



Vulnerability models for multiple hazards

Deliverable 3.3

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Deliverable 3.3 - Vulnerability models for multiple hazards

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Executive summary

This deliverable is a collection of vulnerability models for multiple climate hazards, which were developed with the support of project COMPASS. It is a software deliverable; therefore, this short report is focused on practical application of the models by users. The following models are included:

- Flood vulnerability and flood protection model, based on European flood impact data for 1950-2020 (Paprotny et al. 2025).
- Regional flood vulnerability model based on regional flood damage records and flood damage simulations (Sauer et al. 2021)
- Income- and inequality-specific tropical cyclone vulnerability model for the U.S. (Hassel et al. 2025)
- Multivariate tropical cyclone damage model accounting for variations in compound tropical cyclone hazards.

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1. HANZE flood vulnerability model for European countries, 1950-2020

1.1. Methodological background

The model is part of a larger flood attribution study, [HANZE](#) (Historical Analysis of Natural HaZards in Europe). It developed a series of connected hazard, exposure, and vulnerability models and datasets. Here, the component enabling estimating flood protection levels and relative loss for different impact categories was extracted and reworked as a stand-alone code for quicker implementation in impact attribution studies. The novel feature of the model is the ability to create counterfactual scenarios of vulnerability, as it includes both hydrological and socioeconomic variables as predictors. The model is specifically built to estimate vulnerability at subnational regions ([European Union's NUTS System](#), level 3) in 42 European countries between 1950 to 2020.

The variation of protection levels and vulnerability was inferred from data on historical riverine, coastal, and compound floods and associated impacts obtained from the HANZE database for the period 1950-2020. Actual damaging floods, which imply flood protection was locally inadequate, were contrasted with modeled potential floods, i.e., events that were hydrologically extreme but did not lead to significant impacts, which imply that flood protection was sufficient to prevent losses. Further, the reported magnitude of impacts (fatalities, population affected, and economic losses) was compared with potential impacts computed with depth-damage functions. Finally, the spatial and temporal drivers of both flood protection and vulnerability were derived through a multivariate statistical analysis. Vine-copulas were applied to derive the best predictors out of a set of candidate variables, including hydrological parameters of floods, exposure to floods, socioeconomic development, and governance indicators. The table below summarizes the input variables required by the model.

Model	Variable	Unit	Note
Both	Year of event	year	1950-2020
Both	List of NUTS3 regions affected	List of strings	NUTS v2010
Both	Return period of the flood event	years	Based on river discharge or storm surge return period in the affected area
Flood protection	List of return periods of the flood in each affected region	List of years	
Flood protection	Duration of the event in days	days	Based on the occurrence of discharge above 2-year return period
Flood protection	List of durations of the flood in each affected region	List of days	
Both	Average annual potential modelled economic loss relative to regional GDP	Fraction	Based on HANZE flood database
Both	Number of floods in previous 20 years in the event area	Number	
Vulnerability	Number of floods in previous 30 years in the event area	Number	
Flood protection	List of numbers of floods in previous 30 years in each affected region	List of numbers	Obtained by computing damage with static depth-damage functions over the potential flood zone
Vulnerability	Potential modelled fatalities of the event relative to regional population	Fraction	
Vulnerability	Potential modelled population affected of the event relative to regional population	Fraction	
Vulnerability	Potential modelled economic loss of the event relative to regional population	Fraction	
Vulnerability	Average water depth	Meters	

The functions provide the following outputs:

Model	Variable	Unit
Flood protection	Probability of failure of flood defences during the event	Fraction
Flood protection	List of probabilities of failure of flood defences in each affected region	Fraction
Vulnerability	Mean prediction of relative loss in three impact types: fatalities, persons affected and economic loss	Fraction
Vulnerability	List of samples from the vine-copula models for computing uncertainty intervals	Fraction

1.2. Access to the model

The Python code can be downloaded from the Github repository (https://github.com/dompap/HANZE_vulnerability_model) or Zenodo (<https://doi.org/10.5281/zenodo.20832327>).

1.3. Installation

The code needs packages listed in **requirements.txt**. It was tested with versions indicated but should work with newer versions too. It is recommended to use a virtual environment.

Running the code also requires input data for the vine-copula model, which can be downloaded from Zenodo (<https://zenodo.org/records/15918981>).

1.4. Usage

The model contains two functions:

- **flood_protection_modelling** provides an estimate for the probability that a hydrological extreme event will cause socioeconomic impacts, i.e., flood protection will be insufficient. The estimate is made at event level and also in a breakdown of subnational regions potentially affected. The probabilities are multiplicative.
- **vulnerability_modelling** provides the relative loss as a fraction of the exposure value for three categories: fatalities, persons affected, and economic loss.

Each function requires providing several input variables (predictors). An example usage and explanation of variables is provided in the **implementation_example.py** script.

2. Region-specific flood vulnerability model allowing for the attribution of damage trends

2.1. Methodological background

The regional flood vulnerability model was developed in the context of a flood damage attribution study aiming to disentangle the contributions of climate from confounding changes in exposure and vulnerability (Sauer et al., 2021). It is designed to estimate relative vulnerability changes over time as the ratio between observed and potential flood damage and can be applied to discriminate dynamic vulnerability changes over time, e.g., caused by adaptation, from other impact drivers such as changes in climate and exposure. The model can be applied in combination with any impact model that allows accounting for changes and is suitable to be applied across larger geographical regions. It requires that the simulated impact time series accounts for at least time-variable changes in climate and exposure. As it is assumed that dynamic vulnerability can be derived from the ratio of observed damage (accounting for all relevant drivers: climate, exposure, vulnerability) and simulated damage (accounting for climate and exposure changes). The model estimates vulnerability changes as the smoothed ratio of recorded and simulated impacts applying a singular spectrum analysis (SSA). In the example application, the model accounts for static vulnerability and protection levels, but this is not necessarily required for further applications. The model can be forced with any annual aggregate of recorded extreme event impacts and any annual aggregate of simulated extreme event impacts. It provides a time series of vulnerability factors, which depict the trajectory of dynamic vulnerability over time and adjusts the modeled damage time series to account for changes not only in climate and exposure but also in vulnerability. The vulnerability model is presented in context with an attribution application, where the contributions of climate exposure and vulnerability to the overall trend in observed damage are compared. Note that the assessment of the climate contribution is based on a damage simulation keeping all drivers other than climate at a fixed level. Climate counterfactuals are not used.

The model requires the following inputs:

Model	Variable	Unit	Notes
Dynamic vulnerability/Attribution assessment	Year	Year	Year of damage reporting/modeling
Dynamic vulnerability/Attribution assessment	Observed damage	USD 2005 PPP	Reported damage (dummy variable)
Dynamic vulnerability/Attribution assessment	Modeled damage (dynamic exposure)	USD 2005 PPP	Time series of modeled damage driven by climate reanalysis data and time variable asset distributions.
Attribution assessment	Modeled damage (fixed exposure)	USD 2005 PPP	Time series of modeled damage driven by climate reanalysis data and fixed asset distributions.

The model provides the following output:

Model	Variable	Unit	Notes
Dynamic vulnerability	Vulnerability trajectory derived from SSA	fraction	

Dynamic vulnerability	Vulnerability trajectory derived from a running mean	fraction	
Dynamic vulnerability	Ratios between observed and potential damage	fraction	
Dynamic vulnerability	Adjusted modeled damage (dynamic socio-economic conditions)	USD 2005 PPP	Time series derived from <i>Modeled damage (dynamic exposure)</i>
Attribution assessment	Trend in observed damage	%/year	Relative to baseline period (here 1980-1995)
Attribution assessment	Significance in observed trend	-	p-value of Mann-Kendall Test
Attribution assessment	Contribution of climate	%/year	Relative to baseline period (here 1980-1995)
Attribution assessment	Significance of climate contribution (p-value)	-	p-value of Mann-Kendall Test
Attribution assessment	Contribution of exposure	%/year	Relative to baseline period (here 1980-1995)
Attribution assessment	Contribution of vulnerability	%/year	Relative to baseline period (here 1980-1995)

2.2. Access to the model

The Python code can be downloaded from the GitHub repository (https://github.com/ingajsa/compass_3_3_regional_vulnerability) or Zenodo (<https://doi.org/10.5281/zenodo.20832327>).

2.3. Installation

The environment, including all packages required, can be installed from `compass_3_3_regional_vulnerability/environment/regional_vulnerability.yml`.

2.4. Usage

All steps required to apply the model are described and visualized in the Jupyter notebook **regional_vulnerability_model.ipynb**. The dynamic vulnerability function (**vul_func**) takes the input data described in the input data section of the notebook. The attribution assessment is divided into two steps: I) The trend assessment using the non-parametric Mann-Kendall-Test (**attr_MK**) and II) determining the different drivers (**relative_contributions**).

3. Income and inequality-specific tropical cyclone vulnerability model for the U.S.

3.1 Methodological background

This vulnerability model is part of a study on the socioeconomic drivers of hurricane damage in the United States (Hassel et al. 2025). It developed a calibrated vulnerability function for tropical cyclone wind damage and demonstrated that county-level socioeconomic characteristics, specifically per-capita income and income inequality, are significant predictors of damage vulnerability.

The vulnerability function follows the sigmoidal formulation of (Emanuel 2011), which relates local maximum sustained wind speed to the mean damage ratio. The key parameter is V_{half} , the wind speed at which 50% of damage occurs:

$$f(V) = \frac{v_n(V)^3}{1 + v_n(V)^3} \quad \text{where} \quad v_n(V) = \frac{\max(V - V_{thr,0})}{V_{\text{half}} - V_{thr}}$$

An average value of $V_{\text{half}} = 80.5$ was calibrated against historical damage records from the NCEI Storm Events Database for the period 1996–2021, using wind fields modelled from IBTrACS best-track data and gridded exposed asset data estimated using population density and nighttime-light data (Eberenz et al. 2020). To capture vulnerability differences, counties were further grouped into five quintile classes by either per-capita income or Gini coefficient, and separate V_{half} values were calibrated for each class. The resulting class-specific values range from 63.8 to 97.1 m/s across income classes and from 73.6 to 94.0 m/s across inequality classes, reflecting that poorer and more unequal counties sustain greater damage at equivalent wind speeds:

Income Classes	Upper class bound (USD/capita)	V_{half} (m/s)
1 (lowest income)	18 836	71.9
2	20 912	63.8
3	23 710	77.7
4	28 647	92.1
5 (highest income)	66 522	97.1
Inequality Classes	Upper class bound (Gini coeff.)	V_{half} (m/s)
1 (most equal)	0.430	94.0
2	0.450	81.7
3	0.466	80.1
4	0.489	76.6
5 (most unequal)	0.626	73.6

The provided Jupyter notebook simulates county-level tropical cyclone damage for one or more storms based on either income- or inequality-specific vulnerabilities.

3.2 Access to the model

The vulnerability model is provided as a Jupyter notebook and can be downloaded from its publicly available GitLab repository: https://gitlab.pik-potsdam.de/janhasel/tc_wind_damages or Zenodo (<https://doi.org/10.5281/zenodo.20832327>).

If you simply wish to browse the damage simulation for an exemplary storm, you can find the cached HTML file of an executed notebook here: https://www.pik-potsdam.de/~janhasel/compass_d3.3/wind_simulate_tc_damage.html

3.3 Installation

1. Install CLIMADA

Follow the official installation guide: <https://climada-python.readthedocs.io/en/latest/guide/install.html>

This will create a conda/mamba environment with CLIMADA and its core dependencies.

2. Install additional dependencies

Activate your CLIMADA environment, then add the project's extra packages:

```
mamba activate climada_env # use the name you chose during CLIMADA install
mamba env update -f extra_packages.yml
```

mamba env update adds missing packages to the active environment and skips anything already installed.

3. Obtain LitPop input data

LitPop.from_countries computes the exposure layer locally from two raster datasets. They are handled differently:

NASA Black Marble nightlights — downloaded automatically by CLIMADA on the first run and cached in SYSTEM_DIR (default: ~/.climada/data/). No action required.

GPW v4.11 population count — must be downloaded manually (free [NASA Earthdata](https://earthdata.nasa.gov/) login required):

1. Download the 2015 30-arcsec GeoTIFF ZIP directly from NASA Earthdata:
https://data.earthdata.nasa.gov/nasa-earth/human-dimensions/sedac-root/downloads/data/gpw-v4/gpw-v4-population-count-rev11/gpw-v4-population-count-rev11_2015_30_sec_tif.zip
2. Extract the ZIP. You should get a folder gpw-v4-population-count-rev11_2015_30_sec_tif/ containing a .tif file.
3. Move that folder into CLIMADA's SYSTEM_DIR:

~/.climada/data/gpw-v4-population-count-rev11_2015_30_sec_tif/

If you are unsure where your SYSTEM_DIR is, run:

```
python -c "from climada.util.constants import SYSTEM_DIR; print(SYSTEM_DIR)"
```

3.4 Usage

Open the notebook **simulate_tc_damage.ipynb**. Edit **cell 3 (Configuration)** based on your preferences: Add or remove storms; IBTrACS identifiers can be looked up at <https://www.ncei.noaa.gov/products/international->

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[best-track-archive](#). Then choose the preferred vulnerability predictor: "income_pc" for per-capita income classes or "gini" for income inequality.

Then run all cells. On the first run, the notebook will:

- Download the TIGER/Line 2019 county shapefile (~75 MB) to input/
- Compute the LitPop exposure and cache it to input/litpop_usa_300arcsec_pc_2015.hdf5

Subsequent runs load from cache and complete in a few minutes.

4. Multi-hazard tropical cyclone damage model for the United States

4.1 Methodological background

This vulnerability model will be part of the COMPASS Deliverable 4.2 (D4.2). Use Case 1, which develops a calibrated multi-hazard tropical cyclone damage model for U.S. counties. Unlike single-indicator approaches that model TC damage from wind speed alone, the D4.2 model jointly accounts for three TC hazards: sustained wind speed, accumulated rainfall, and storm surge.

The damage model is inspired by Gori et al. (2025) and follows a Poisson Pseudo-Maximum Likelihood (PPML) specification with a log link, predicting expected absolute damage in county s during storm i as:

$$\mathbb{E}[L_{i,s}] = \exp(\beta_0 + \beta_1 \ln(1 + W_{i,s}) + \beta_2 \ln(1 + R_{i,s}) + \beta_3 \ln S_{i,s})$$

Wind and rain predictors use a $\log(1+)$ transformation to accommodate zero values; surge is log-transformed and therefore strictly positive.

Each predictor $X_{i,s} \in \{W_{i,s}, R_{i,s}, S_{i,s}\}$ is an asset-weighted sum of the transformed hazard intensity across all grid cells within the county:

$$X_{i,s} = \sum_{c \in i} k_c \cdot f(H_{c,s})$$

where k_c is the fixed-capital exposure value at cell c and $f(\cdot)$ is a hazard-specific intensity transform. For wind, f is the sigmoidal wind-damage function of Emanuel (2011):

$$f_{\text{sig}}(V) = \frac{v_n^3}{1 + v_n^3}, \quad v_n = \frac{\max(V - V_{\text{thr}}, 0)}{V_h - V_{\text{thr}}}$$

with $V_{\text{thr}} = 25.7$ m/s and $V_h = 112.0$ m/s. Rain and surge both use a linear (identity) transform. Minimum intensity thresholds are applied before aggregation: wind cells below 25.7 m/s (implicitly via V_{thr}), lifetime accumulated rain cells below 25 mm, and surge cells outside 0.3–10 m contribute zero to their respective indicators.

The model was calibrated against reported damage from the NCEI Storm Events Database for the period 1996–2024, using TC wind fields derived from IBTrACS best-track data with CLIMADA's TropCyclone module, lifetime accumulated TC rainfall from CLIMADA Petals TCRain, and pre-computed GeoClaw storm surge flood depths from the ISIMIP3a dataset (Mengel et al., 2025). Gridded asset exposure was represented by COMPASS fixed-capital values (Paprotny 2025). The training sample consists of 1,271 county-storm pairs with positive reported damage and non-zero surge, spanning 100 storms and 206 coastal counties. The fitted coefficients are

$$\hat{\beta}_0 = 8.13, \hat{\beta}_1 = 0.29 \text{ (wind)}, \hat{\beta}_2 = 0.10 \text{ (rain)}, \text{ and } \hat{\beta}_3 = 0.16 \text{ (surge)}.$$

4.2 Access to the model

The vulnerability model is provided as a Jupyter notebook and can be downloaded from its publicly available GitLab repository: https://gitlab.pik-potsdam.de/janhasel/tc_multi_damages or Zenodo (<https://doi.org/10.5281/zenodo.20832327>).

If you simply wish to browse the damage simulation for an exemplary storm, you can find the cached HTML file of an executed notebook here: https://www.pik-potsdam.de/~janhasel/compass_d3.3/multi_simulate_tc_damage.html

4.3 Installation

1. Install CLIMADA

Follow the official installation guide: <https://climada-python.readthedocs.io/en/latest/getting-started/install.html>

2. Install CLIMADA Petals

The applied rain module TCRain is part of [CLIMADA Petals](#), which must be installed separately after CLIMADA Core.

Follow the official installation guide's section for CLIMADA Petals: <https://climada-python.readthedocs.io/en/latest/getting-started/install.html#install-climada-petals-optional>

3. Install additional dependencies

Activate your CLIMADA environment, then add the project's extra packages:

```
mamba activate climada_env # use the name you chose during CLIMADA install
mamba env update -f extra_packages.yml
```

mamba env update adds missing packages to the active environment and skips anything already installed.

4. Obtain LitPop input data

LitPop.from_countries computes the exposure layer locally from two raster datasets. They are handled differently:

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GPW v4.11 population count — must be downloaded manually (free [NASA Earthdata](#) login required):

1. Download the 2015 30-arcsec GeoTIFF ZIP directly from NASA Earthdata:
https://data.earthdata.nasa.gov/nasa-earth/human-dimensions/sedac-root/downloads/data/gpw-v4/gpw-v4-population-count-rev11/gpw-v4-population-count-rev11_2015_30_sec.tif.zip
2. Extract the ZIP. You should get a folder gpw-v4-population-count-rev11_2015_30_sec.tif/ containing a .tif file.
3. Move that folder into CLIMADA's SYSTEM_DIR:
~/climada/data/gpw-v4-population-count-rev11_2015_30_sec.tif/

If you are unsure where your SYSTEM_DIR is, run:

```
python -c "from climada.util.constants import SYSTEM_DIR; print(SYSTEM_DIR)"
```

4.4 Usage

Open the notebook **simulate_tc_damage.ipynb** and edit **cell 1**:

- STORMS — add or remove storms (IBTrACS identifiers can be looked up at <https://www.ncei.noaa.gov/products/international-best-track-archive>)

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Then run all cells. On the first run, the notebook will:

- Download the TIGER/Line 2019 county shapefile (~75 MB) to input/
- Compute the LitPop exposure and cache it to input/litpop_usa_300arcsec_pc_2015.hdf5

Subsequent runs load from cache and complete in a few minutes.

5. References

- Eberenz, S., Stocker, D., Rössli, T., & Bresch, D. N. (2020). Asset exposure data for global physical risk assessment. *Earth System Science Data*, 12(2), 817–833. <https://doi.org/10.5194/essd-12-817-2020>
- Emanuel, K. (2011). Global Warming Effects on U.S. Hurricane Damage. *Weather, Climate, and Society*, 3(4), 261–268. <https://doi.org/10.1175/WCAS-D-11-00007.1>
- Gabriela Aznar Siguan, David N. Bresch, Samuel Eberenz, Jan Hartman, Marine Perus, Thomas Rössli, Dario Stocker, Veronica Bozzini, Carmen B. Steinmann, Evelyn Mühlhofer, Rachel Bungerer, Inga J. Sauer, Samuel Lüthi, Pui Man (Mannie) Kam, Simona Meiler, Alessio Ciullo, Thomas Vogt, Benoit P. Guillod, Chahan M. Kropf, ... Dahyann Araya. (2025). *CLIMADA Core Python Package* (Version v6.1.0) [Computer software]. Zenodo. <https://doi.org/10.5281/ZENODO.17233409>
- Gori, A., Lin, N., Chavas, D., Oppenheimer, M., & Xian, S. (2025). Sensitivity of tropical cyclone risk across the US to changes in storm climatology and socioeconomic growth. *Environmental Research Letters*, 20(6), 064050. <https://doi.org/10.1088/1748-9326/add60d>
- Hassel, J., Vogt, T., Frieler, K., & Otto, C. (2025). *Poor and unequal US counties are more vulnerable to hurricane damage* (SSRN Scholarly Paper No. 5929136). Social Science Research Network. <https://doi.org/10.2139/ssrn.5929136>
- Mengel, M. (2025). *Counterfactual dataset of tropical cyclone-affected areas* (Version 1.0) [Dataset]. ISIMIP Repository. <https://doi.org/10.48364/ISIMIP.693793>
- Paprotny, D. (2025). *Exposure datasets at multiple scales* (Version v2) [Dataset]. Zenodo. <https://doi.org/10.5281/ZENODO.17572467>
- Paprotny, D., Tilloy, A., Treu, S., Buch, A., Vousedoukas, M. I., Feyen, L., Kreibich, H., Merz, B., Frieler, K., & Mengel, M. (2025). Attribution of flood impacts shows strong benefits of adaptation in Europe since 1950. *Science Advances*, 11(33), eadt7068. <https://doi.org/10.1126/sciadv.adt7068>
- Sauer, I. J., Reese, R., Otto, C., Geiger, T., Willner, S. N., Guillod, B. P., Bresch, D. N., & Frieler, K. (2021). Climate signals in river flood damages emerge under sound regional disaggregation. *Nature Communications*, 12(1), 2128. <https://doi.org/10.1038/s41467-021-22153-9>