. While there exists some certainty for population distributions as sub-national population counts have been collected for centuries, the uncertainty in the distribution of GDP is much larger as reported sub-national GDP and assets estimates are still unavailable for most countries at present. Additionally, GDP at the grid level is used to approximate local assets. While this assumption seems reasonable for the spatial resolution used in this work, there might still exist large discrepancies for specific grid cells and economic sectors. Furthermore and due to a lack of data, we use 2016 national assets/GDP ratios to approximate assets structure for all years between 1950 and 2015. As a consequence, the assets value of fast developing countries might be overestimated for earlier years.

3. Validation of exposure estimates

TCs and their impacts are comprehensively studied in the United States. We therefore use the United States as a test region to compare TCE-DAT estimates with more comprehensive observational records for storm size and in order to evaluate the reliability of our methodology.

Our validation is based on the extended best track HURDAT (HURDAText) archive. This archive is equally maintained by the NHC and - in extension to the regular HURDAT archive - provides size estimates for most North Atlantic TCs since 1988 for the wind speed thresholds 34 kn, 50 kn, 64 kn, and maximum wind speed) [*Demuth et al.*, 2006]. No size information is available for intermediate wind speeds. Data by HURDAText is preprocessed (as described in [*Geiger et al.*, 2016]) and compared to results from TCE-DAT for the variables wind speed at landfall and exposed population at 34 kn, 64 kn, and 96 kn for 87 TCs between 1988 and 2012.

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The comparison of the TC's maximum recorded wind speed above land (Fig. 4a) shows a good qualitative agreement between both data sets with a Pearson correlation of r=0.86. Perfect agreement cannot be expected and is precluded for several reasons:

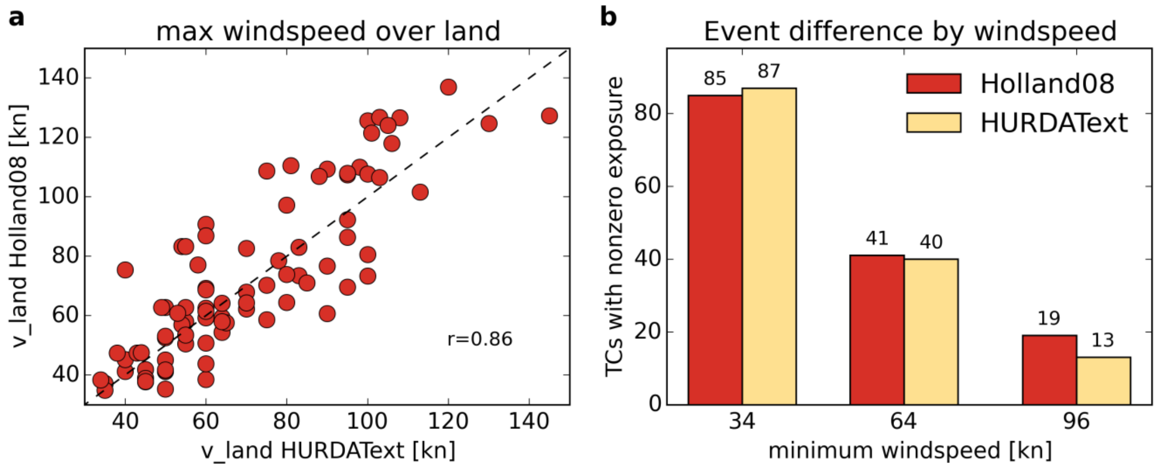

Figure 4: Comparison of wind speed at landfall by event (a) and the aggregated number of TCs with nonzero exposure for different wind speed thresholds (b) between 1988 and 2012 using estimates based on the Holland08 wind field model and the observed HURDAText data base.

First, the Holland08 model estimates TC wind speed indirectly based on minimum central pressure, thereby inhibiting a direct comparison of wind speeds at landfall. Second, the HURDAText data set provides observed wind speed in incremental steps (34 kn, 50 kn, 64 kn, and maximum wind speed). For TCs with no direct landfall of the storm's center (near misses) this provides only an approximate value for the real wind speed. As, however, near misses also affect people and assets they are also included in TCE-DAT. Therefore, a single grid cell can decide between a miss and a near miss and consequently the results strongly depend on the exact wind field. This also explains why the actual number of TCs with nonzero exposure slightly varies between both data sets (see Figure 4b). The relatively large difference in numbers of landfall for the 96 kn threshold is due to the fact that the HURDAText archive does not provide size estimates for 96 kn directly, but for the radii of maximum winds only.[1] Major TCs that do not hit land with their maximum winds are thus only included as TCs exceeding 64 kn despite the fact that a fraction of the wind field above land might well exceed the 96 kn threshold.

In a next step we compare the obtained exposure measures for different intensity thresholds, both on the individual event- and aggregated level (see Figure 5).

For 34 kn winds we find a good agreement (r=0.83) for exposed population between Holland08 and HURDAText (see Figure 5a). There are a few outliers where the exposed population based on HURDAText is several orders of magnitude

[1] For completeness we decided to compare also the 96 kn threshold being aware that a proper comparison is infeasible as no direct size estimates exist for this threshold.

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larger than based on Holland08. Such large deviations are, however, expected as individual storms can strongly deviate from regular-sized TCs. Superstorm Sandy that hit the U.S. East coast in 2012 is a good example: Sandy's wind field of tropical storm force was huge in comparison to mean extensions of comparable events and extended all the way to Florida despite its landfall location in New Jersey. Similar deviations are also reflected in the exposure estimates across all TCs at 34 kn (see Figure 5b): while mean affected population is comparable there are large deviation for higher percentiles.
Differences in TC exposure derived from observational and approximated wind fields become smaller with increasing intensity (Figure 5c), and the mean numbers as well as the different percentiles of exposed population across all landfalling TCs between 1988-2012 compare well (see Figure 5d). For 96 kn winds the number of TCs available for comparison is rather small (Figure 5e,f), and there exists an additional bias as the 96 kn wind speed threshold is not provided in HURDAText explicitly, see discussion above. Nonetheless and up to one outlier, we find good agreement between the exposure estimates from both data sets.

Based on the validation exercise for the United States we conclude that there exists a good qualitative and quantitative agreement between risk estimates drawn from the observation-based HURDAText and the generic Holland08 wind field data, despite known shortcomings of the Holland08 wind field model. Consequently, there exists confidence that exposure estimates for other parts of the world and other time periods can be used to approximate exposure given the lack of observed wind fields. Due to the generic wind field modeling approach, however, more confidence should be put into aggregated exposure estimates than single event exposure, in particular if additional information about this event is scarce.

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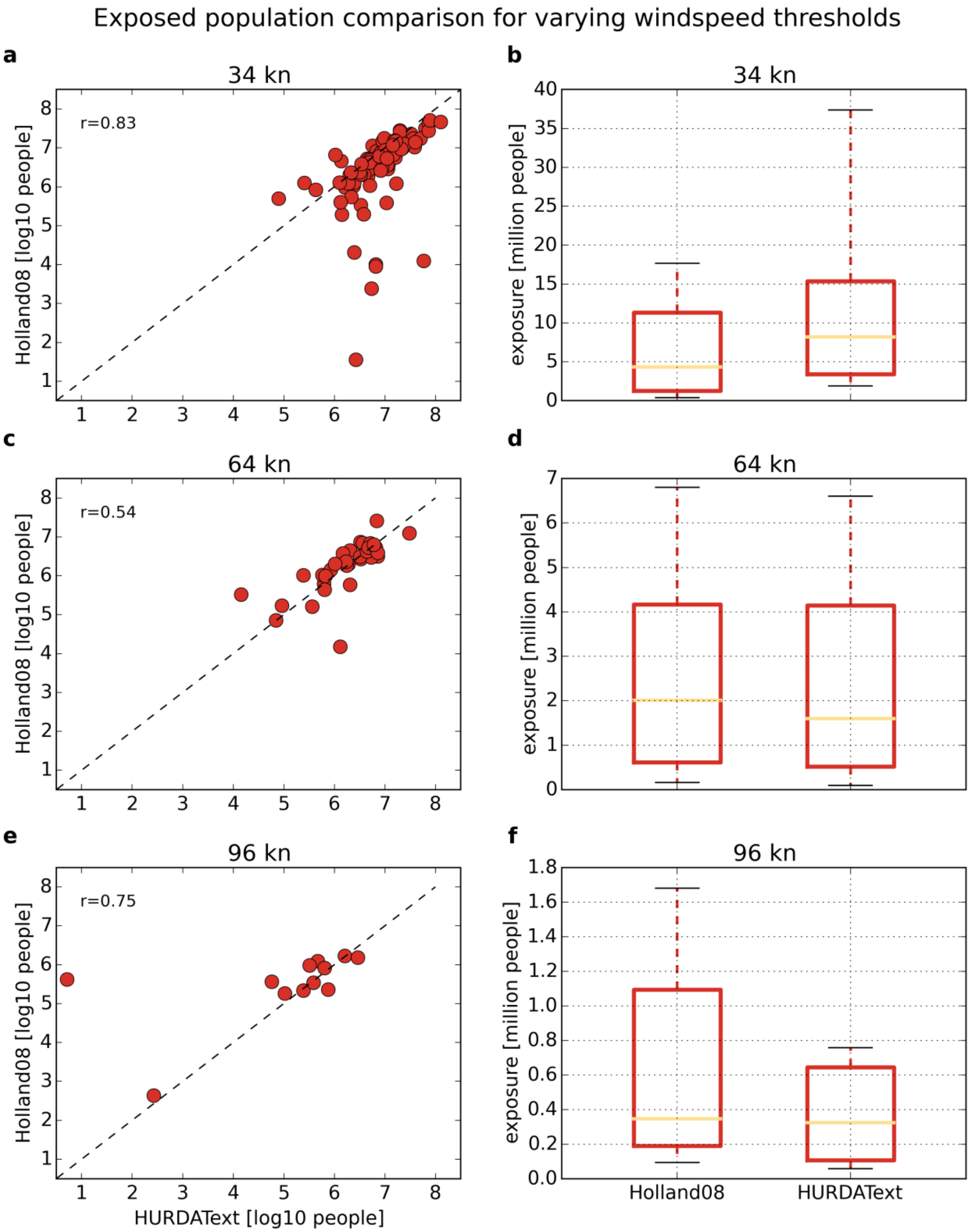

Figure 5: Comparison of exposed population by event (a,c,e) and across events (b,d,f) for different wind speed thresholds using estimates from the Holland08 wind field model and the observed HURDAText data base. In the right panels, boxes (whiskers) indicate the 25%-75% (10%-90%) percentile range, while yellow lines are medians.

4. Data availability

TCE-DAT was produced using publicly-available data only. In particular, the open-source climada modeling tool module ISIMIP v1.0 (https://github.com/davidnbresch/climada_module_isimip/releases/tag/v1.0) was used to generate TCE-DAT. In addition to the data sources mentioned above, the already pre-processed socio-economic data can also be accessed via the input data tab available at https://www.isimip.org/. The final TCE-DAT repository can be found at http://doi.org/10.5880/pik.2017.005.

5. Conclusions

We here provide a new and comprehensive data set TCE-DAT for global historical TC exposure between 1950 and 2015. The data set contains exposed population and exposed assets by event and country for 5335 events based on 2713 TCs, additionally separating exposure to wind speeds above 34 kn, 64 kn, and 96 kn, respectively. This data set provides an assessment by overlying estimated wind fields with gridded information about population and assets. While this approach has some limitations, it also overcomes various other issues that arise due to biased and/or changing reporting standards across time and space. Pure data of exposed population and assets, i.e. relying only on TC properties, is not available elsewhere. As a further benefit, TCE-DAT was created using only freely available input data and established methods and the freely available modeling tool climada with module ISIMIP.

In conclusion, this work provides a valuable additional resource to the community studying TC related impacts, in particular for non-experts in this field. It avoids present endogeneity issues, in particular relevant for econometric assessments of TC impacts, by creating a TC exposure database based on physical storm properties. Based on this data set new insights are expected for global and region-specific vulnerability assessments and the long-run economic consequences of natural disasters in general.

6. Author contribution

TG and DNB wrote the code, created, and analyzed the data set, TG, DNB, KF designed the research and wrote the paper.

7. Competing Interests

The authors declare that they have no conflict of interest.

8. Acknowledgements

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References

Bakkensen, L. A., and R. O. Mendelsohn (2016), Risk and Adaptation: Evidence from Global Hurricane Damages and Fatalities, *J. Assoc. Environ. Resour. Econ.*, *3*(3), 555–587, doi:10.1086/685908.

Bresch, D. N. (2014), climada – the open-source Economics of Climate Adaptation (ECA) tool, implemented in MATLAB/Octave, Available from: https://github.com/davidnbresch/climada

Chavas, D. R., N. Lin, D. R. Chavas, N. Lin, and K. Emanuel (2015), A Model for the Complete Radial Structure of the Tropical Cyclone Wind Field. Part I: Comparison with Observed Structure*, *J. Atmos. Sci.*, *72*(9), 3647–3662, doi:10.1175/JAS-D-15-0014.1.

CreditSuisse (2016), Global Wealth Databook 2016, Available from: https://www.credit-suisse.com/de/en/about-us/research/research-institute/global-wealth-report.html?WT.i_short-url=%2Fgwr&WT.i_target-url=%2Fde%2Fen%2Fabout-us%2Fresearch%2Fresearch-institute%2Fglobal-wealth-report.html&ref=https%3A%2F%2Fwww.credit-suisse.

Dellink, R., J. Chateau, E. Lanzi, and B. Magné (2017), Long-term economic growth projections in the Shared Socioeconomic Pathways, *Glob. Environ. Chang.*, *42*, 200–214, doi:10.1016/j.gloenvcha.2015.06.004.

Demuth, J. L., M. DeMaria, and J. A. Knaff (2006), Improvement of advanced microwave sounding unit tropical cyclone intensity and size estimation algorithms, *J. Appl. Meteorol. Climatol.*, *45*(11), 1573–1581.

Emanuel, K. (2013), Downscaling CMIP5 climate models shows increased tropical cyclone activity over the 21st century., *Proc. Natl. Acad. Sci. U. S. A.*, *110*(30), 12219–24, doi:10.1073/pnas.1301293110.

Estrada, F., W. J. W. Botzen, and R. S. J. Tol (2015), Economic losses from US hurricanes consistent with an influence from climate change, *Nat. Geosci.*, *8*(11), 880–884, doi:10.1038/ngeo2560.

Frieler, K. et al. (2016), Assessing the impacts of 1.5°C global warming - simulation protocol of the Inter-Sectoral Model Intercomparison Project (ISIMIP2b), *Geosci. Model Dev.*, (October), submitted, doi:10.5194/gmd-2016-229.

Geiger, T., and K. Frieler (2017), Continuous national Gross Domestic Product (GDP) time series for 195 countries: past observations (1850-2005) harmonized with future projections according the Shared Socio-economic Pathways (2006-2100), , doi:10.5880/PIK.2017.003. Available from: http://doi.org/10.5880/pik.2017.003 (Accessed 19 July 2017)

Geiger, T., K. Frieler, and A. Levermann (2016), High-income does not protect against hurricane losses, *Environ. Res. Lett.*, *11*(8), 084012, doi:10.1088/1748-9326/11/8/084012.

Gettelman, A., D. N. Bresch, C. C. Chen, J. E. Truesdale, and J. T. Bacmeister (2017), Projections of future tropical cyclone damage with a high-resolution global climate model, *Clim. Change*, 1–11, doi:10.1007/s10584-017-1902-7.

Guha-Sapir, D. (2017), EM-DAT: The Emergency Events Database - Université catholique de Louvain (UCL) - CRED, Brussels, Belgium, Available from: www.emdat.be

Guha-Sapir, D., and R. Below (2002), The quality and accuracy of disaster data: A comparative analyse of 3 global data sets, *Disaster Manag. Facil. World Bank, Work. Pap. ID*, (191).

Holland, G. (2008), A Revised Hurricane Pressure–Wind Model, *Mon. Weather Rev.*, *136*(9), 3432–3445, doi:10.1175/2008MWR2395.1.

Holland, G., and C. L. Bruyère (2014), Recent intense hurricane response to global climate change, *Clim. Dyn.*, *42*(3-4), 617–627, doi:10.1007/s00382-013-1713-0.

Holland, G. J. (1980), An Analytic Model of the Wind and Pressure Profiles in Hurricanes, *Mon. Weather Rev.*, *108*(8), 1212–1218, doi:10.1175/1520-0493(1980)108<1212:AAMOTW>2.0.CO;2.

Holland, G. J., J. I. Belanger, and A. Fritz (2010), A Revised Model for Radial Profiles of Hurricane Winds, *Mon. Weather Rev.*, *138*(12), 4393–4401, doi:10.1175/2010MWR3317.1.

Hsiang, S., and A. Jina (2014), The Causal Effect of Environmental Catastrophe on Long-Run Economic Growth: Evidence From 6,700 Cyclones, *Natl. Bur. Econ. Res.*, http://www.nber.org/papers/w20352.

Hsiang, S. M. (2010), Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America., *Proc. Natl. Acad. Sci. U. S. A.*, *107*(35), 15367–15372, doi:10.1073/pnas.1009510107.

IPCC (2014), *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.*, edited by C. B. Field et al., Cambridge University Press, , Cambridge, United Kingdom and New York, NY, USA,.

Jones, B., and B. C. O'Neill (2016), Spatially explicit global population scenarios consistent with the Shared Socioeconomic Pathways, *Environ. Res. Lett.*, *11*(8), 084003, doi:10.1088/1748-9326/11/8/084003.

Klein Goldewijk, K., a. Beusen, and P. Janssen (2010), Long-term dynamic modeling of global population and built-up area in a spatially explicit way: HYDE 3.1, *The Holocene*, *20*(4), 565–573, doi:10.1177/0959683609356587.

Klein Goldewijk, K., A. Beusen, G. Van Drecht, and M. De Vos (2011), The HYDE 3.1 spatially explicit database of human-induced global land-use change over the past 12,000 years, *Glob. Ecol. Biogeogr.*, *20*(1), 73–86, doi:10.1111/j.1466-8238.2010.00587.x.

Knapp, K. R., M. C. Kruk, D. H. Levinson, H. J. Diamond, and C. J. Neumann (2010), The international best track archive for climate stewardship (IBTrACS) unifying tropical cyclone data, *Bull. Am. Meteorol. Soc.*, *91*(3), 363–376.

MunichRe (2015), Munich Re NatCatSERVICE, *Top. Geo 2014*. Available from: http://www.munichre.com/natcatservice

Murakami, D. and Yamagata, Y. (2017), Estimation of gridded population and GDP scenarios with spatially explicit statistical downscaling., *Environ. Res. Lett.*, (under review), available at https://arxiv.org/abs/1610.09041.

Peduzzi, P., B. Chatenoux, H. Dao, a. De Bono, C. Herold, J. Kossin, F. Mouton, and O. Nordbeck (2012), Global trends in tropical cyclone risk, *Nat. Clim. Chang.*, *2*(4), 289–294, doi:10.1038/nclimate1410.

Pielke, R. A., J. Gratz, C. W. Landsea, D. Collins, M. A. Saunders, and R. Musulin (2008), Normalized Hurricane Damage in the United States: 1900–2005, *Nat. Hazards Rev.*, *9*(February), 29–42, doi:10.1061/(ASCE)1527-6988(2008)9:1(29).

UNISDR (2015), *Making Development Sustainable: The Future of Disaster Risk Management. Global Assessment Report on Disaster Risk Reduction: United Nations Office for Disaster Risk Reduction (UNISDR).*, Geneva, Switzerland.

Wirtz, A., W. Kron, P. Löw, and M. Steuer (2014), The need for data: natural disasters and the challenges of database management, *Nat. Hazards*, *70*(1), 135–157, doi:10.1007/s11069-012-0312-4.