AUTHORS' RESPONSE

Research article: "Regional tropical cyclone impact functions for globally consistent risk assessments" (Nat. Hazards Earth Syst. Sci. Discuss., https://doi.org/10.5194/nhess-2020-229; in review, submitted on 09 July 2020)
Authors: Samuel Eberenz, Samuel Lüthi, David N. Bresch

We thank anonymous referee #1 and Andrew Gettelman for their comments, which have improved the quality of the manuscript. The original comments from the referees are listed below directly followed by our responses in *blue and italic* and changes to the manuscript in **blue and bold**. The marked-up version of the revised manuscript attached below shows all proposed changes.

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1) RESPONSE TO COMMENTS BY ANONYMOUS REFEREE #1

1.0) This manuscript by Eberenz et al. evaluates the model-simulated damages from trop- ical cyclones, and provides suggestions to improve this assessment and reduce the uncertainty of simulations by using regionally calibrated data. While the premise of the paper seems straightforward (e.g. "improving the calibration of the model will re- sult in closer simulation of observed events"), the execution of the work in the paper is well done as it explores the limitations of their proposed approach. While overall the manuscript is well-presented and organised, there are opportunities to improve the text, particularly the analysis in the case study for the Philippines.

1.1a) Some initial minor comments include better consistency in the risk language used in the paper; overall, it is good but there are some errors, e.g. para 35: "natural risk" –> is this hazard? risk? and para 180 "from natural catastrophes are records are available" and following line ("natural disasters"). As you might well know it is a common refrain in the disaster/hazard community that "there are no natural disasters" – so do double check for the consistency.

We would like to thank the referee for pointing out the inconsistencies of terminology. We have revised wording in the paragraphes mentioned by the referee. As for the lines 38f, we suggest replacing "natural risk" with "risk from natural hazard".
In lines 178f, we suggest restructuring both sentences to tackle the issue raised above and improve readability at the same time.

On a side note: Originally, the wording "natural and technological disaster" was taken from the EM-DAT data description: "EM-DAT distinguishes between two generic categories for disasters: natural and technological." (https://www.emdat.be/explanatory-notes, last accessed 29/09/202). Still, we agree with the comment that this wording is not necessarily the most broadly accepted.

Suggested changes to the manuscript:
L. 38f: "~~Natural risk~~ **Risk from natural hazards** is frequently modelled as a function of severity and occurrence frequency, [...]"
L. 178f: "~~Damage estimates from natural catastrophes are records~~ **Reported damage estimates for disasters worldwide** are available from the International Disaster Database EM-DAT (Guha-Sapir, 2018). EM-DAT provides ~~global~~ data ~~on natural and technological disasters~~ **per event and country**, including disaster type and subtype, date of the event, and impact **estimates** ~~data at the country level~~."

1.1b) I also think that in para 55 where you say "one [...] function... might be inappropriate [...]", as this is the main argument of your work, could be made even stronger to create a deeper impression of the purpose of your research.

Indeed, this paragraph in the introduction is formulated more cautiously than what previous studies and our results indicate. Therefore, we follow the referee's suggestion to reformulate the sentence to express our position in a more confident way:

L. 56ff:
"However, due to global heterogeneities in the tropical cyclone climatology (Schreck et al., 2014), building codes, and other socioeconomic vulnerability factors (Yamin et al., 2014), **it is inadequate to use a single** ~~one~~ universal impact function ~~might be inappropriate~~ for global TC risk assessments."

1.2) I find it interesting that the model over-simulates damages in the NWP basin, as it could be easily imaged that the damage function would not be able to simulate the myriad impacts of the associated hazards you mention such as the storm surges. In line with this I think it would have been interesting to provide an hypothesis for your research question, for example in para 70 where you pose this question.

This point is well taken! An attribution of the interregional differences in vulnerability to TC damage to the drivers of vulnerability would be really interesting to look at. While such an attribution study would be out of scope of this study, we agree that it is important to discuss the different drivers and factors determining the vulnerability, that is, the shape of the calibrated impact functions.
In the manuscript, this is already touched upon, e.g. in the introduction:
L. 56f:
"[...] global heterogeneities in the tropical cyclone climatology (Schreck et al., 2014), building codes, and other socioeconomic vulnerability factors (Yamin et al., 2014) [...]"

… and in the discussion:
L. 501ff:
"[...] the results for the North West Pacific region (WP4), consisting of Japan, South Korea, Macao, Hongkong, and Taiwan, deviate substantially from GAR 2013. Simulated relative AAD in the region ranges from 0.2-0.8 ‰ as compared to 3.1 ‰ in GAR 2013. This difference implies that, besides the use of building type specific impact functions, the TC impact model of GAR 2013 substantially overestimates TC damages in WP4 compared to reported data."
In order to give a clearer message regarding attribution to the readers of the paper, we propose to add the following brief paragraphs to the manuscript:

In Section 1 (Introduction):
"While the attribution of vulnerability to regional drivers is outside the scope of this study, the results can serve as a starting point for further research disentangling the socio-economic and physical drivers determining vulnerability to TC impacts locally and across the globe."

In Section 6 (Conclusion and Outlook):
"**The substantial over-estimation of TC damages in the North West Pacific with the default impact function opens the question for the drivers of the apparently lower vulnerability in this region. Considering the inability of the model setup to directly represent the impacts from TC surge and pluvial flooding, one would rather expect aggregated calibrated impact functions to be steeper than the default wind impact function. Therefore, we suggest investigating interregional differences in possible other drivers, including building standards but also damage reporting practices."**

My main comments are related to the case study of the Philippines.

1.3) Firstly, there is some confusion in the TC nomenclature which should be addressed for consistency (Table A4). For example, Ondoy is the local name and Ketsana is the international name.

We would like to thank the referee for helping to clarify the confusion around the Typhoon names in the Philippines. Both in the text and in Table A4, we will adapt the following event names for consistency, mentioning the local names in brackets:

- "Bopha" → **"Bopha (Pablo)"**
- "Pedring (Nesat)" → **"Nesat (Pedring)"**
- "Pepeng (Parma)" → **"Parma (Pepeng)"**
- "Ondoy (Ketsana)" → **"Ketsana (Ondoy)"** *(also in L. 459 and Figure 6c)*
- "Fengshen (Franck)" → **"Fengshen (Frank)"**

Change in L. 422f, also removing double mentioning of water supply:
"~~Most events~~**TCs in the Philippines** inflict damage on several sectors, most costly on housing and agriculture, but also on schools and hospitals, power and water supply, roads, and bridges (Table A4). Single events were also reported to damage and disrupt airports and ports (Typhoon Haiyan) **and**~~,~~ dikes (~~Pedring~~**Nesat and Xangsane**)~~, and water supply (Bopha and Fengshen).~~"

1.4) Additionally this case study of the Philippines is very brief and only an assessment of asset exposure, and not vulnerability. I think that this section could use more context of the vulnerabilities associated with the Metro Manila region, enhanced by locally-led scientific literature on vulnerability (e.g. Porio 2011) as well as an analysis of the hazard events themselves to give the reader more context (see e.g. the work of Lagmay et al, Abon et al re: Ketsana and Haiyan (incl. effect of mountain ranges to improve your Done 2019 reference), Cayanan et al 2011 and Cruz/Narisma on SW monsoon effect on TCs, Yumul et al on TC Fengshen). Indeed I think these references could also be visited as Espada (2018) is often your only reference (Table A4).

See combined reply to 1.4 and 1.5 in next point.

1.5) There are some paragraphs that could use more attention and more geographical nuance, for example para 470 on Typhoon Haiyan (2013). This TC impacted mainly Tacloban City; indeed, this reflection of imbalanced damages appears to be simulated in your model output (Figure 6c) but Iloilo and Cebu cities are mentioned in lieu of this.

Thank you very much for providing additional insights and references with regards to the case study of the Philippines. We answer both comments 1.4 and 1.5 together, since the improvements requested in 1.5 can be improved with reference to the additional literature suggested in comment 1.4.

We agree to the referee that integrating more local context and geographical accuracy will improve the informative content and accuracy of the case study. Doing so actually helps sharpen the argument of the whole of Section 4, that is, adding further support for the hypothesis that (1) a differentiation of urban and rural exposures and vulnerabilities would *increase the accuracy for sub-regional TC damage simulations, and (2) explicitly modeling of damage caused by sub-perils like storm surge and torrential rainfall would substantially improve TC damage simulations in the Philippines. Thus, an integration of the additional information will improve the manuscript while not affecting but rather strengthening the conclusions we draw from the case study.*

At the same time, the case study is intended as an explorative excursion and not the main focus of the paper. Therefore, we suggest to incorporate the additional context most relevant for the discussion while not overly inflating the text body of Section 4 altogether.

As a consequence, we propose to incorporate additional local context provided by the proposed references in Sections 4.1 to 4.3 of the manuscript as follows:

Section 4.1 Tropical cyclones in the Philippines:
L. 419f:
"In summary, TCs making landfall in the Philippines cause damage due to large wind speed, storm surge, as well as rain induced floods and landslides. **Meteorologically, the storm systems interact with the monsoon season, affecting both dynamics and the severity of torrential rain (Bagtasa, 2017; Cayanan et al., 2011; Yumul et al., 2012). TCs in the Philippines** ~~Most events~~ inflict damage on several sectors [...]"

Section 4.2 Urban vs. rural exposure:
L. 430ff:
"Most of the asset exposure value of the Philippines is concentrated around the metropolitan area of Manila **(Metro Manila).**~~, located~~ **Located** around 14.5°N, 121.0°E (Fig. ~~6~~**7**a)**, Metro Manila is Philippine's political and socio-economic center (Porio, 2011)**. The Typhoons Angela (1995), Xangsane (2006), and Rammasun (2014) are prominent TCs hitting ~~the Manila region~~**Metro Manila** directly. In our analysis, ~~they~~ these TCs come with particularly large EDRs, [...]"

In Section 4.3 Impact of storm surge and torrential rain:
L. 461ff:
"**While urban vulnerability to strong winds in Metro Manila appears to be overestimated by the calibrated impact function, Metro Manila is known to be highly exposed and vulnerable to regular, large scale flooding (Porio, 2011). The main drivers of flood vulnerability are its geographical setup, largely unregulated urban growth and sprawl, and substandard sewerage systems, especially in low-income areas (Porio, 2011).** Tropical Storm **Ketsana, locally known as** Ondoy (2009) is an example with very low simulated damages **coinciding with large reported damages associated to flood in Metro Manila: Ketsana's** ~~Ondoy's~~ EDR is 0.002, i.e. its simulated damage is more than two orders of magnitude smaller than reported. The large reported damage (NRD=401 million USD) was mainly due to floods and landslides: Torrential rainfall caused severe river flooding in the ~~Manila metropolitan region~~**Metro Manila** and landslides around Baguio City, resulting in severe damages (Abon et al., 2011; Cruz and Narisma, 2016; Nakasu et al., 2011; NDCC, 2009a).

~~These~~ **The flood** damages were not resolved by the wind-based impact model, with intensities well below 50 ms-1 and neither affecting Manila nor the northern Baguio City directly (Fig. **7**~~6~~d). **Notably, even for TCs with large overestimation of simulated damage due to high wind speeds in Metro Manila, namely Fengshen and Xangsane, a substantial part of the reported damage was actually caused by pluvial flooding and landslides and not by wind alone (Yumul et al., 2008, 2011, 2012).**"

L. 470ff:
"It should be noted that ~~these~~ sector specific impacts are not resolved in the impact model and Haiyan did not affect Manila directly. ~~However, r~~**R**elatively large damages were simulated **around Tacloban City, Leyte, which was actually devastated by Haiyan's storm surge. Large wind impacts were also simulated further West** around the cities Iloilo and Cebu (Fig. ~~6~~**7**c) **that were not as exposed to surge as Leyte province."**

In Table A4:
Add references per event, associated disasters, and affected assets for TCs Haiyan, Ketsana, Fengshen, and Xangsane. Additional information are based on the following publications: **Abon et al. (2011), Cruz and Narisma (2016), Lagmay et al. (2015), and Yumul et al. (2008, 2011, 2012)***.*

1.6) Having more context would also provide you an opportunity to refute an argument you pose earlier in your paper related to the CLIMADA setup, in that "[...] no impact is expected for low wind speeds," when it is evident many high-impact events in exposed and vulnerable regions cannot be estimated on wind speeds alone; geography/topography, exposure and vulnerability, local climate conditions (e.g. SW monsoon) play a significant and sometimes, larger role in realised damages from TCs.

See point 1.2 above and combined reply to 1.6 and 1.7 in next point.

1.7) With a better focus on this I think it would provide a richer and more meaningful assessment of exposure and vulnerability that give better context to your paper and the need for more regionalised calibration of damage estimates from TCs.

Reply to both comments 1.6 and 1.7: We agree that the limitations of a TC impact model based on wind speed as the only hazard intensity can not be stressed enough. Generally, we believe that the manuscript reflects upon these limitations and uncertainties to a sufficient degree and the need for more regionalised calibration, especially for local applications, have already been firmly emphasized in the discussion and outlook sections of the manuscript. For instance, in the last paragraph of Section 6:
"Limitations of our research motivate future work. For TC impact models, we echo the call for a more refined representation of TC hazard as a combination of wind, surge, and rain induced flood and landslide events. Furthermore, our case study for the Philippines suggests that differentiating between urban and rural asset exposure, considering topography in wind speed

estimations, and the inclusion of exposed agricultural assets could further increase model accuracy." (L. 587f)

The case study on the Philippines, with the improvements suggested in comment 1.4 and 1.5, adds detail and evidence of the discussion of these uncertainties and recommendations for further model development in the outlook.

Regarding the specific argument regarding low wind speeds from Section 2.2.3, we suggest to narrow the statement and also emphasise the learnings from the case study in these regards in Section 4.4, see suggested changes in the manuscript below:

L. 144 (Section 2.2.3):
"Since no ~~impact~~ **directly wind induced damage** is expected for low wind speeds, [...]"

L. 476ff (Section 4.4):
"The case of the Philippines reveals limitations of the model and calibration due to the lack of an explicit representation of sub-perils such as storm surge, torrential rainfall, and landslides (Sect. 4.3). **The flood damage caused by Ketsana is a showcase example for severe damages associated with a TC with relatively low wind speeds, that is, an event that cannot be adequately reproduced with a wind-based impact function.** Adding to the stochastic uncertainty, the magnitude of rainfall during a TC events in the Philippines is not only determined by the intensity of the TC event, but also by the coinciding monsoon season, as in the case of the Typhoons Fengshen and Haiyan (Espada, 2018; IFRC, 2009**; Yumul et al., 2012**)."

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2) RESPONSE TO COMMENTS BY REFEREE #2 (ANDREW GETTELMAN)

2.0) Review of Regional tropical cyclone impact functions for globally consistent risk assessments by Eberenz et al.
This manuscript dives into loss functions used in a Tropical Cyclone (TC) damage model and tries to adjust damage functions by region to better match the observed record of damages. The paper is generally well written and should be published in Natural Hazards and Earth System Sciences with minor revisions.

2.1) I have some specific comments below, but I would like to see a bit more explanation for some of the figures and analysis. Especially, some of the appendix (and the two figures) could be folded into the main text.

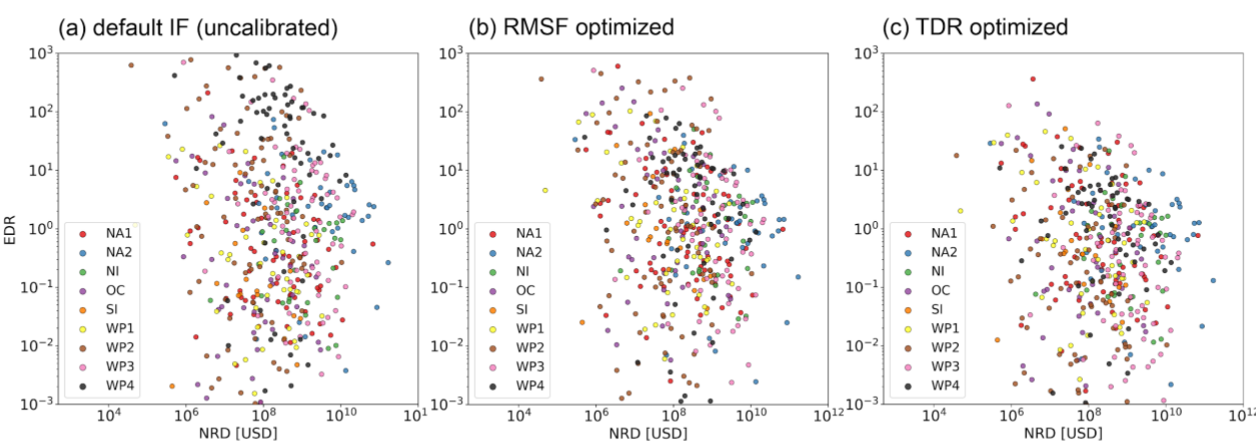
Thank you for the suggestions regarding the figures and explanations in the manuscript. They are most welcome and we will reply more in-depth and suggest changes together in our answers to the specific comments below.

Most notably, instead of folding figures A1 and A2 into the main text, we suggest a new figure (EDR boxplot per region, c.f. Comment 2.13) to be added to the results section, c.f. responses to comments 2.13, 2.17, 2.19, and 2.20.

2.2) Also, it's not clear whether the trend for simulated damages is an over or under estimation of damages before calibration and whether this is due to strong or weak storms. Maybe this is in the figures, and could be mentioned in the discussion/conclusions.

Whether damages are on average over- or underestimated is shown explicitly in the manuscript: For the average per region, Figure 5 and Table A2a provide this information as conveyed by uncalibrated total damage ratio (TDR), i.e., the grey bars in Figure 5b, next to the values after calibration. These numbers are also discussed in the text (L. 288ff, Section 3.1.1). For the single countries the spread of uncalibrated event damage ratios (EDR) information is displayed in Figure S2 in the supplementary materials. We agree that EDR per region could be shown more explicitly in the main text. The regional findings with regards to over- and underestimation before calibration form the basis for the whole calibration and are reflected both in the results and discussion section.
As for the question whether strong or weak storms are driving the average over- or underestimation (i.e. as measured by TDR), we agree to the referee that this is not yet discussed broadly in the manuscript. Our results show no significant correlation between normalized reported damage (NRD, here taken as a measure of TC severity) and EDR (measure of over-/underestimation of damage in CLIMADA). In response to this comment, we also plotted scatter plots of EDR vs NDR, finding no evidence of any significant relationship between TC severity and over- or underestimation.

We will add these scatter plots to the appendix of the manuscript as new ***Figures A3****:*



"Figure A3: No significant correlation between event damage ratio (EDR) and normalized reported damage (NRD) was found. The scatter plots show the relationship for 473 TC events worldwide computed with three different sets of impact functions: (a) uncalibrated default (V_{half}=74.7 ms-1), (b) RMSF optimized, and (c) TDR optimized. The nine calibration regions are differentiated by colour."

Suggested addition to Section 3.2.2.:
L. 298: *"*The EDR values within regions show a large spread over several orders of magnitudes (Fig A1). **There is no significant correlation between EDR and NRD (Fig. A3), suggesting that the over- and underestimation of simulated event damages is not related to TC severity.** The largest spread, as expressed by the RMSF [...]*"*

To clarify that Figure 5b shows over/underestimation of average damages per region, we will explain this better in the figure caption of Figure 5:

L. 337ff (caption Figure 5):
"Figure 5: Calibration results and cost functions for nine calibration regions and all regions combined**, each shown before (grey) and after calibration (blue and red)**: (a) Vhalf: fitted impact function parameter; (b) TDR: ratio of total simulated and normalized reported damage; (c) RMSF: root-mean-squared fraction; and (d) AAD: **normalized reported (green) and simulated** annual expected damage **(AAD)**. [...]"

Furthermore, in our response to comment 2.13, we suggest to show uncalibrated EDR per region in a new figure in the beginning of the results section.

2.3) Also, the analysis focuses on tuning v-half. What would happen if you either used or added v-thresh (the minimum wind speed for damages) as an adjustment parameter? Would that help? Why or why not? Can you test it?

This comment touches upon one of the most pivotal decisions during calibration: the choice of free parameters in the impact function. Thank you for pointing out that more justification for the decision to only vary V_{half} should be provided. The very short reason is that we concluded that fitting more than one of the linear dependent parameters (c.f. L. 154f) increases the risk of overfitting. Here is the long justification.

The approach of this paper builds on the Master Thesis by one of the authors with the title "Applying Machine Learning Methods to the Assessment of Tropical Cyclone Impacts" (Samuel Lüthi, 2019, available at https://doi.org/10.3929/ethz-b-000398592).
In the Master Thesis, regional TC impact functions were calibrated with Bayesian optimization methods based on almost the same data set of TC tracks and EM-DAT entries per event and country. Also, the same wind field model and impact engine as implemented in CLIMADA was applied. Differences between the Lüthi (2019) and the present paper under discussion mainly lay in the definition of the regions but also further refinements and quality control of the underlying data added for the present paper: EMDAT events which produce no damage in CLIMADA had not been excluded from the analysis in Lüthi (2019). This can cause artefacts, e.g. if a Carribean TC undergoes extratropical transition and then makes "landfall" a second time as a low pressure system.

Lüthi compared regional calibration results of two multi-parameter impact functions: (i) a sigmoid function similar to the function by Emanuel (2012) with three free parameters (slope, offset, and maximum intensity) and (ii) a 12-step staircase function. Figures 3.4 and C.1 of Lüthi (2019) show the resulting impact functions and RMSF scores:

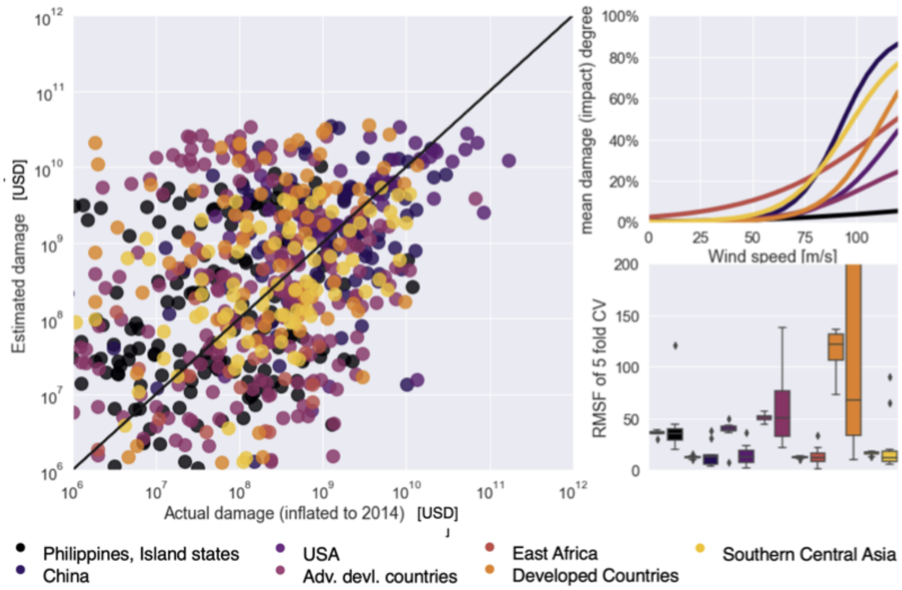


FIGURE C.1: Estimated vs. actual damages for all storms of all regions (left, log-scale) using sigmoid damage functions, including regional damage functions (top-right), and regional training (left box per region) and validation (right box per region) RMSF error (bottom-right). Damages are calculated using the regional damage functions which result from the calibration using all data per region. Training and validation RMSF are the output of a 10-fold cross validation per region. This plot corresponds to Figure 3.4.

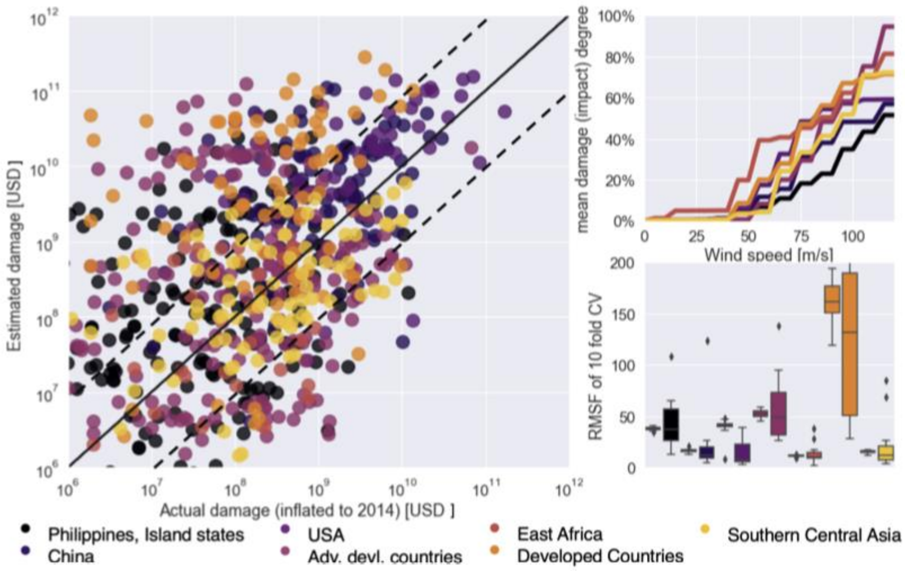


FIGURE 3.4: Estimated vs. actual damages for all storms of all regions (left, log-scale), including regional damage functions (top-right), and regional training (left box per region) and validation (right box per region) RMSF error (bottom-right). The solid line indicates correctly estimated storms, storms in between the two dotted lines are estimated in the right order of magnitude. Damages are calculated using the regional damage functions which result from the calibration using all data per region. Training and validation RMSF are the output of a 10-fold cross validation per region.

Based on his results as partially shown in the two figures displayed above, Lüthi (2019) concludes: "The comparison of different calibration approaches (Section 3.3) reveals that sigmoid functions are an attractive tool. As these functions depend solely on three parameters, they can be calibrated comparatively fast and at lower computational cost. However, they can produce counter-intuitive results. As an example, the resulting damage function for East Africa (Figure C.1, appendix) shows mean damage degree values larger than zero at zero wind. On the other hand, the multi-step function shows a similar performance using twelve parameters." (p. 25) and "While the damage functions look quite different, the estimated damages and also the training and validation errors are similar. This is due to the fact that the damage functions are quite similar in the region of 30-50 m/s." (p. 41)

For the parameterization used in the present study, this implies that a shift of V_{tresh} alone would require relatively large shifts to unrealistically low or even negative wind speeds (Indian Ocean) or very large intensities (North West Pacific region). Changing multiple parameters is problematic because the parameters ***V_{thresh}, V_{half},*** *and* ***scale*** *are not linear independent. This introduces a risk of overfitting considering the large uncertainties in the damage data underlying the calibration; Fitting a more flexible, multi-step function with larger resolution from 30-50m/s could be a valid alternative to the sigmoidal function. However, as Lüthi (2019) showed, this more computationally expensive approach does not result in any considerable improvement in skill. Therefore, we decided to keep the fitting as simple and transparent as possible as long as the other uncertainties are not reduced.*

*In light of the findings by Lüthi (2019), our approach comes with the following advantages: (i) thanks to the fixed value of **V_{thresh}**, it only produces physically plausible curves, (ii) allowing only 1 free parameter yields a relatively fast (computationally cheap) calibration and (iii) results are easy to interpret and compare. Comparing the RMSF values after calibration of the two studies shows that the results are generally similar; often RMSF numbers retrieved for this study are lower. In the case of China (WP3), the only region which has the same underlying countries in both studies, the calibration in this study produces lower RMSF values. It should be noted that RMSF in Lüthi (2019) are negatively affected by events which produce no damage in CLIMADA (as mentioned above, these events have been excluded in the analysis for this paper).*

*In response to this comment and also comment 2.11 below, we suggest to add a brief discussions of the choice of fitting parameters with reference to Lüthi (2019) in the manuscript, that is, in Section **2.2.3 Impact Function**, L. 165ff:*

"**In a comparison of calibration results based on a sigmoidal impact function with a more complex 12-step staircase function, Lüthi (2019) found no improvement of calibration skill with the more complex function. Therefore, we use the sigmoidal function in this study.** We define a default impact function with V_{thresh} = 25.7 ms^{-1} and V_{half} = 74.7 ms^{-1} that is used for a first, uncalibrated, simulation of global TC damages, and as a starting point for calibration. While V_{half} is fitted during the calibration process, we keep the lower threshold V_{thresh} constant throughout the study. **This is based on the finding by Lüthi (2019) that the variation of more than one of the linearly dependent parameters most likely results in an overfitting during calibration, with physically implausible values for V_{thresh} in some world regions.**"

2.4) In addition, US Damage is conveniently a function of wind speed for a specific reason: damage is often insured loss and that does not include flood. Can you comment on that?

Your point is well taken and we thought about this before starting our work. As for flood-related (as well as for rain and surge) damage, that's a wider field. Indeed standard US policies do not cover flood (or explicitly state an exclusion). But in recent cases (such as Katrina, 2005), the insurance commissioner forced direct insurance companies to cover damages 'as they occurred' and many (if not most) times even loss adjusters could not separate (wind/surge/rain) in hindsight, hence reported damages do often include the flooding component. But as the aim of the present effort is to provide a globally consistent and readily available impact model, calibrating to EM-DAT provides such a global yet at least regionally adjusted perspective - and it is not quite clear what EM-DAT reported damages cover in detail (some numbers look rather like total direct rather than only insured damage, some event reportings might even include total economic damage, inclusive - some - business interruption, i.e. indirect impacts). That's why we consider EM-DAT as a lower bound and rather 'best guidance' than 'ground truth' (which unfortunately can not be established in hindsight).

2.5) Wouldn't it be wise to check the large scale data against 'small scale' engineering data based on different structure types? Or generally, why is the damage different, is it a physical reason (buildings are stronger or weaker than the US.) or a social reason: lower capital, less cost to rebuild, lower value? It would be nice to discuss this, in the conclusions if necessary.

A comparison of the large scale calibration with socio-economic indicators and engineering based impact functions would certainly be a great gain for further research and improvement of the vulnerability component of TC impact models. However, this is a rather wide and complex field: The regional impact functions are a proxy for the aggregate of multiple types of damages to all kinds of different building types. At the same time, the quality of impact data is not good enough to differentiate between these. Furthermore, engineering data is often not publicly available and if so, only available for richer countries and building codes are hard to compare across regions.

A comparison against specific bottom-up data is beyond the scope of this paper that focussed on the question how much can be achieved with an event-based, top-down fitting of impact function against reported damage data.
The approach followed for GAR 2013 (Yamin et al., 2014) is definitely a good starting point to regionalize impact functions based on vulnerability indicators rather than empirically. However, our study shows the limitations of such an approach when no comparison to reported damages is done.

Following your suggestion, a welcome next step could be a study combining the empirical evidence provided by reported damage data on the one hand with building codes / socio-economic indicators on the other hand. This approach would be quite challenging, as it adds even more layers of complexity and cascading uncertainties to the calibration. Still, we agree that it could help to gain a better understanding of the drivers of the inter-regional differences in TC vulnerability. Sensitivity analysis on a more local and regional level could be a feasible starting point.

As comment 1.2 by referee #1 points into a similar direction (asking for hypotheses on the reasons for the inter-regional differences between calibrated impact functions), part of the changes to the manuscript we suggest here to take up are duplicates of our suggestions in reaction to comment 1.2. Please refer to AR1 for the full answer to 1.2.

Proposed changes in the manuscript:

In Section 1 (Introduction):
"While the attribution of vulnerability to regional drivers is outside the scope of this study, the results can serve as a starting point for further research dissecting the socio-economic and physical drivers and factors determining vulnerability to TC impacts locally and across the globe."

In Section 6 (Conclusion and Outlook):

“**The substantial over-estimation of TC damages in the North West Pacific with the default impact function opens the question for the drivers of the apparently lower vulnerability in this region. Considering the inability of the model setup to directly represent the impacts from TC surge and pluvial flooding, one would rather expect aggregated calibrated impact functions to be steeper than the default wind impact function. Therefore, we suggest investigating interregional differences in possible other drivers, including protection and construction quality and standards – but also damage reporting practices. A study combining the empirical evidence provided by reported damage data on the one hand with socio-economic indicators on the other hand would be desirable but rather challenging, as this would add even more layers of complexity and cascading uncertainties to the calibration, especially on a global level.”**

2.6) Finally, would this be applicable to other models beyond CLIMADA? Why or why not?

Generally yes, the impact functions are not specific to the CLIMADA modeling framework. Also, we would expect the relative inter-regional differences to be robust with other TC impact modeling set-ups, i.e. that the North West Pacific shows the lowest vulnerability as expressed by the flat impact function.
The precise shape and scaling of the calibrated impact functions are, however, to a certain degree specific to the decisions and components of the modeling setup, including most prominently:

1. *The representation of hazard by wind alone: an explicit representation of surge and rain would require different impact functions, also for wind.*
2. *The choice of free parameters in the impact function, as already discussed in response to your comment 2.3.*
3. *The value of total asset values (TAV, c.f. Table A3): impact functions would scale differently with a different assumed total inventory value of exposed assets.*
4. *Spatial resolution: The impact functions are calibrated for 10 km resolution. Parameters could change, if hazard and exposure is represented on a higher or lower resolution.*

The first point is now already reflected upon in the manuscript, most prominently in the discussion:
“The regionalized impact functions presented here were calibrated for wind-based damage modelling on a spatially aggregated level. Model setups with an explicit representation of related sub-perils like storm surge or torrential rain require different (i.e. flatter) impact functions for the wind-induced share of TC damage, as well as additional impact functions for all sub-perils. Likewise, impact models with an explicit representation of building types and agricultural assets require a more differentiated set of impact functions.” (L. 562ff)

However, we agree that points 2, 3 and 4 could be stated more explicitly, to support the use of the study results outside CLIMADA. Therefore, we will add the following limitations to the discussion:

L. 562ff (Section 5.2 Uncertainties and limitations):

"**While the results of this study are not specific to the CLIMADA modeling framework, the precise shape and scaling of the calibrated impact functions are, however, to a certain degree specific to the choices and input data of the modeling setup: (1) The choice of free parameters in the impact function (c.f. Section 2.2.3 and Lüthi, 2019); (2) The TAVs (c.f. Table A3): impact functions would scale differently with a different assumed inventory of exposed assets; (3) spatial resolution; and (4) the representation of hazard intensity:** The regionalized impact functions presented here were calibrated for wind-based damage modelling on a spatially aggregated level. [...]"

Specific Comments:

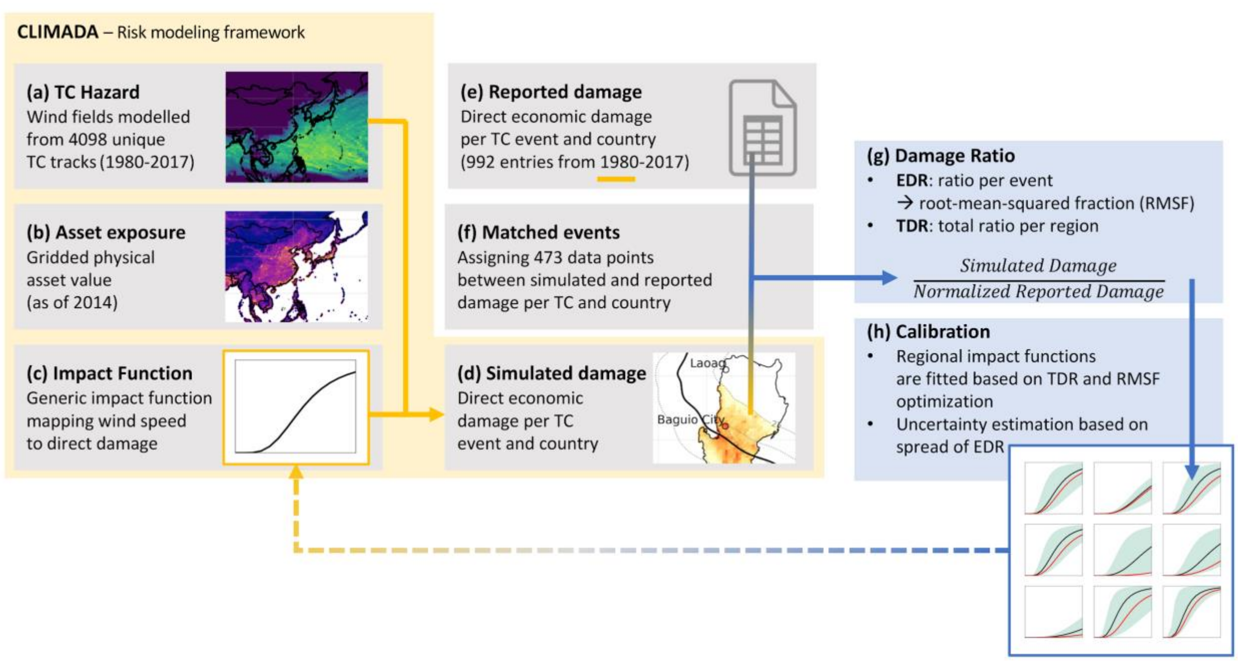
2.7a) Page 3, L81: Figure 1 is hard to follow. I suggest that perhaps each panel can be labeled a,b,c, etc, and then referred to in the text, rather than focusing on the section numbers. I had to read this 3 times to follow it, and only some of the panels are discussed.

2.7b) Page 3, L90: figure 1: careful with the arrows. For example the arrows in the second row probably point the wrong way. You want 2.2.4 and 'simulated damage' to point to 2.3.2. Not 2.3.1 pointing to them. This highlights the nomenclature problem with the figure.easier to label a,b,c, etc.

Thank you for the well thought out suggestions to make Figure 1 easier to follow. We are taking up both suggestions and propose the following adjustments to Figure 1 and its caption and reference in the manuscript to improve readability:

L. 86:

Figure 1: (1) replace section numbers in panels by labels (a) to (h); (2) remove arrow heads pointing towards panels (e) and (d).



L. 89 (caption Figure 1):

"Figure 1: Schematic overview of the data and methods applied to calibrate regional TC impact functions in a globally consistent manner. From left to right: TC event damages are first simulated within the CLIMADA framework based on TC ~~tracks~~ **hazard (a)**, asset exposure **(b)**, and a default impact function **(c), c.f. Sect. 2.1 to 2.2.3** ~~(a, Sect. 2.1 to 2.2.3)~~. Resulting simulated damages **(d)** are ~~matched and~~ compared to reported damage data from EM-DAT **(e) for 473 matched TC events (f) by means of the damage ratio (g), c.f. Sect. 2.2.4 to 2.3.2** ~~(b, 2.2.4 to 2.3.2)~~. During calibration **(h), steps (c) to (g) are repeated several times with varied impact functions for each region, optimizing the cost functions TDR and RMSF (c.f. Sect. 2.3.3)** ~~impact modelling and damage comparison are repeated several times for regional impact functions with varied slope (2.3.3)~~. The result is a set of best fitting impact functions for nine world regions **(Sect. 3.2)**~~(c)~~. Finally, the calibrated impact functions are plugged into CLIMADA **once more** (d**ashed arrow**) to compute annual average damage per region **(Sect. 3.3)**."

L. 80ff:

"To regionally calibrate TC impact functions, simulated damages are compared to reported damages, as illustrated in Figure 1: In a first step, direct economic damage caused by TCs are simulated in the impact modelling framework CLIMADA (**Fig. 1a-d,** Sect. 2.1 to 2.2.2) with one single default impact function applied globally to start from (Sect. 2.2.3). Then, damage data points per country and storm are assigned to entries of reported damage (**Fig. 1e-f,** Sect. 2.3.1). For the matched events, the ratio between simulated and reported damage is calculated (**Fig. 1g**, Sect. 2.3.2). For calibration, countries are clustered into regions and two complementary cost functions are optimized based on the damage ratios, by regionally fitting the slope of the impact function (**Fig. 1h**, Sect. 2.3.3)."

2.8) Page 3, L103: chosen resolution.

Suggested change in L.103:

"The setup ~~does~~ work**s** equally well at higher **chosen** resolution~~s~~ [...]"

2.9) Page 3, L106: this description is a little confusing, and I think it is because you need to be clear about terminology. What is a hazard? What is exposure data? Maybe start from the concept of damage = exposed assets x damage ratio, and damage ratio is an impact function x hazard intensity. I think those are the correct terms.

Suggested change in L.103ff:

"**In the CLIMADA framework, damage is defined as the product of exposed assets and a damage ratio. In our case,** ~~Simulated~~ damage per TC event and country is ~~computed~~ **simulated** as ~~following~~ **follows: For each grid cell and event, damage is calculated as the product of total exposed asset values and the mean damage ratio. The mean damage ratio (0 to 100%) results from plugging the hazard intensity (maximum sustained wind speed) into the impact function. Finally, damage per event is aggregated over all grid cells within the country.** ~~(1) For each grid cell and event, the mean damage ratio (0 to 100%) is determined by plugging the maximum sustained wind speed (hazard intensity) into an impact~~

~~function. (2) Absolute damage per grid cell is computed by multiplying the mean damage ratio with the value of exposed assets at the grid cell. (3) The total damage per country and event is computed as the sum over all grid cells within the country.~~"

2.10) Page 4, L145 : can be constrained

*We correct the typo in L. 145 ("*constraint*" to "***constrained*").*

2.11) Page 5, L175: is v-thresh fixed? Seems like you just vary v-half, but I can see how v-thresh depends on building type. I.e wood v. Stone.

As already mentioned in response to comment 2.5, the regional impact functions are a proxy for the aggregate of multiple types of damages to all kinds of different building types. Due to the global and aggregated scope of this study, our approach did not start from differences of v_thresh with regards to building types but rather explored how far we get with a top-down approach that is "blind" to bottom-up specifications.
Still, we agree that a variation of v_thres could be worthwhile. We have explained our reasons to vary v_half only in the answer to comment 2.3 above. Please refer there for the detailed response and also the additional clarifications with reference to Lüthi (2019) we suggest to add the manuscript before publication.

2.12) Page 7, L226: is the 20% difference significant? Or is the goal here to make sure the 58% number from climada matches the 76% value from observations?

In Section 2.3.1, we state percentages to examine and illustrate what share of simulated and reported TC damages is represented by the matched TC events, that is, considered in the analysis. The fact that both normalized reported damages and simulated damages represent more than half of the total damage inventory of the two data sets gives us confidence that a representative calibration can be based on the matched events. If the shares were much lower, we would be much less confident that the calibration results are representative.

In light of the reason to calculate these shares, the difference of 20% has not been of major interest or concern to us: it simply reflects that the two datasets are both not necessarily complete inventories of damaging TCs, and also that the reported damage data comes with substantial uncertainties as discussed in Section 5.2. The mismatch between the event inventories of the two data sets was one of the reasons to limit calibration on those events with a validated match between the TC track from IBTrACs and the data point from EM-DAT.

2.13) Page 7, L234: what does the distribution of EDR look like un optimized? Can you plot it?

The distribution of un-optimized EDR can indeed be shown in a more concise fashion. The distribution of uncalibrated EDR per calibration region is shown below as boxplots, highlighting the differences between the regions. Furthermore, we plotted histograms for global EDR in response to the referee's request: The histograms of the global distribution of uncalibrated EDR *show a large spread, as already discussed in the manuscript (L. 298ff), with both over- and underestimation of simulated damages occurring. Calibration reduces the spread to a certain degree, placing more than half of events in the EDR range from 0.1 to 10, that is, simulated event damage is of the same order of magnitude as normalized reported damage.*

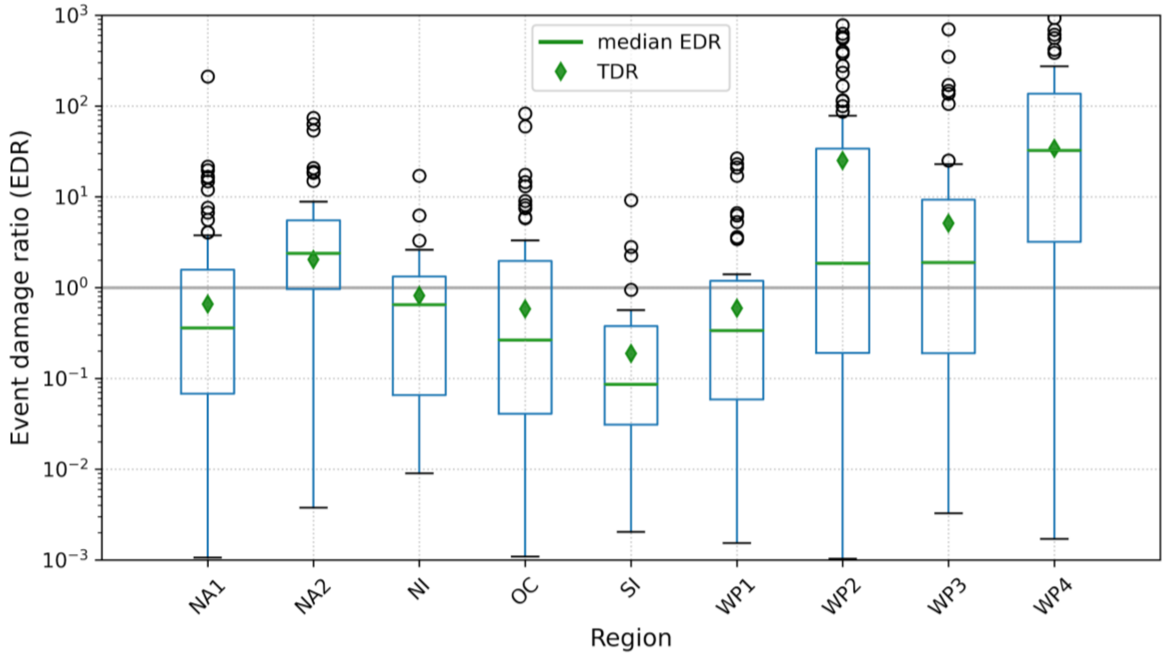


Figure: Spread of event damage ratio (EDR, boxplot) and total damage ratio (TDR) per region before calibration (V_{half}=74.7 ms^{-1}) per region. The plots are based on data from 473 TC events affecting 53 countries. The EDR boxplots show the median (green line), the first and third quartiles (IQR, blue box), data points outside the IQR but not more than 1.5·IQR distance from either the first or the third quartile (black whiskers), and outliers (black circles). The additional markers show TDR before calibration (green diamond).

For the distribution of EDR per country please refer to the boxplots in the Supplement (URL, updated figures also attached to the end of this document).
Change to the manuscript: We suggest to add the regional boxplots of EDR to the results Section 3.1 (L. 283, "Damage ratio with default impact function"*) the histogram to the supplement of the manuscript.*

2.14) Page 7, L238: a plot of the TDR by country would be useful too.

We have already provided plots of the distribution of uncalibrated EDR per country in Figure S2 in the supplement. To satisfy your request for TDR per country, we added TDR (which can be read as a weighted average of EDR) to these plots, both before and after calibration.

The updated Figures S2a-f are attached below, at the end of this document, for your consideration.

Change in Section 2.3.2 of the manuscript:
L. 238f:
"The distribution of EDR and TDR before calibration as well as TDR after calibration is shown per region in Figures 6 and S4 and per country in the supplementary Figure S2."

2.15) Page 7, L245: is a data point a matched storm event? I.e 43 of the 376 events have damage in the USA and Canada?

Yes, the number of matched events per region is listed in Table A2.
To clarify L.245, we suggest the following change in the manuscript:

L.245:
"a minimum desired number of 30 data points **(matched TC events)** per region"

2.16) Page 8, L281: what if you fit v-thresh instead or in addition? Might this help? Why or why not?

To avoid redundancy between the responses, please refer to the replies to comments 2.3 and 2.11 for a discussion of the choice of free parameters in the impact function.

2.17) Page 9, L286:figure a1 and a2 should be part of the main text. Comment further please on the uncertainties. Is damage higher or lower? Where? What are the general issues?

The referee has a valid point in suggesting to add a figure showing the spread of EDR to the main text. In our opinion, it is not necessarily required to add Figures A1 and A2 to the main text to answer the questions asked with this comment, not to overload the manuscript with figures. The question whether and where damage is higher or lower before and after calibration is now already answered on an aggregated and more digestible level in Figure 5 within the main manuscript: Figure 5b compares TDR with and without calibration for each region and globally, Figure 5d shows normalized reported damage and total simulated damage per region, again with and without calibration. As for the spread of EDR (damage ratio of single events), we agree that this should be shown in the main text. We suggest showing this in the form of boxplots per region, as they also show the spread of EDR to get a better feeling for the uncertainties. The suggested Figure is shown in response to comment 2.13.

Ad uncertainties: The uncertainties are commented on quite extensively in Section 5.6 ("Uncertainties and limitations") already. The spread of uncalibrated EDR within each region shown in Figure A1 now already illustrates the quantitative extent of the uncertainties, this will be further improved with the suggested figure. Furthermore, the discrepancy between TDR and RMSF calibration gives a hint on how robust the calibration is for each region (Figures 5b and 5c). This is already discussed in the manuscript already, i.e. in line 319: "The comparison of complementary calibration approaches gives an indication of the robustness of the calibration per region." and line 520f: "The deviation between the results of the two calibration approaches indicates how robust the calibration is with regards to the model's ability to represent the correct *order of magnitude of single event damage. Whereas the model setup returns reasonable risk estimates and consistent calibration results for Central and North America, we found an extensive spread in EDR and calibration results for other regions, especially in East Asia."*

Suggested changes to the manuscript: c.f. Comment 2.13.

2.18) Page 9, L291: higher or lower?

There are both cases, regions with higher and with lower simulated damages. As described in lines 291ff, uncalibrated TDR is below 1 in some regions and above 1 in others, c.f. answer to comment 2.2 above.

To clarify, we suggest the following reformulation in Section 3.2.1:
L. 289ff:
"Both **the ratios EDR and the cost functions** RMSF ~~(Fig. 5b) and the ratios EDR (Fig. A1)~~ and TDR ~~(Fig. 5c)~~ **show inter-regional differences**~~, indicating~~ **with regard to** the deviation of the damages simulated with the default impact function from reported damages **(Fig. 4 and 6)**~~, show inter-regional differences~~. **For most regions, total simulated and normalized reported damage deviates less than one order of magnitude (Table A2)** ~~TDR is less than one order of magnitude different from one~~."

2.19) Page 9, L300: maybe it's just showing and figA1 and A2, but I in you should show one more step before figure 5. It's too hard to interpret what the optimization is doing and whether simulated damage is generally too high or too low.

This is a valid point: insights into the optimization and its consequences for damage ratios is a crucial aspect of this publication. As already mentioned in our responses to comments 2.2 and 2.19, Figure 5b does indeed show where simulated damages are generally too high or too low as compared to reported damages, both before and after calibration.
As for your request to get more insight in what the optimization is doing on a more detailed level, we hope that our responses and propositions in response to comments 2.2, 2.13, and 2.14 allow for a more thorough interpretation of what the implications of the calibration on a more detailed level, e.g. with regards to TC severity and per country. In our opinion, the additional figure suggested in response to comment 2.13 serves to show the additional step before Figure 5 as requested by the referee.

A further, more complex insight into the optimization on the basis of fitted V_{half} is provided in Figure S3 in the supplement, providing insight in the robustness of TDR and RMSF to changes in the impact function. We agree that this could be mentioned more explicitly in the text, though, as proposed below.

Proposed changes in the manuscript:
L. 316f: "~~Plots~~ **The sensitivity** of TDR and RMSF per region ~~as functions of~~ **to changes in** Vhalf ~~are provided~~ **is visualized** in the Supplement**: Regions with a large uncertainty, i.e. a**

large spread of EDR, generally show a relatively low robustness of the cost functions (Fig. S3). **On a globally aggregated level, calibration reduces the spread of EDR to a certain degree, placing more than half of events in the EDR range from 10^{-1} to 10."**

2.20) Page 10, L324:is there a clearer way (eg fig A1) to show h overestimation?

The over- and underestimation of TC damages as expressed by TDR (aggregated level) and EDR (single events) is shown in Figure 5 and Figures A1 and A2. For the aggregated level, TDR before and after calibration shows the average under- and overestimation aggregated per region in Figure (5b), c.f. Also our response to comment 2.2.
For the event level, please refer to the EDR plots per country as shown in Figure S2 in the supplement. Beyond this, we hope that our explanations and additional figures proposed in response to your comments 2.2 and 2.13 help to clarify the communication of over- and underestimation of TC damages.

2.21) Page 19, L591: can you speculate a little more on what next steps might be? Modify or add a flood risk component?

We would strongly suggest to work towards future TC risk assessments based on modelled TC events and an explicit representation of surge and rain.

Adding a storm surge component, requires high resolution to resolve topography.

Representation of torrential rain, requires to take into account transition speed of the TC, as in the case of Hurricane Harvey that stayed stationary over Houston for a long time, dumping more rain than expected in the same area. Also, interaction with other weather phenomena like monsoon need to be taken into account, as in the case of the Philippines.

To further improve the impact functions, it would be worthwhile to combine damage data based calibration with socio-economic and engineering type data, as discussed in response to comment 2.5. Especially if impact functions for different sub-perils (wind, surge, rain) need to be combined, more information and knowledge than the one provided by reported damage data is required to constrain calibration. This could also involve expert judgement and engineering based impact functions.

The last point can be stressed more in the manuscript, we therefore suggest to add the following sentences in the outlook (Section 6):

L. 589ff:
"When modeling multiple TC sub-perils, aggregated reported damage data are not sufficient to constrain impact function calibration. This might be resolved by consulting socio-economic and engineering type data and knowledge."

Appendix to AC2: Reworked Figures from the Supplement (Figures S2, c.f. comment 2.14 above):

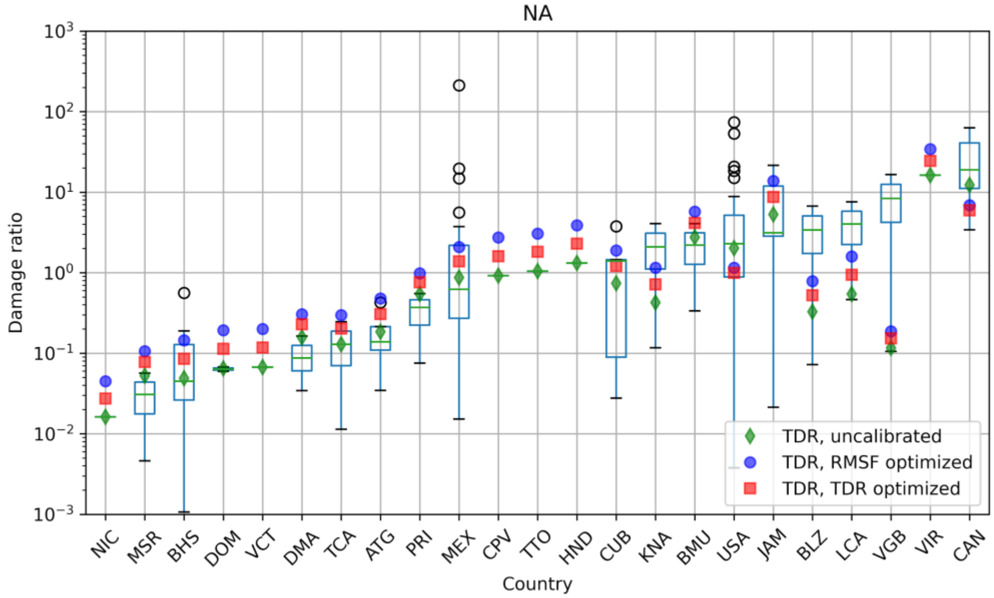


Figure S2a: Spread of event damage ratio (EDR, uncalibrated) and total damage ratio (TDR) per country in the North Atlantic and North East Pacific basin (NA). The plots are based on data from 23 countries. The EDR boxplots show the median (green line), the first and third quartiles (IQR, blue box), data points outside the IQR but not more than 1.5·IQR distance from either the first or the third quartile (black whiskers), and outliers (black circles). The additional markers show TDR before calibrated (green diamond) and after calibration (blue circle: RMSF optimized and red squares: TDR optimized).

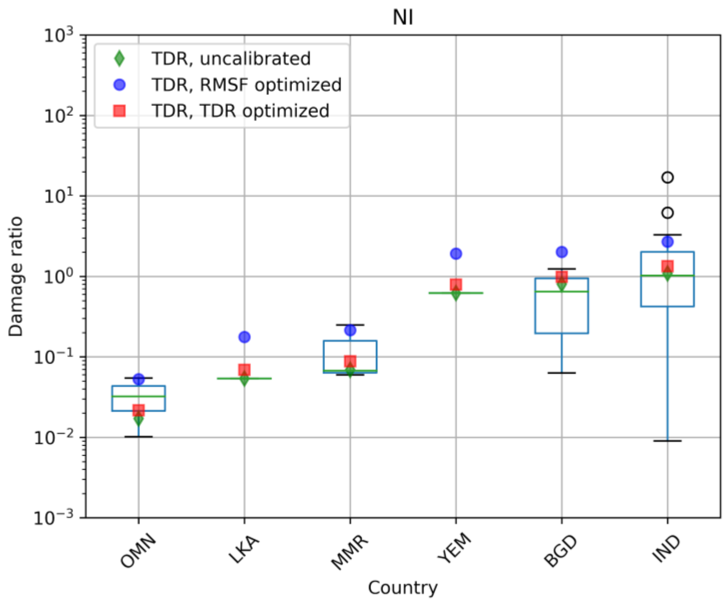


Figure S2b: Spread of event damage ratio (EDR, uncalibrated) and total damage ratio (TDR) per country in the North Indian Ocean basin (NI). The plots are based on data from six countries. The EDR boxplots show the median (green line), the first and third quartiles (IQR, blue box), data points outside the IQR but not more than 1.5·IQR distance from either the first or the third quartile (black whiskers), and outliers (black circles). The additional markers show TDR before calibrated (green diamond) and after calibration (blue circle: RMSF optimized and red squares: TDR optimized).

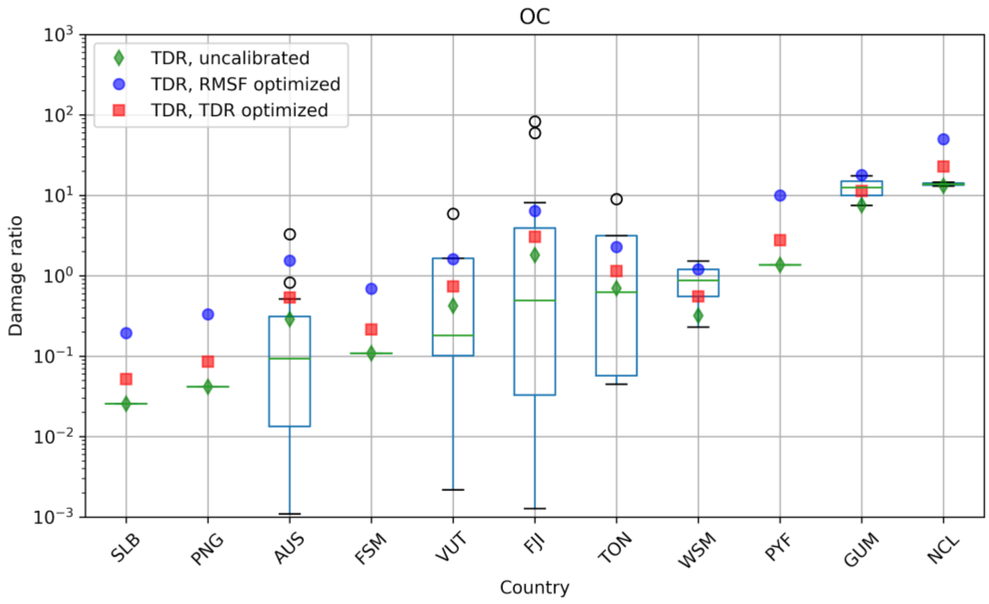


Figure S2c: Spread of event damage ratio (EDR, uncalibrated) and total damage ratio (TDR) per country in Oceania with Australia (OC). The plots are based on data from 11 countries. The EDR boxplots show the median (green line), the first and third quartiles (IQR, blue box), data points outside the IQR but not more than 1.5·IQR distance from either the first or the third quartile (black whiskers), and outliers (black circles). The additional markers show TDR before calibrated (green diamond) and after calibration (blue circle: RMSF optimized and red squares: TDR optimized).

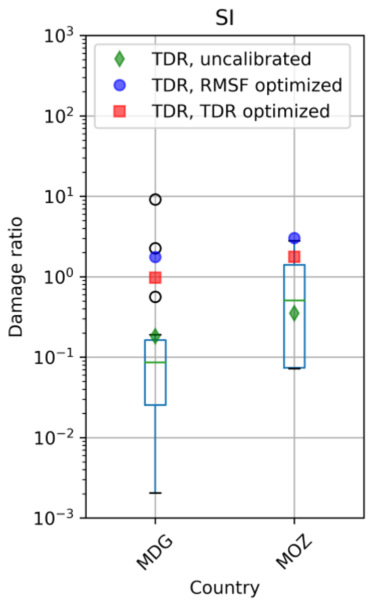


Figure S2c: Spread of event damage ratio (EDR, uncalibrated) and total damage ratio (TDR) per country in the South Indian Ocean basin (SI). The plots are based on data from two countries. The EDR boxplots show the median (green line), the first and third quartiles (IQR, blue box), data points outside the IQR but not more than 1.5·IQR distance from either the first or the third quartile (black whiskers), and outliers (black circles). The additional markers show TDR before calibrated (green diamond) and after calibration (blue circle: RMSF optimized and red squares: TDR optimized).

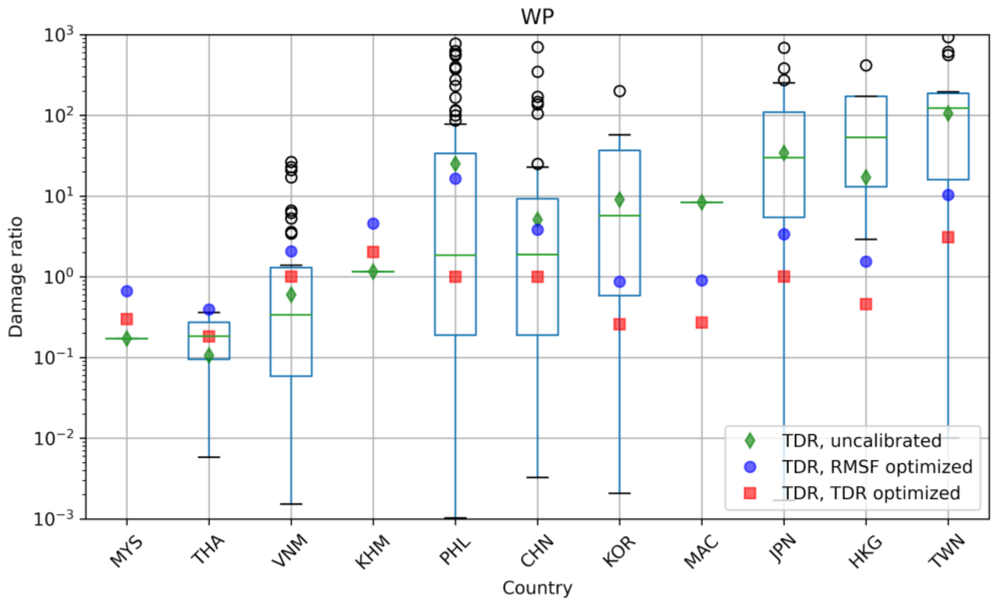


Figure S2d: Spread of event damage ratio (EDR, uncalibrated) and total damage ratio (TDR) per country in the North West Pacific basin (WP). The plots are based on data from 11 countries. The EDR boxplots show the median (green line), the first and third quartiles (IQR, blue box), data points outside the IQR but not more than 1.5·IQR distance from either the first or the third quartile (black whiskers), and outliers (black circles). The additional markers show TDR before calibrated (green diamond) and after calibration (blue circle: RMSF optimized and red squares: TDR optimized).

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3) ADDITIONAL MINOR CHANGES TO REVISED MANUSCRIPT

3.1)
L.489: We realized that the sentence below was incomplete: The windfield by Holland (2008) does not completely neglect surface roughness, simulating 1-minute sustained wind speeds at 10 meter above "clear, flat terrain". What is neglected are variations in surface effects.
L.489: "The wind field model adapted from Holland (2008) does however not take into account **variation in** topography and surface roughness."

3.2)
L. 655 (Acknowledgements): "**We would like to thank Andrew Gettelman and one anonymous referee for their thorough and valuable reviews.**"

3.3)
In addition, some minor changes in spelling, grammar, punctuation, and figure numbers (due to new additional Figure 4) were introduced in the revised manuscript. These changes do not affect the meaning of the text in any way and are not listed here. However, all changes, including new references, are tracked in the revised manuscript attached.

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4) REVISED MANUSCRIPT (MARKED-UP VERSION)

Regional tropical cyclone impact functions for globally consistent risk assessments

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Abstract

Assessing the adverse impacts caused by tropical cyclones has become increasingly important, as both climate change and human coastal development increase the damage potential. In order to assess tropical cyclone risk, direct economic damage is frequently modelled based on hazard intensity, asset exposure and vulnerability, the latter represented by impact functions. In this study, we show that assessing tropical cyclone risk on a global level with one single impact function calibrated for the USA – which is a typical approach in many recent studies – is problematic, biasing the simulated damages by as much as a factor of 36 in the North West Pacific. Thus, tropical cyclone risk assessments should always consider regional differences in vulnerability, too. This study proposes a calibrated model to adequately assess tropical cyclone risk in different regions by fitting regional impact functions based on reported damage data. Applying regional calibrated impact functions within the risk modelling framework CLIMADA at a resolution of 10 km worldwide, we find global annual average direct damage caused by tropical cyclones to range from 51 up to 121 billion USD (current value of 2014, 1980-2017), with the largest uncertainties in the West Pacific basin, where the calibration results are the least robust. To better understand the challenges in the West Pacific and to complement the global perspective of this study, we explore uncertainties and limitations entailed in the modelling setup for the case of the Philippines. While using wind as a proxy for tropical cyclone hazard proves to be a valid approach in general, the case of the Philippines reveals limitations of the model and calibration due to the lack of an explicit representation of sub-perils such as storm surge, torrential rainfall, and landslides. The globally consistent methodology and calibrated regional impact functions are available online as a Python package, ready for application in practical contexts like physical risk disclosure and providing more credible information for climate adaptation studies.

1 Introduction

Tropical cyclones (TCs) are highly destructive natural hazards affecting millions of people each year (Geiger et al., 2018; Guha-Sapir, 2018) and causing annual average direct damages in the order of 29 to 89 US$ billions (Cardona et al., 2014; Gettelman et al., 2017; Guha-Sapir, 2018). Climate change and coastal development could significantly increase the impact of TCs in the future (Gettelman et al., 2017; Mendelsohn et al., 2012). Increasing risks from TCs and other extreme weather events pose a challenge to exposed population and assets, but also to governments and investors as actors in globally connected economies. Governments, companies, and investors increasingly express the need to understand their physical risk under current and future climatic conditions ~~(TCFD, 2017)~~(Bloomberg et al., 2017). Thus, quantitative risk assessments require a globally consistent representation of the economic impact of TCs and other natural hazards.

Probabilistic risk models can provide the quantitative basis for risk assessments and adaptation studies. Since the mid-2000s, there have been increasing scientific efforts in developing and improving global scale natural hazard risk assessments

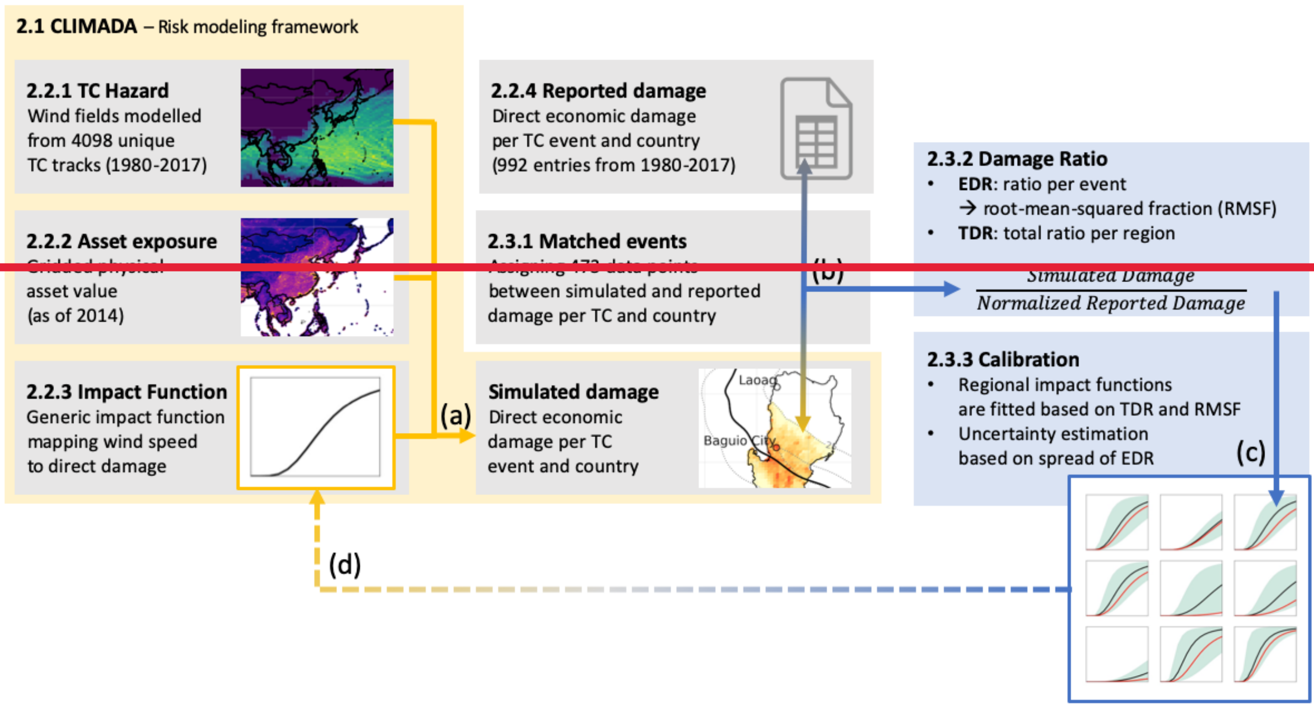
(Cardona et al., 2014; Gettelman et al., 2017; Ward et al., 2020). ~~Natural risk~~Risk from natural hazards is frequently modelled as a function of severity and occurrence frequency, which can be computed by combining information on hazard, exposure, and vulnerability (IPCC, 2014). Global and regional scale TC risk models often represent hazard as the spatial distribution of the maximum sustained surface wind speed per TC event (Aznar-Siguan and Bresch, 2019; Ward et al., 2020). In past studies, wind fields modelled from historical TC tracks were used to assess economic risk in the Global Assessment Report (GAR) 2013 (Cardona et al., 2014; UNDRR, 2013) and to quantify affected population (Geiger et al., 2018), among others. For the assessment of future risk, historical TC records can be complemented with events simulated in downscaling experiments based on the output of global climate models (Gettelman et al., 2017; Korty et al., 2017), or synthetic resampling algorithms (Bloemendaal et al., 2020). The exposure component can be represented by the spatial distribution of people, assets or economic values potentially affected by TCs (Geiger et al., 2018; Ward et al., 2020). For the modelling of direct economic damage, exposure is usually derived from building inventories for local risk assessments (Sealy and Strobl, 2017), or estimated by spatially disaggregating national asset value estimates (De Bono and Mora, 2014; Eberenz et al., 2020; Gettelman et al., 2017).

The vulnerability of an exposed value to a given hazard can be represented by impact functions, also called damage functions or vulnerability curves, relating hazard intensity to impact. Impact functions for the assessment of direct economic damage caused by TCs usually relate wind speed to relative damage (Emanuel, 2011). For the USA, TC impact functions are available specific to different building types (Federal Emergency Management Authority [FEMA], 2010; Yamin et al., 2014), as well as on an aggregate level (Emanuel, 2011). Emanuel (2012) found a lack of sensitivity of simulated TC damage to the exact shape of the impact function for the USA. However, due to global heterogeneities in the tropical cyclone climatology (Schreck et al., 2014), building codes, and other socioeconomic vulnerability factors (Yamin et al., 2014), ~~one~~ it is inadequate to use a single universal impact function ~~might be inappropriate~~ for global TC risk assessments. Bakkensen et al. (2018b) used reported damage data to calibrate TC impact functions for China, highlighting both the potential of this approach and the considerable uncertainties related to the quality of reported damage data. Still, there is a lack of globally consistent and regionally calibrated impact functions. Due to this lack, impact functions calibrated for the USA have been used in a variety of local and regional studies outside the USA, i.e. the Caribbean (Aznar-Siguan and Bresch, 2019; Bertinelli et al., 2016; Ishizawa et al., 2019; Sealy and Strobl, 2017), China (Elliott et al., 2015), and the Philippines (Strobl, 2019). A similar impact function has also been applied for modelling TC damages on a global level (Gettelman et al., 2017). For the GAR 2013, building type specific impact functions from FEMA were assigned to exposure points based on global data based on development level, complexity of urban areas, and regional hazard level at each location (De Bono and Mora, 2014; Yamin et al., 2014). However, the impact functions were not calibrated regionally against reported damage data. Furthermore, the required complexity in exposure data exceeds the scope of many risk assessments.

Can globally consistent TC impact modelling be improved by calibrating the vulnerability component on a regional level? This article addresses this question by calibrating regional TC impact functions in a globally consistent TC impact modelling framework, as implemented within the open-source weather and climate risk assessment platform CLIMADA (Aznar-Siguan and Bresch, 2019). This study contributes to reaching the goal of consistent global TC risk modelling and a better connection of global and regional impact studies. The objectives of this study are to (1) calibrate a global TC impact model by regionalizing the impact function; (2) assess the annual average damage per region and compare the results to past studies; and (3) evaluate the robustness of the calibration and discuss the limitations and uncertainties of both the model setup and the calibration. To inform the discussion of uncertainties, we complement aggregated calibration results (Sect. 3) with an event level case study for the Philippines (Sect. 4). While the attribution of vulnerability to regional drivers is outside the scope of this study, the results can serve as a starting point for further research disentangling the socio-economic and physical drivers determining vulnerability to TC impacts locally and across the globe.

2 Data and Method

To regionally calibrate TC impact functions, simulated damages are compared to reported damages, as illustrated in Figure 1: In a first step, direct economic damage caused by TCs are simulated in the impact modelling framework CLIMADA (Fig. 1a-d, Sect. 2.1 to 2.2.2) with one single default impact function applied globally to start from (Sect. 2.2.3). Then, damage data points per country and storm are assigned to entries of reported damage (Fig. 1e-f, Sect. 2.3.1). For the matched events, the ratio between simulated and reported damage is calculated (Fig. 1g, Sect. 2.3.2). For calibration, countries are clustered into regions and two complementary cost functions are optimized based on the damage ratios, by regionally fitting the slope of the impact function (Fig. 1h, Sect. 2.3.3).



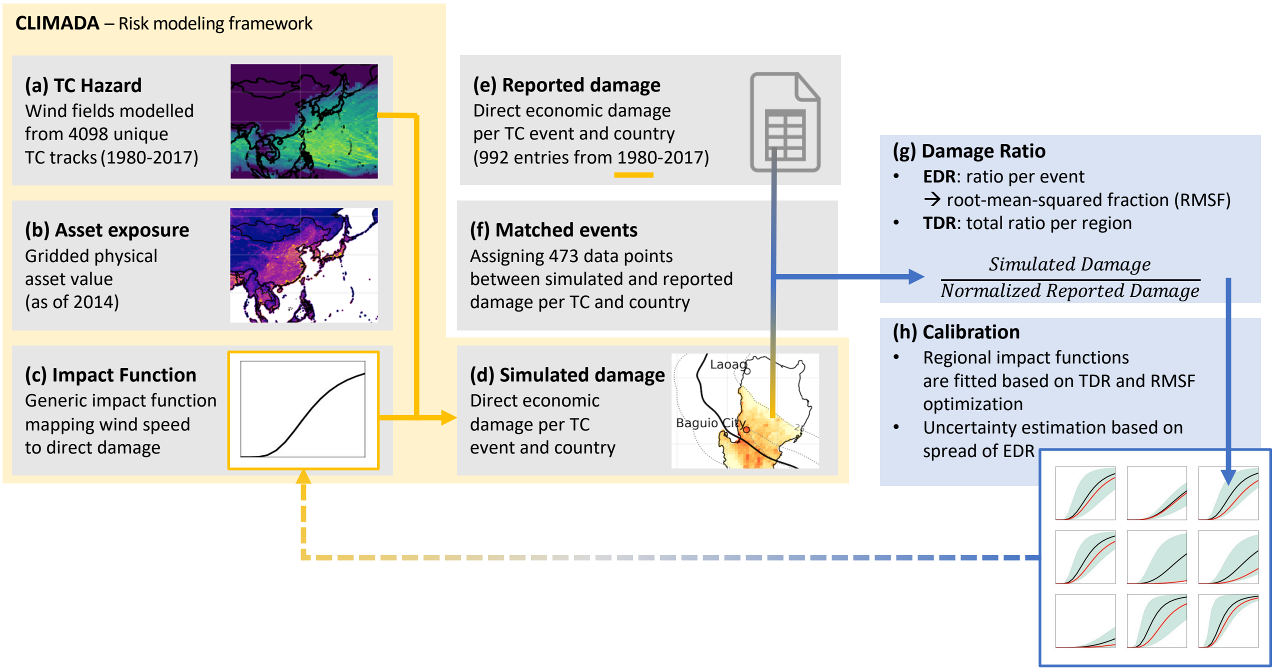


Figure 1: Schematic overview of the data and methods applied to calibrate regional TC impact functions in a globally consistent manner. From left to right: TC event damages are first simulated within the CLIMADA framework based on TC ~~tracks, asset exposure, and a default impact function (a, Sect. 2.1 to 2.2.3). Resulting simulated damages are matched and compared to reported damage data from EM-DAT (b, 2.2.4 to 2.3.2). During calibration, impact modelling and damage comparison are repeated several times for regional impact functions with varied slope (2.3.3). The result is a set of best fitting impact functions for nine world regions (c). Finally, the calibrated impact functions are plugged into CLIMADA (d) to compute annual average damage per region.~~ hazard (a), asset exposure (b), and a default impact function (c), c.f. Sect. 2.1 to 2.2.3. Resulting simulated damages (d) are compared to reported damage data from EM-DAT (e) for 473 matched TC events (f) by means of the damage ratio (g), c.f. Sect. 2.2.4 to 2.3.2. During calibration (h), steps (c) to (g) are repeated several times with varied impact functions for each region, optimizing the cost functions TDR and RMSF (c.f. Sect. 2.3.3) . The result is a set of best fitting impact functions for nine world regions (Sect. 3.2). Finally, the calibrated impact functions are plugged into CLIMADA once more (dashed arrow)to compute annual average damage per region (Sect. 3.3).

2.1 CLIMADA – spatially explicit TC risk modelling

The CLIMADA (CLIMate ADAptation) impact modelling framework has been developed at ETH Zurich as a free, open-source software package (Aznar-Siguan and Bresch, 2019). It is written in Python 3.7 and made available online both on GitHub (Bresch et al., 2019a) and the ETH Data Archive (Bresch et al., 2019b). We use CLIMADA for the pre-processing of hazard and exposure data, and for the spatially explicit computation of direct damage on a global grid at 10 km resolution. The setup ~~does work~~works equally well at higher ~~resolutions~~chosen resolution, but given uncertainties especially in calibration data and computational constraints justify the chose resolution. ~~Simulated~~In the CLIMADA framework, damage is defined as the product of exposed assets and a damage ratio. The damage ratio is an impact function multiplied with hazard intensity.

In our case, damage per TC event and country is ~~computed~~simulated as following: ~~(1)~~ For each grid cell and event, damage is calculated as the product of total exposed asset values and the mean damage ratio. The mean damage ratio (0 to 100%) ~~is determined by~~results from plugging the hazard intensity (maximum sustained wind speed ~~(hazard intensity~~) into ~~an~~the impact function. ~~(2) Absolute~~Finally, damage per ~~grid cell is computed by multiplying the mean damage ratio with the value of exposed assets at the grid cell. (3) The total damage per country and~~ event is ~~computed as the sum~~aggregated over all grid cells within the country. Please refer to Sect. 2.1 and 2.2.3 in Aznar-Siguan and Bresch (2019) for a more detailed description of impact calculation.

2.2 Data

2.2.1 TC Hazard

TCs typically inflict damage due to strong sustained surface winds, storm surge inundation, and torrential rain (Bakkensen et al., 2018a; Baradaranshoraka et al., 2017; Park et al., 2013). Next to maximum wind speed, storm size is an important factor controlling TC impacts (Czajkowski and Done, 2013). Since the severity of surge and rain are to a certain extend correlated to wind speed and storm size (Czajkowski and Done, 2013), the latter are often taken as a proxy hazard intensity (Emanuel, 2011; Gettelman et al., 2017).

Here, TC hazard intensity is represented by wind fields, i.e. the geographical distribution of the 1-min sustained wind speed per TC event, referred to as "wind speed" or "hazard intensity" in the following. We model wind speed at a horizontal resolution of 10 x 10 km from historical TC tracks as a function of time, location, radius of maximum winds, and central and environmental pressure, based on the revised hurricane pressure-wind model by Holland (2008). Please also refer to Geiger et al. (2018) for a detailed description and illustration of the wind field model and its limitations.

Historical TC tracks were obtained from the International Best Track Archive for Climate Stewardship (IBTrACS) (Knapp et al., 2010). As data quality and global coverage improved after approximately 1980 (Geiger et al., 2018), we selected and processed 4'098 historical TC tracks from 1980 to 2017 based on data completeness criteria with regards to data fields provided within IBTrACS, following the approach described by Geiger et al. (2018) and Aznar-Siguan and Bresch (2019). Out of the 4'098 TCs, we identified 1'538 landfalling events with the potential of causing damage. Potential damage is given if at least one grid cell of a TCs wind field with an intensity of 25.7 ms^{-1} (~50 knots) or more coincides with an asset exposure value larger than zero. A worldmap showing the maximum intensity per grid cell for all tracks is shown in the Supplement (Fig. S1).

2.2.2 Asset exposure

Asset exposure for the assessment of direct economic risk is represented by the spatially explicit monetary value potentially impacted by a disaster. Here, we use gridded asset exposure value at a resolution of 10 km x 10 km. The dataset is based on the disaggregation of national estimates of total asset value (TAV, Table A3) proportional to the product of nightlight intensity and population count (Eberenz et al., 2020). Following the approach in GAR 2013 (De Bono and Mora, 2014), the TAV per country is represented by produced capital stock of 2014 from the World Bank Wealth Accounting (World Bank, 2019a). Out of the 62 countries used for calibration, 32 come with produced capital estimates. For the remaining 30, an estimate of non-financial wealth is used as a fall back (Eberenz et al., 2020), based on GDP of 2014 from the World Bank Open Data portal (World Bank, 2019b) combined with an GDP-to-wealth factor from the Global Wealth Report (Credit Suisse Research Institute, 2017). The asset exposure dataset utilized here and a detailed overview over limitations and data availability per country is documented in Eberenz et al. (2020).

2.2.3 Impact Function

In CLIMADA, vulnerability is represented by impact functions. They are used to compute damage for each TC event at each exposed location by relating hazard intensity to relative impact. Since no ~~impact~~directly wind induced damage is expected for low wind speeds, TC impact functions for the spatial explicit modelling of direct damages can be ~~constraint~~constrained by a minimum threshold V_{thresh} for the occurrence of impacts and an upper bound of a 100% direct damage (Emanuel, 2011).

Empirical studies suggest a high power-law function for the slope, i.e. the increase of damage with wind speed (Pielke, 2007). An idealized sigmoidal impact function satisfying these constraints was proposed by Emanuel (2011):

$$f = \frac{v_n^3}{1+v_n^3} \quad \text{, with} \qquad v_n = \frac{MAX[(V - V_{thresh}), 0]}{V_{half} - V_{thresh}} \qquad \text{(Equation 1)}$$

Equation 1 defines the impact function f as a function of wind speed V. The function takes two shape parameters as inputs: V_{thresh} and V_{half}. A lower threshold V_{thresh} of 25.7 ms^{-1} (50 kn) was proposed for the USA by Emanuel (2011) and empirically supported for China (Elliott et al., 2015). The slope parameter V_{half} signifies the wind speed at which the function's slope is the steepest and a damage ratio of 50% is reached (Fig. 2). It should be noted that the effects of varying V_{thresh} and V_{half} on resulting impacts are not linearly independent.

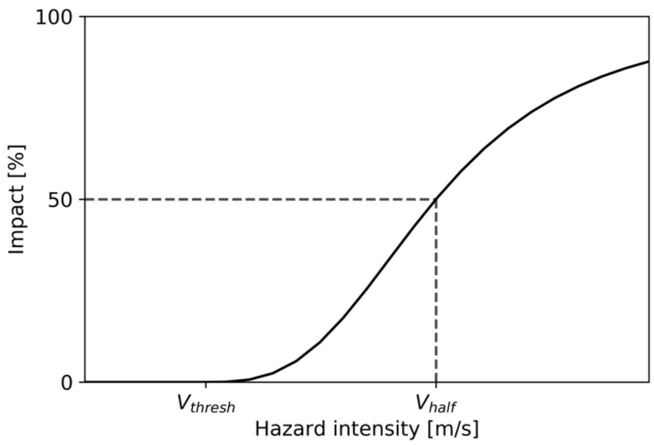


Figure 2: Idealized TC impact function based on Emanuel (2011). V_{half} is the hazard intensity (i.e. maximum sustained wind speed) at which the relative impact reaches 50% of the exposed asset value. No impact occurs for an intensity below V_{thresh}.

Based on the reference data provided by FEMA (2010), V_{half} for damage to buildings can range from 52 to 89 ms^{-1} depending on building type and surface roughness (Elliott et al., 2015). Applying FEMA impact functions that were verified with reported damage data for US Hurricanes Andrew [1992], Eric [1995], and Fran [1996], Sealy and Strobl (2017) estimated V_{half} to range from 71.7 to 77.8 ms^{-1}, depending on building type, with a mean value of 74.7 ms^{-1}.

~~We define a default impact function with V_{thresh} = 25.7 ms^{-1} and V_{half} = 74.7 ms^{-1} that is used for a first, uncalibrated, simulation of global TC damages, and as a starting point for calibration. While V_{half} is fitted during the calibration process, we keep the lower threshold V_{thresh} constant throughout the study.~~

In a comparison of calibration results based on a sigmoidal impact function with a more complex 12-step staircase function, Lüthi (2019) found no improvement of calibration skill with the more complex function. Therefore, we use the sigmoidal function in this study. We define a default impact function with V_{thresh} = 25.7 ms^{-1} and V_{half} = 74.7 ms^{-1} that is used for a first, uncalibrated, simulation of global TC damages, and as a starting point for calibration. While V_{half} is fitted during the calibration process, we keep the lower threshold V_{thresh} constant throughout the study. This is based on the finding by Lüthi (2019) that the variation of more than one of the linearly dependent parameters most likely results in an overfitting during calibration, with physically implausible values for V_{thresh} in some world regions.

Since we are not looking at single buildings but at a grid with a resolution of 10 km by 10 km, we don't necessarily expect full damage to occur to all buildings in a grid cell. However, the wind-speed dependent impact function is also implicitly accounting for the damage caused by storm surge and torrential rain, when calibrated against reported damage data. For these two reasons, we allow for values of V_{half} lower and larger than the literature range for pure wind induced building damage in the calibration. By varying V_{half} with $V_{half} > V_{thresh}$, we are looking for the functional slope best fit to simulate the direct economic damage of TCs in regional clusters of countries for a regional calibration of the impact function (Sect. 2.3.3).

2.2.4 Reported damage data

Reported damage data for historical TC events are required on a global level to calibrate TC impact functions. ~~Damage~~Reported damage estimates ~~from natural catastrophes are records~~for disasters worldwide are available from the International Disaster Database EM-DAT (Guha-Sapir, 2018). EM-DAT provides ~~global~~ data ~~on natural~~per event and ~~technological disasters~~country, including disaster type and subtype, date of the event, and impact ~~data at the country level~~estimates. The main data sources of EM-DAT are UN agencies, governmental and non-governmental agencies, reinsurance companies, research institutes, and the press.

EM-DAT provides one entry per country and event. Therefore, one meteorological TC can be listed in EM-DAT several times, with one entry for each country affected. In the following, each of these entries per storm and country will be referred to as single ‘TC events’. For instance, Hurricane Irma comes with 17 events in EM-DAT (Disaster no. 2017-0381), as it impacted 16 Caribbean countries and the USA. From 1980 to 2017, there are 1650 TC events reported in EM-DAT of which 991 come with a reported monetary damage value.

The EM-DAT database provides total damage per event and country in current USD. In contrast, the asset exposure data used for the modelling of damage is kept fixed at a current USD value of 2014 (Sect. 2.3). To allow for a comparison of reported and simulated damages that is independent of economic development, reported damage values need to be normalized to a reference year. For instance, Weinkle et al. (2018) applied two normalization methodologies for hurricane damage in the continental USA 1900-2017, adjusting reported impact for inflation, per-capita wealth, and the population of affected counties (Collins and Lowe, 2001; Pielke et al., 2008). Due to a lack of global time series of wealth data, we apply a GDP scaling for normalization. This is based on a less prerequisite approach applied in Munich Re’s NatCat, where recorded damages are normalized proportional to regionalized GDP (Munich Re, 2018). This normalization approach assumes that timeseries in current GDP serve as a first order approximation of economic development, implicitly accounting for inflation, changes in wealth per capita and population. To obtain estimates of normalized reported damage per event *E*, reported damage (RD) is scaled proportional to the affected country’s change in GDP between the year of occurrence *y* and the year 2014:

$$NRD_E = RD_E * \frac{GDP_{2014}}{GDP_y} \qquad \text{(Equation 2)}$$

We found that GDP scaling removes the significant positive trend from the yearly impacts in the USA (p-values of 0.04 before and 0.14 after normalization). This is in agreement with the findings of existing normalization studies for past TC impacts in the USA (Pielke et al., 2008; Weinkle et al., 2018).

2.3 Methods

2.3.1 Event Matching: Assigning reported damage data to simulated TC events

For the comparison of simulated and reported TC damage, reported events from EM-DAT per TC and country need to be assigned to TC tracks from IBTrACS. Tracks were matched based on the country affected and timestamps (Lüthi, 2019): (1) In a first step, the impacted countries per TC track is determined, i.e. in which countries a storm does make landfall. (2) Subsequently, the best fitting tracks are assigned to the reported events, based on an iterative comparison of start dates provided in the datasets. Given that countries are hit by several TCs in a relatively short time, the assignment certainty varies. Finally, (3) tracks with a low assignment certainty are double checked manually for removal or re-assigning.
In total, we matched 848 EM-DAT events to their respective tracks. These events account for 913 billion USD reported economic damages out of the total 959 billion USD from the 991 EM-DAT events (95%). For 534 of the 848 assigned events, there is an economic damage larger than zero simulated in CLIMADA with the respective TC track. Generally, we found the difference between simulated and reported damage per matched event to span several orders of magnitude. Extreme outliers are likely to be associated either to a mismatch or flawed values of reported damage. Therefore, we exclude 61 extreme outliers from calibration, i.e. all events that come with a deviation of more than factor 1’000 between normalized reported damage and damage simulated with the default impact function.
Eventually, a total of 473 assigned events remain for analysis, referred to as ‘matched events’ in the following. These matched events, representing damage per TC and country, are based on 376 TC tracks making landfall in 53 countries (One TC can make landfall in several countries). The total reported damage from these 473 matched events accounts to 91% of the sum of all TC-related reported damages from 1980 to 2017 in EM-DAT (76% after normalization). Damage simulated for the 376 TCs with the default impact function amount to 58% of the total global simulated damage from all 4’098 TC tracks.

2.3.2 Damage Ratios: EDR and TDR

For the analysis of regional differences in TC vulnerability, event damages are simulated with CLIMADA for all matched events with the default impact function (Sect. 2.4). The event damage ratio (EDR) is computed per matched event *E* as the ratio of simulated event damage (SED) over normalized reported damage (NRD):

$$EDR_E = \frac{SED_E}{NRD_E} \qquad \text{(Equation 3)}$$

An EDR of 1.0 indicates a perfect fit between SED and NRD. An EDR greater (smaller) than 1.0 indicates an overestimation (underestimation) of the simulations as compared to reports. As there are considerable deviations between the distribution of EDRs between countries, the median of EDR per country is used to define calibration regions in Sect. 2.3.3.
To compare the aggregated damage on a global or regional level, we use total damage ratio (TDR) defined as the sum of simulated damages divided by the sum of normalized reported damages:

$$TDR_R = \frac{\sum_{E=1}^{N} SED_E}{\sum_{E=1}^{N} NRD_E} \qquad \text{(Equation 4)}$$

Where *N* is the number of matched events *E* in a region *R*.
The distribution of EDR and TDR before calibration as well as TDR after calibration is shown per region in Figures 6 and S4 and per country in the supplementary Figure S2.

2.3.3 Calibration of regional impact functions

As a first step towards regional calibration of the TC impact model, distinct calibration regions were defined based on three criteria regarding (1) geography, (2) data availability, and (3) patterns in damage ratios before calibration: (1) We clustered countries by hemispheric ocean basins. This results in five high level regions: North Atlantic and East Pacific oceans (NA), North Indian Ocean (NI), Oceania (OC), South Indian Ocean (SI), and North West Pacific (WP). This first geographical separation is applied to account for differences in TC characteristics and data sources between the ocean basins (Schreck et al., 2014). The five basins are then subdivided based on (2) a minimum desired number of 30 data points (matched TC events) per region; and (3) the median EDR per country. Applying criteria 2, three countries come with a sufficient amount of data points to be calibrated for themselves: China (N=69), the Philippines (N=83), and the USA (N=43, including three events in Canada). Applying criterion 3, the remaining countries in WP are further subdivided into two regions: South East Asia with median EDR<1.2 and the rest of the North West Pacific with EDR>5 (see Fig S2d in the Supplement). In summary, the nine calibration regions are the Caribbean with Central America and Mexico (NA1), the USA and Canada (NA2), North Indian Ocean (NI), Oceania with Australia (OC), South Indian Ocean without Australia (SI), South East Asia (WP1), the Philippines (WP2), China mainland (WP3), and the North West Pacific (WP4) (see Fig. 3 and Table A1).

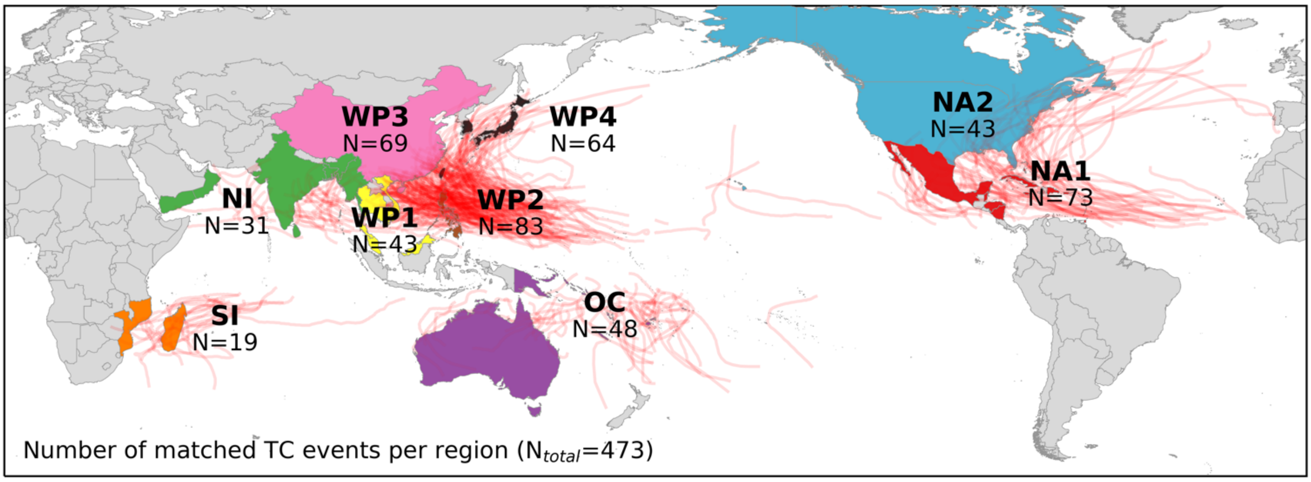


Figure 3: World map highlighting the 53 countries used for calibration, color coded per calibration region. The tracks of 376 TCs used for calibration are plotted as red lines. The number of resulting matched events N is displayed per region. Regions by color: red: the Caribbean with Central America and Mexico (NA1); blue: the USA and Canada (NA2); green: North Indian Ocean (NI); purple: Oceania with Australia (OC); orange: South Indian Ocean (SI); yellow: South East Asia (WP1), brown: the Philippines (WP2), rose: China Mainland (WP3); black: rest of North West Pacific Ocean (WP4). The countries per region are listed in Table A1.

Regional impact functions are calibrated following two complementary approaches, based on (1) minimizing the spread of EDR and (2) the optimization of TDR. For the first calibration approach, the root-mean-squared fraction (RMSF) is introduced as a cost function:

$$RMSF = exp\left(\sqrt{\frac{1}{N}\sum_{E=1}^{N}[\ln{(EDR_E)}]^2}\right) \qquad \text{(Equation 5)}$$

Input variables are the number of events *N* and the natural logarithm of EDR (c.f. Eq. 3). The RMSF is am measure of the spread in EDR, i.e. the relative deviation between modelled and reported damage for all matched events in a region. In the computation of RMSF, each event *E* has the same weight, independent of the absolute damage values. The natural logarithm ensures that an overestimation is penalized the same as an underestimation. RMSF is optimized by identifying the impact function associated to the lowest value of RMSF. A value of 1 would indicate perfect fit of all events. For the second calibration approach, TDR is optimized. A TDR larger than 1 implies that the summed simulated damage exceeds the reported values and vice versa. Therefore, TDR is optimized by identifying the impact function associated to a TDR as close to 1 as possible. As TDR is a ratio of damage aggregated over several events, the TDR approach is biased towards better representing events with large absolute damage values. In both calibration approaches, the slope of the generic impact function (Fig. 2) is calibrated by fitting the parameter V_{half} in Equation 1. An increase in V_{half} corresponds to a flattening of the function and thus lower resulting simulated damage (c.f. Fig. 2). For the fitting of V_{half}, damage is simulated for all matched events and an array of V_{half} ranging from 25.8 ms^{-1} to 325.7 ms^{-1} in increments of 0.1 ms^{-1}. For each increment, EDR is computed for all matched events. Consequently, the values of the cost functions RMSF and TDR are computed for each region and increment of V_{half}. Subsequently, the value of V_{half} associated to optimal results for each cost function is identified. V_{half} optimized per region is used to calculate fitted impact functions per region. The calibrated impact functions are used to compute the annual average damage (AAD) per region, allowing for the comparison of results with other studies in Section 3.3.

3 Results

3.1 Damage ratio with default impact function

The comparison of TC damage simulated globally with a default impact function (Eq. 1 with V_{half} = 74.7 ms^{-1}) reveals (1) inter-regional differences and (2) considerable uncertainties in CLIMADA's ability to reproduce the reported damage values per event. The distribution of uncalibrated EDR per region is shown in Figure 4. EDR per matched event is shown in Figure A1, the distribution of EDR per country is shown in Figure S2 in the Supplement.

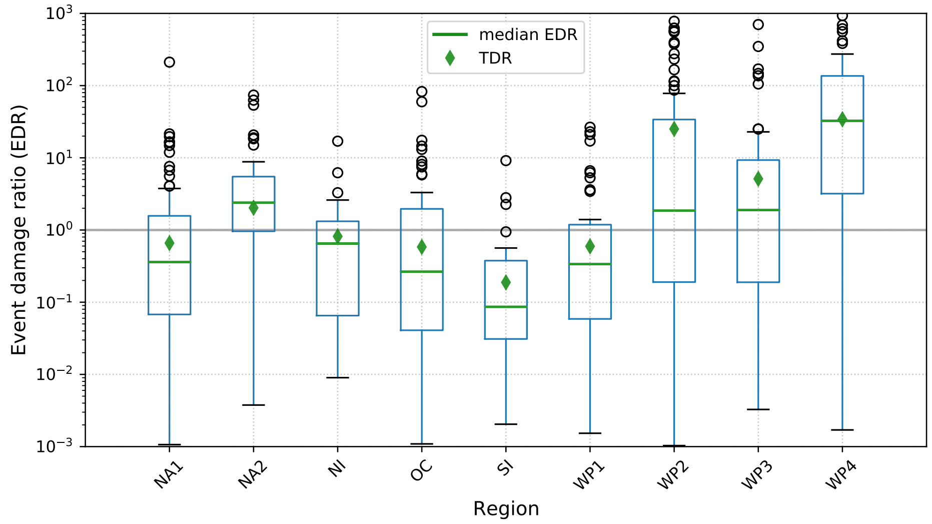


Figure 4: Spread of event damage ratio (EDR, boxplot) and total damage ratio (TDR) per region before calibration (V_{half}=74.7 ms^{-1}) per region. The plots are based on data from 473 TC events affecting 53 countries. The EDR boxplots show the median (green line), the first and third quartiles (IQR, blue box), data points outside the IQR but not more than 1.5·IQR distance from either the first or the third quartile (black whiskers), and outliers (black circles). The additional markers show TDR before calibrated (green diamond). The regions are the Caribbean with Central America and Mexico (NA1); the USA and Canada (NA2); North Indian Ocean (NI); Oceania with Australia (OC); South Indian Ocean (SI); South East Asia (WP1), the Philippines (WP2), China Mainland (WP3); rest of North West Pacific Ocean (WP4).

3.1.1 Inter-regional differences

Both ~~RMSF (Fig. 5b) and~~ the ratios EDR ~~(Fig. A1)~~ and the cost functions RMSF and TDR ~~(Fig. 5c), indicating~~show inter-regional differences with regard to the deviation of the damages simulated with the default impact function from reported damages~~, show inter-regional differences.~~ (Fig. 4 and 6). For most regions, ~~TDR is~~total simulated and normalized reported damage deviates less than one order of magnitude ~~different from one.~~(Table A2). The outliers are the regions WP4 (TDR=35.6; Hongkong, Japan, Macao, South Korea, Taiwan) and WP2 (TDR=25.9; the Philippines). For those two regions, the large value of TDR reveals a mean overestimation of simulated damage as compared to reported damage. In regions with TDR<1, the uncalibrated model potentially underestimates the damages caused by TCs. These regions are~~ in~~ the Indian Ocean (SI and NI), South East Asia (WP1), Oceania with Australia (OC), and the Caribbean (NA1). The region SI (Madagascar and Mozambique) shows the overall lowest TDR of 0.2, indicating an underestimation of damages by a factor of 5.

3.~~2~~1.2 Intra-regional uncertainties

The EDR values within ~~regions~~each region show a large spread over several orders of magnitudes (Fig ~~A1).~~4). There is no significant correlation between EDR and NRD (Fig. A3), suggesting that the over- and underestimation of simulated event damages is not related to TC severity. The largest spread, as expressed by the RMSF, can again be found in the regions WP4 and WP2 (Fig. ~~5c~~6c). The lowest RMSF was found for the regions NI, NA2, and NA1, i.e. the North Indian and North Atlantic basins. While the large inter-regional differences show the need for a regional calibration of impact functions, the spread of EDR within some regions point towards uncertainties and limitations of the modelling setup that will not be removed by calibrating the impact function alone.

3.2 Regional impact functions

We calibrated regional impact functions to address inter-regional differences in TDR. The resulting impact functions calibrated with two complementary approaches are shown in Figure 45. The resulting impact functions vary between the regions, both in slope and level of uncertainty, with V_{half} ranging from 46.8 to 190.5 ms^{-1} (Fig. ~~5a~~6a and Table A2). Additional to the regional impact functions, global impact functions were fitted based on all 473 data points combined, resulting in V_{half} ranging from 73.4 (RMSF optimization, i.e. RMSF=min.) to 110.1 ms^{-1} (TDR optimization, i.e. TDR=1). Applying the regional impact functions, TDR calculated for all regions combined is 4.7 for the default impact function and 2.2 for the RMSF optimized impact functions (Fig. ~~5b~~6b). With the calibration based on TDR optimization, the bias in aggregated simulated damages can be removed, i.e. an impact function is fitted that leads to TDR=1. This does not mean that the simulated damage of each single event is equal to the reported damage. In fact, there is a large spread in the values of V_{half} that would fit best for individual events. This uncertainty is visualized by the interquartile range of the array of impact functions fitted to the individual events per region (shading in ~~Figure 4~~Fig. 5). For the individual fitting per event, the value of V_{half} is determined by what would be required to obtain an EDR equal to 1. ~~Plots~~The sensitivity of TDR and RMSF per region ~~as functions of~~ to changes in V_{half} ~~are provided~~is visualized in the Supplement~~.~~: Regions with a large uncertainty, i.e. a large spread of EDR, generally show a relatively low robustness of the cost functions (Fig. S3). On a globally aggregated level, calibration reduces the spread of EDR to a certain degree, placing more than half of events in the EDR range from 10^{-1} to 10.

The comparison of complementary calibration approaches gives an indication of the robustness of the calibration per region. In all regions, the calibrated impact functions based on both approaches lie within the interquartile range of the individually fitted curves (Fig. 45). However, the difference between V_{half} for the two approaches ranges from 3 ms^{-1} (region NA2) to 104 ms^{-1} (WP2). The largest uncertainties were found in the fitting of V_{half} for regions WP2-4 in the North West Pacific. In these regions, the TDR optimization fits values of V_{half} that are much larger than for the RMSF optimization (Fig. ~~5a~~6a). This corresponds to rather flat impact functions as shown in the bottom row of Figure 45. Since TDR gives larger weight to events with large damage values, these results indicate that these events are systematically overestimated by the model in the regions WP2-4. The flat calibrated impact functions partly compensate this overestimation. As a further indication of large uncertainties, TDR optimization in these three regions returns RMSF values that are larger than with the uncalibrated impact function (Fig. ~~5c~~6c). Possible reasons for the uncertainties in the model are explored in a case study for the Philippines in Sect. 4 and further discussed in Sect. 5.

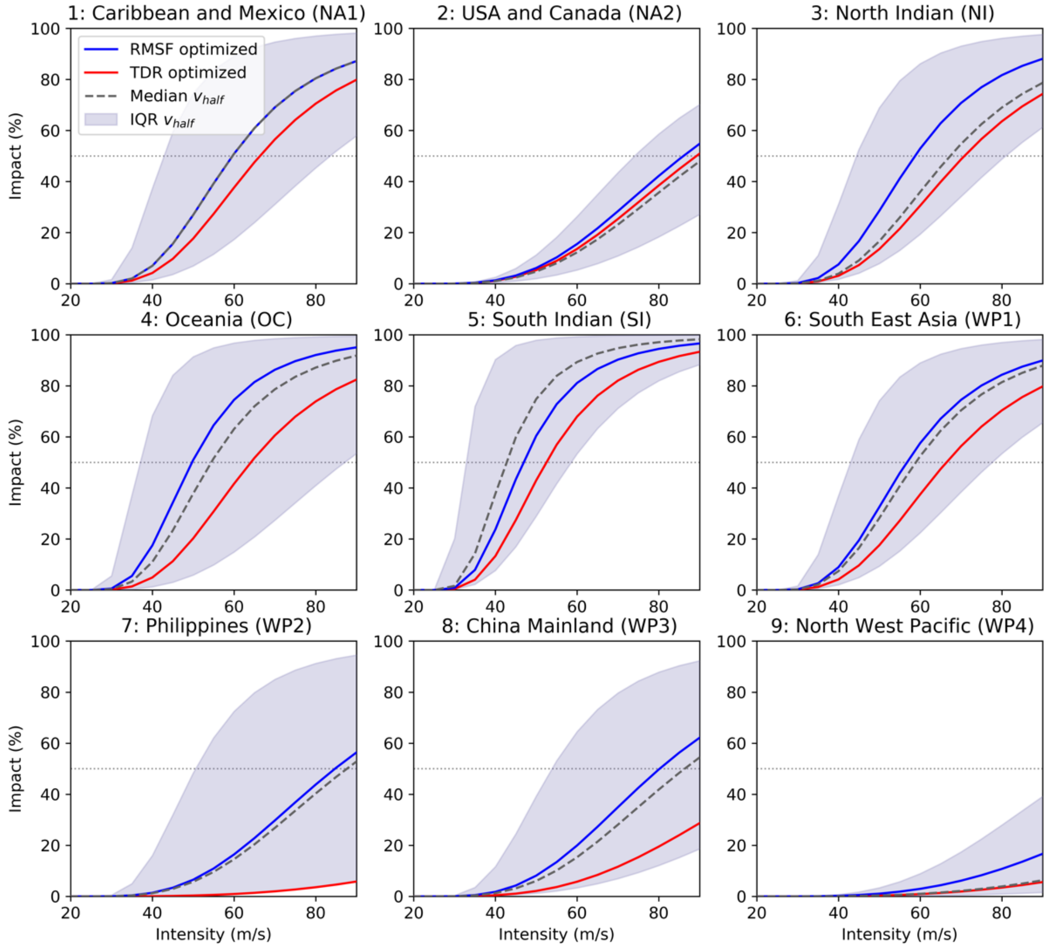


Figure 45: Regional impact functions for nine calibration regions, based on complementary calibration approaches: RMSF optimized (blue), TDR optimized (red), and the median V_{half} obtained from fitting impact functions for each individual event to obtain an EDR of 1 (dashed). The shading demarcates the range containing 50% of the individually fitted impact functions per region, i.e. the interquartile range (IQR).

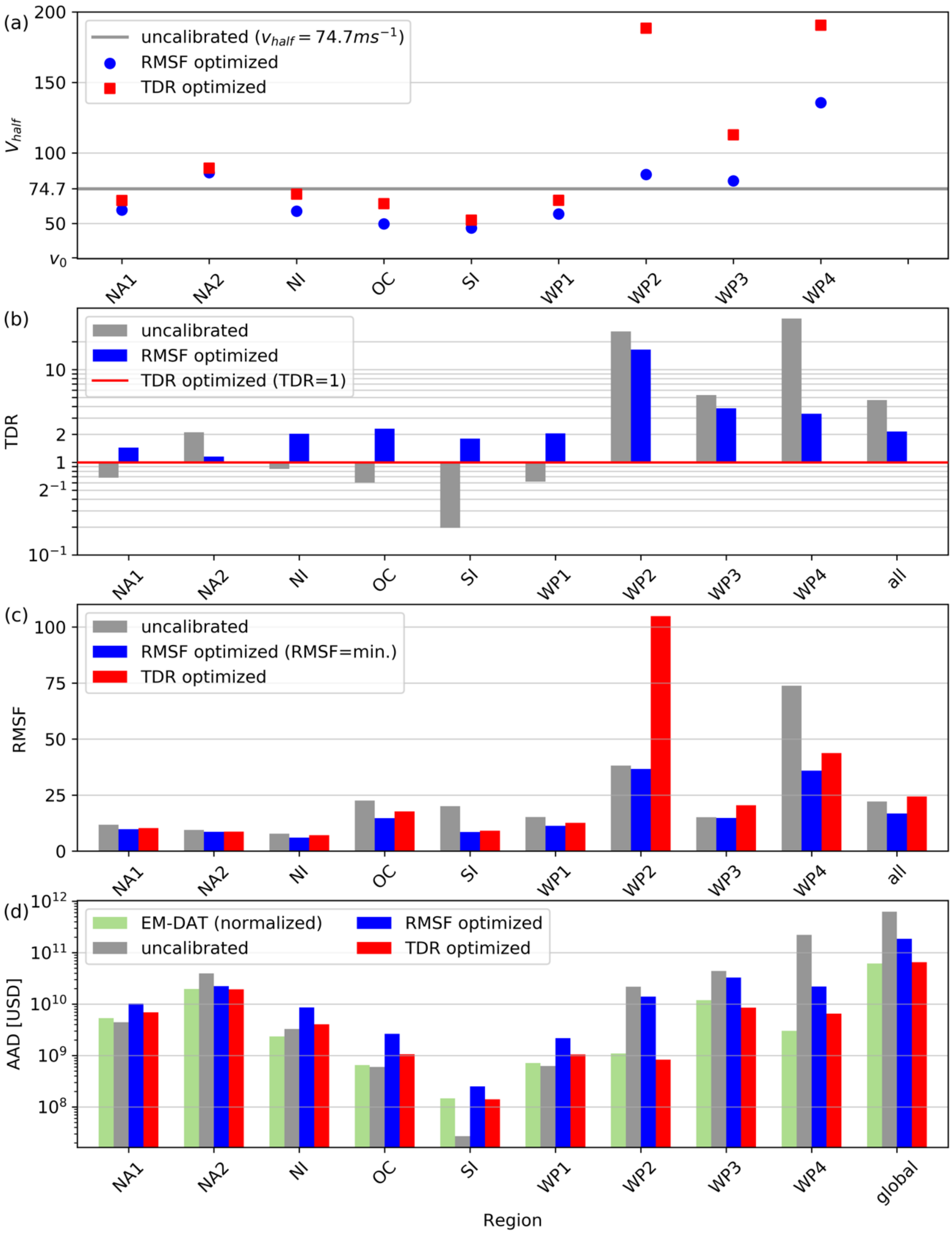


Figure ~~5~~6: Calibration results and cost functions for nine calibration regions and all regions combined~~.~~, each shown before (grey) and after calibration (blue and red): (a) V_{half}: fitted impact function parameter; (b) TDR: ratio of total simulated and normalized reported damage; (c) RMSF: root-mean-squared fraction; and (d) AAD: normalized reported (green) and simulated annual expected damage~~.~~ (AAD). AAD is computed from all events available in EM-DAT (N=1650, green) and IBTrACS (N=4098), not just the 473 matched events used for calibration (a-c). Please refer to Tables 1 and A2 for numerical values. The regions are the Caribbean with Central America and Mexico (NA1); the USA and Canada (NA2); North Indian Ocean (NI); Oceania with Australia (OC); South Indian Ocean (SI); South East Asia (WP1), the Philippines (WP2), China Mainland (WP3); rest of North West Pacific Ocean (WP4).

3.3 Annual average damage AAD

Despite considerable interannual variability of TC occurrence and impacts, AAD is often used as a reference value for the mean risk per country or region. Here, we compare AAD computed with the regionalized TC impact model to values from EM-DAT and literature (Table 1). AAD from EM-DAT represents values normalized to 2014, based on all 991 damaging events reported in the database from 1980-2017. Based on the calibrated impact functions, direct damage is simulated based on the full set of TC tracks (N=4'096) and all countries. AAD values per country are provided in the Supplement. The computation of global AAD considers all countries, not only those used for calibration. Thereby, the regionally calibrated impact functions are used for other countries in the same region (c.f. Table A1). AAD in countries not attributed to any region is calculated with impact functions calibrated globally. The resulting AAD for the calibration regions and the global aggregate are shown in Figure ~~5d~~6d and Table 1. The standard deviation of AAD is generally of the same order of magnitude as AAD (Table 1).

For the years 1980 to 2017, we find aggregated global AAD to range from 51 up to 121 billion USD (current value of 2014). In comparison, global AAD from EM-DAT is 46 billion USD. Values from GAR 2013 and Gettelman (2017) range from 67.0 to 88.9 billion USD. It should be noted, however, that the two studies consider different time periods than our study (1950 to 2010 and 1979 to 2012, respectively), as well as deviant TAVs per country. Global TAV for 224 countries aggregates to 251 trillion USD, as compared to 156 trillion USD in Gettelman et al. (2017) and only 96 trillion USD in GAR 2013 (Table 1). Therefore, the comparison of AAD relative to TAV is a better measure to compare the results of the three studies. Relative to TAV, simulated global AAD amounts to 0.2-0.5‰ in our calibrated model, as compared to 0.4-0.5‰ in Gettelman et al. (2017) and 0.9‰ in GAR 2013 (Table 1).

The aggregated region with the largest simulated AAD is East Asia (WP, 17-71 billion USD), followed by the USA with 19-22 billion USD and the North Indian Ocean with 4-9 billion USD. The regions WP2 and WP4 show the largest discrepancy in AAD simulated with the two alternative calibrated impact functions. This is consistent with the large uncertainties found for these regions during calibration (Sect. 3.1 and 3.2). In the most southern regions NI, SI, OC, and WP1, simulated relative AAD is consistently larger than in GAR 2013. This indicates that the calibration corrects for a systematic underestimation of TC vulnerability in these regions. For the Philippines (WP2), the largest AAD relative to TAV was simulated (22.3‰ with the RMSF optimized impact function). While the damage estimates simulated for WP2 come with large uncertainties, the range of relative AAD (1.3-22.3‰) entails the 11.0‰ for the Philippines in GAR 2013. The case of the Philippines will be further analyzed and discussed in the following Sect. 4.

Table 1: Annual average damage (AAD) from calibrated CLIMADA, as well as AAD from EM-DAT (normalized to 2014), GAR 2013 and Gettelman et al. (2017). Total AAD and the standard deviation of annual damage (in brackets) per region is given in current billion USD ($B). AAD relative to total asset value (TAV, c.f. Table A3) is provided in permille (‰). TAV values per region and study are reported in Table A3. Please note that both GAR 2013 and Gettelman et al. (2017) included synthetic TC tracks in their analysis, which are based on historical tracks. The last row (world) considers all countries. AAD values by country are provided in the Supplement.
***) USA and Bermuda, without Canada.**

Region	AAD EM-DAT	AAD Calibrated CLIMADA: RMSF optimized		AAD Calibrated CLIMADA: TDR optimized		AAD GAR 2013		AAD Gettelman et al. (2017)	
	$B (2014)	*$B (2014)*	*‰ of TAV*	*$B (2014)*	*‰ of TAV*	*$B (2005)*	*‰ of TAV*	*$B (2015)*	*‰ of TAV*
NA1	5.3 (14.2)	10.3 (16.1)	*2.2*	6.9 (11.7)	*1.5*	4.6	*2.1*	9.5 (17.8)	*0.3-1.1*
NA2	19.7 (43.1)	22.4 (32.5)	*0.4*	19.4 (28.2)	*0.3*	11.8	*0.5*	11.0 (15.5)	*0.2**
NI	2.3 (3.8)	8.6 (13.9)	*1.4*	4.1 (6.7)	*0.6*	0.3	*0.2*		
OC	0.7 (0.8)	2.6 (3.6)	*0.4*	1.1 (1.6)	*0.2*	0.1	*0.1*		
SI	0.1 (0.3)	0.3 (0.6)	*5.7*	0.1 (0.4)	*3.2*	0.0	*2.8*		
WP1	0.7 (1.2)	2.2 (3.4)	*1.0*	1.1 (1.6)	*0.5*	0.0	*0.0*		
WP2	1.1 (1.8)	14.0 (34.6)	*22.3*	0.8 (2.3)	*1.3*	2.0	*11.0*		
WP3	11.9 (14.8)	32.9 (39.4)	*1.0*	8.6 (10.3)	*0.3*	9.0	*2.0*		
WP4	3.0 (4.0)	21.9 (24.3)	*0.8*	6.6 (7.3)	*0.2*	60.0	*3.1*		
Σ WP	16.8	71.0	*1.2*	17.0	*0.3*	71.1	*2.8*	61.4 (53.8)	*0.9-1.0*
Σ all	45.0 (54.8)	115.2 (72.4)	*0.8*	48.6 (33.2)	*0.3*	87.9	*1.6*		
World	**46.3 (55.6)**	**120.9 (73.9)**	***0.5***	**50.6 (33.6)**	***0.2***	**88.9**	***0.9***	**84.6 (63.9)**	***0.4-0.5***

4. Explorative case study: the Philippines

For a better understanding of the uncertainties involved in the TC impact function calibration, we exploratively examine simulated and reported damages of matched events in the Philippines (region WP2). The Philippines is the region with the least robust calibration results, with a large spread in EDR and the largest discrepancy between the two calibration approaches: The difference in V_{half} between the two calibration approaches exceeds 100 ms^{-1} (Fig. ~~5a~~6a). Consequently, there is a large spread in simulated AAD, ranging from 0.8 to 14 billion USD (Table 1). This corresponds to an underestimation of annual risk by 0.3 billion USD up to an overestimation by 21.2 billion USD as compared to normalized values from EM-DAT with an AAD of 1.1 billion USD.

The goal of this explorative case study is to better understand what drives these uncertainties in the TC impact model within the region, discuss the limitations of the calibrated model, and identify points for improvement for the future development of global TC impact models. Thereby, we assess the following hypotheses: (1) Potential differences between urban and rural exposures and vulnerabilities as considered in the GAR 2013 (De Bono and Mora, 2014) are not fully resolved in the model. (2) The simplified representation of the TC hazard intensity with wind speed alone is not capable to adequately model the impact of TCs with over-proportional damage caused by sub-perils like storm surge and torrential rainfall (Baradaranshoraka et al., 2017; Park et al., 2013). In the following, we explore these hypotheses by the example of 83 matched TC events in the Philippines, while keeping in mind that the model setup is not designed to represent single events perfectly, due to the large inherent stochastic uncertainty. To explore these hypotheses, we review reports and literature on TC impacts in the Philippines, and examine the relationship between EDR per event with the spatial distribution of the wind field and subsequent simulated damages associated to each single event.

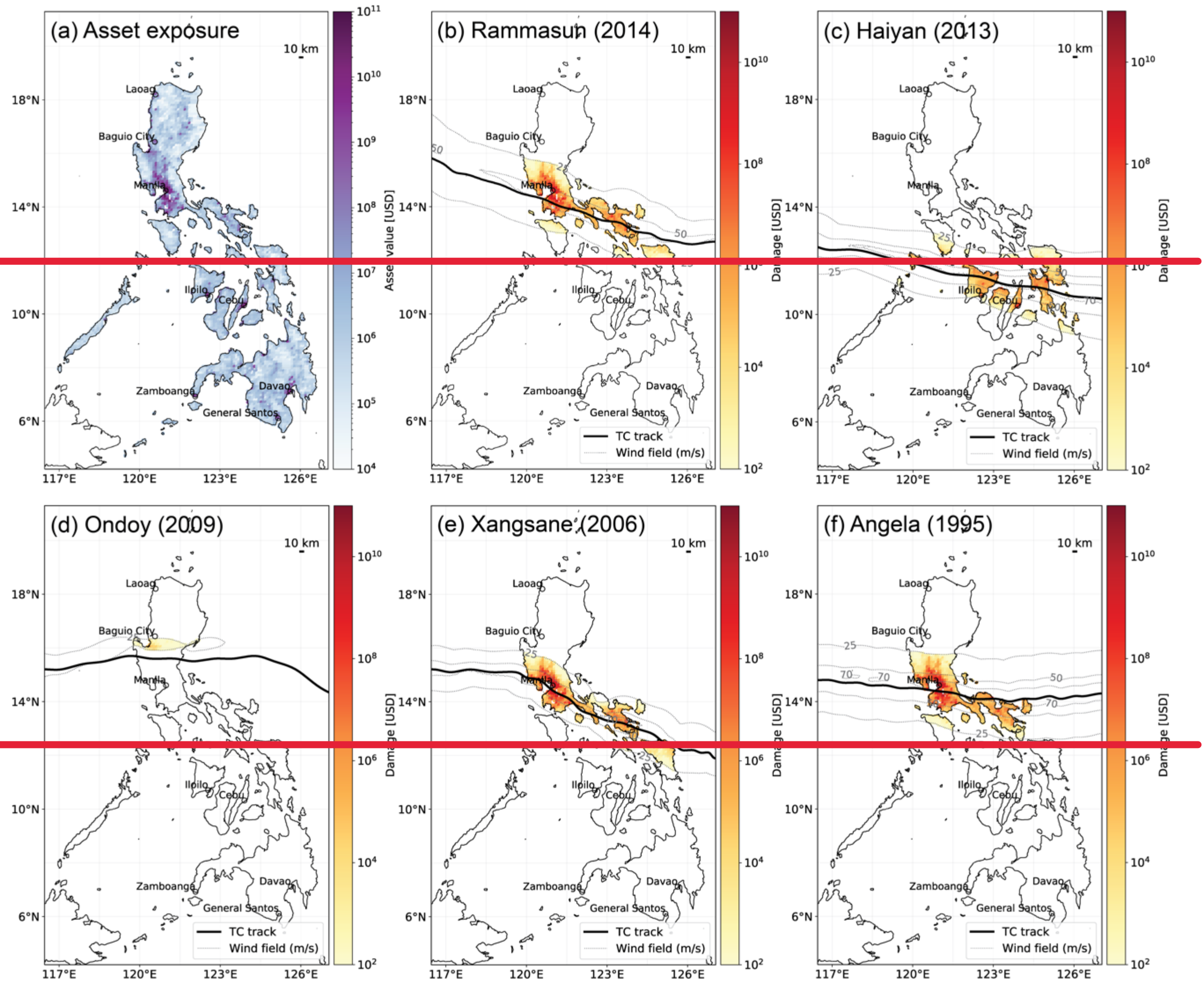
4.1 Tropical cyclones in the Philippines

The Republic of the Philippines is one of the most TC-prone countries in the world (Blanc and Strobl, 2016). From 1951 to 2014, an annual average of 19.4 TCs entered the Philippine Area of Responsibility (Cinco et al., 2016), with six to nine TCs making landfall in the Philippines each year (Blanc and Strobl, 2016; Cinco et al., 2016). This is a relative high frequency compared to five to eight landfalls in China (Zhang et al., 2009), and an average of three landfalls per year in the North Indian Ocean region (Wahiduzzaman et al., 2017) as well as in the USA (Lyons, 2004). The north and east of the Philippines are the regions most exposed to TC landfalls, with most TCs crossing the Philippines from east to west (Cinco et al., 2016; Espada, 2018). Rainfalls associated to TCs contribute around 35% of annual precipitation in the Philippines, with regional values ranging from 4 % to 50 % (Cinco et al., 2016).

In total, 83 matched TCs making landfall in the Philippines were used for calibration. For 11 of the 21 most damaging TC events, reports and scientific literature on associated sub-perils and impacts were reviewed (Table A4). In summary, TCs making landfall in the Philippines cause damage due to large wind speed, storm surge, as well as rain induced floods and landslides. ~~Most events inflict damage on several sectors, most costly on housing and agriculture, but also on schools and hospitals, power and water supply, roads, and bridges (Table A4). Single events were also reported to damage and disrupt airports and ports (Typhoon Haiyan), dikes (Pedring), and water supply (Bopha and Fengshen).~~Meteorologically, the storm systems interact with the monsoon season, affecting both dynamics and the severity of torrential rain (Bagtasa, 2017; Cayanan et al., 2011; Yumul et al., 2012). TCs in the Philippines inflict damage on several sectors, most costly on housing and agriculture, but also on schools and hospitals, power and water supply, roads, and bridges (Table A4). Single events were also reported to damage and disrupt airports and ports (Typhoon Haiyan) and dikes (Nesat and Xangsane). This complexity of how and where TCs cause damage in the Philippines is in stark contrast to the relatively simple representation of hazard and exposure in our modelling setup. It is therefore not surprising, that our calibrated TC impact model is over- and underestimating the damage of individual events, as illustrated for the Philippines by the wide spread of EDR. In the following, we will take a closer look at events with over- and underestimated simulated damage to explore the two hypotheses above.

4.2 Urban vs. rural exposure

Most of the asset exposure value of the Philippines is concentrated around the metropolitan area of Manila~~, located around 14.5°N, 121.0°E (Fig. 6a). The Typhoons Angela (1995), Xangsane (2006), and Rammasun (2014) are prominent TCs hitting the Manila region. In our analysis,~~ (Metro Manila). Located around 14.5°N, 121.0°E (Fig. 7a), Metro Manila is Philippine's political and socio-economic center (Porio, 2011). The Typhoons Angela (1995), Xangsane (2006), and Rammasun (2014) are prominent TCs hitting the Metro Manila directly. In our analysis, these TCs come with particularly large EDRs, i.e. an overestimation of simulated vs reported damages, even with calibrated impact functions (Table A4). All three typhoons show maximum sustained wind speeds in Manila larger than 50 ms^{-1} (Fig. ~~6b~~7b,e,f), corresponding to relative damage ranging from 6 up to 37 % of asset exposure value with the calibrated impact function. These large relative damages in combination with the ~~large~~ concentration of asset exposure value in the Manila region are likely to explain the large EDRs of these events. The analysis of all 83 TC events used for calibration support this hypothesis, underpinning the crucial role ~~that~~ the large asset exposure values in the ~~metropolitan area of~~Metro Manila plays for the wind-based damage simulation: An overestimation of simulated damages (e.g. EDR>10) consistently coincides with large wind speeds over Metro Manila ~~metropolitan region~~: Out of 19 TCs affecting Manila directly, we find 16 (84%) with an EDR>10 and zero occurrences of EDR<0.1 (Fig. ~~7~~8). In contrast, only 9 of 64 TCs not affecting Manila directly come with an EDR>10. In summary, we found simulated damage of an event more usual to substantially exceed normalized reported damage if the event hit Manila directly. This confirms hypothesis (1) that a special treatment of the impact functions for urban areas could improve the TC impact model.



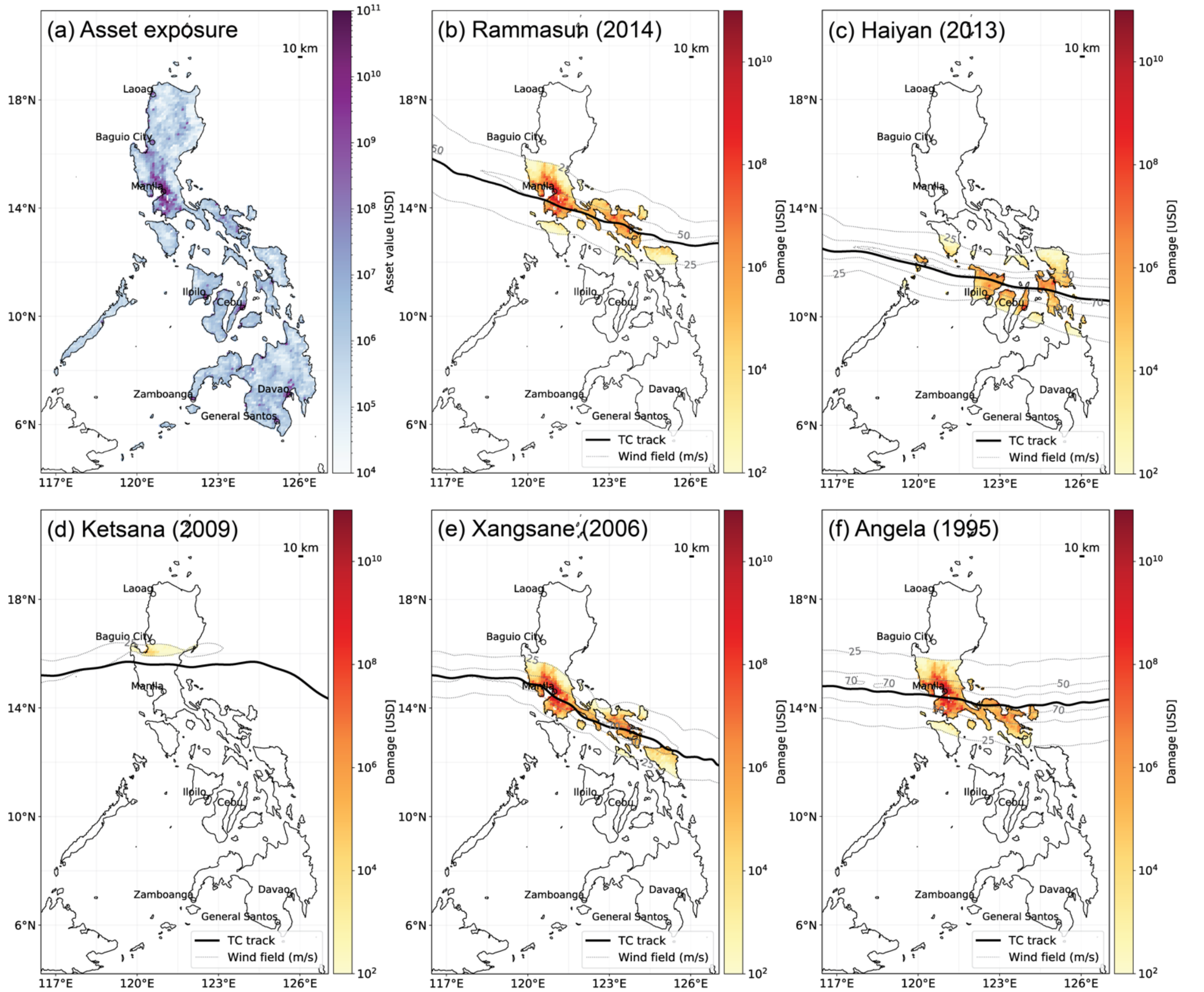


Figure ~~6~~7: Maps of the Philippines showing (a) the spatial distribution of asset exposure value in the Philippines [current US dollar of 2014] based on Eberenz et al (2020); and (b-f) mapped TC impacts for Typhoon Rammasun (b), Typhoon Haiyan (c), Tropical Storm ~~Ondoy~~Ketsana (d), Typhoon Xangsane (e), and Typhoon Angela (f). For each event, the map shows the TC track from IBTrACS (bold solid line), the spatial distribution of simulated maximum sustained wind speed in ms^{-1} (dashed lines at 25, 50, and 70 ms^{-1}), and simulated direct damage at a 10km resolution (color shading). Coast lines and the location of major cities based on Cartopy (Met Office, 2010).

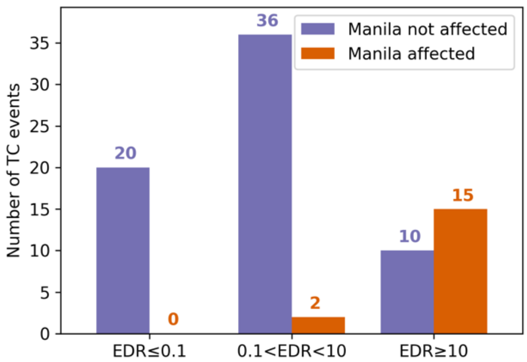


Figure ~~7~~8: Distribution of the event damage ratio (EDR) for 83 TCs making landfall in the Philippines from 1980 to 2017. The number of events for three ranges of EDR are compared, differentiating whether Manila was directly affected by the TC's wind field (orange) or not (purple). Manila is considered to be affected if the hazard intensity exceeds 25 ms^{-1} at 14.5°N, 121.0°E.

4.3 Impact of storm surge and torrential rain

~~Tropical Storm Ondoy (2009) is an example with very low simulated damages: Ondoy's EDR is 0.002, i.e. its simulated damage is more than two orders of magnitude smaller than reported. The large reported damage (NRD=401 million USD) was mainly due to floods and landslides: Torrential rainfall caused severe river flooding in the Manila metropolitan region and landslides around Baguio City resulting in severe damages (Nakasu et al., 2011; NDCC, 2009a). These damages were not resolved by the wind-based impact model, with intensities well below 50 ms^{-1} and neither affecting Manila nor the northern Baguio City directly (Fig. 6d).~~

While urban vulnerability to strong winds in Metro Manila appears to be overestimated by the calibrated impact function, Metro Manila is known to be highly exposed and vulnerable to regular, large scale flooding (Porio, 2011). The main drivers of flood vulnerability are its geographical setup, largely unregulated urban growth and sprawl, and substandard sewerage systems, especially in low-income areas (Porio, 2011). Tropical Storm Ketsana, locally known as Ondoy (2009) is an example with very low simulated damages coinciding with large reported damages associated to flood in Metro Manila: Ketsana's EDR is 0.002, i.e. simulated damage is more than two orders of magnitude smaller than reported. The large reported damage (NRD=401 million USD) was mainly due to floods and landslides. Torrential rainfall caused severe river flooding in Metro Manila and landslides around Baguio City, resulting in severe damages (Abon et al., 2011; Cruz and Narisma, 2016; Nakasu et al., 2011; NDCC, 2009a). The flood damages were not resolved by the wind-based impact model, with intensities well below 50 ms^{-1} and neither affecting Manila nor the northern Baguio City directly (Fig. 7d). Notably, even for TCs with large overestimation of simulated damage due to high wind speeds in Metro Manila, namely Fengshen and Xangsane, a substantial part of the reported damage was actually caused by pluvial flooding and landslides and not by wind alone (Yumul et al., 2008, 2011, 2012).

For the most severe TC in the recent history of the Philippines, Typhoon Haiyan (2013), normalized reported damage and simulated damage are in the same order of magnitude resulting into an EDR of 0.17. Haiyan, with sustained 1-min surface wind speeds up to 87.5 m/s, caused thousands of casualties and around 10 billion USD of economic damage in the Philippines (Guha-Sapir, 2018; Mas et al., 2015). Devastating wind and storm surge associated to Haiyan caused damage to multiple sectors, including ports and an airport. It should be noted ~~that these sector~~thatsector specific impacts are not resolved in the impact model and Haiyan did not affect Manila directly. ~~However, relatively~~Relatively large damages were simulated around Tacloban City, Leyte, which was actually devastated by Haiyan's storm surge. Large wind impacts were also simulated further West around the cities Iloilo and Cebu (Fig. ~~6c).~~7c) that were not as exposed to surge as Leyte province. The relatively good performance of the model in the case of Haiyan is thus not explained by a perfect location and representation of the impact in the model. It is rather based on overestimated urban wind damages partly balancing the lack of damages caused by storm surge.

4.4 Conclusions from the case study

The case of the Philippines reveals limitations of the model and calibration due to the lack of an explicit representation of sub-perils such as storm surge, torrential rainfall, and landslides (Sect. 4.3). The flood damage caused by Ketsana is a showcase example for severe damages associated with a TC with relatively low wind speeds, that is, an event that cannot be adequately reproduced with a wind-based impact function. Adding to the stochastic uncertainty, the magnitude of rainfall during a TC events in the Philippines is not only determined by the intensity of the TC event, but also by the coinciding monsoon season, as in the case of the Typhoons Fengshen and Haiyan ~~(Espada, 2018; IFRC, 2009).~~(Espada, 2018; IFRC, 2009; Yumul et al., 2012).

Next to a lack of representation of all components of hazard intensity, differences in exposure and vulnerability between urban and rural areas exposed to TCs are likely to contribute to the large spread in EDR and subsequently uncertainty in the impact function calibration. This has been illustrated in Sect. 4.2: The large overestimation of simulated event damage of TCs affecting the Manila metropolitan area points towards relevant sources of epistemic uncertainty: On the one hand, a large share of exposed asset values in the model is concentrated in urban areas, while exposed agricultural assets in rural areas are neglected. On the other hand, one single impact function might not be sufficient to represent both urban and rural building vulnerability. Another factor contributing to the high simulated damages in Manila could be the wind field model: Manila is located in a bay on the west coast of the main island Luzon. Most TCs are approaching Luzon from the east. The wind field model adapted from Holland (2008) does however not take into account variation in topography and surface roughness. This could lead to an overestimation of simulated wind speeds downstream of elevated land, as in the case of Manila. A better representation of wind speed over land could mitigate this problem (Done et al., 2019).

5 Discussion

5.1 Relevance for TC risk assessments

In this study, we showed how the regionalization of impact functions improves the assessment of TC risk in numerous world regions, correcting a overestimation of aggregated TC damages by a factor of potentially up to 36 in the North West Pacific, and an underestimation by the factor 5 in the South Indian Ocean. To complement the global perspective, we explored the limitations of the TC impact modelling setup by the case study of TC events in the Philippines.

The calibration resulted in large regional differences in the slope of impact functions, with considerable consequences on the magnitude of simulated damages. In Sect. 3.2, we compared average damages simulated with regionalized impact functions to results from literature. While the comparison is limited by differences in the model setups, we found that regional damage estimations relative to the exposed asset values generally agree well to the results of previous studies. However, the results for the North West Pacific region (WP4), consisting of Japan, South Korea, Macao, Hongkong, and Taiwan, deviate substantially from GAR 2013. Simulated relative AAD in the region ranges from 0.2-0.8 ‰ as compared to 3.1 ‰ in GAR 2013. This difference implies that, besides the use of building type specific impact functions, the TC impact model of GAR 2013 substantially overestimates TC damages in WP4 compared to reported data. Consistent with this finding, the uncalibrated simulation showed the largest overestimation of aggregated damages in this region. Assuming that the order of magnitude of reported direct damages from EM-DAT is reasonable, the regionalization of impact functions presented here is an improvement for TC risk assessments in the region.

For calibration, two complementary approaches were employed: The optimization of aggregated simulated compared to reported damages (TDR), and the minimization of the spread of damage ratios of single events (RMSF).
Annual average damage simulated based on the TDR optimized set of impact functions are generally closer to the values found in EM-DAT than the values based on RMSF optimization. This is not surprising, since TDR is designed to represent aggregated damage per region. For the assessment of TC risk on an aggregated level, it is therefore most appropriate to employ the more conservative TDR optimized model, even though single events can be massively underestimated with the flatter impact functions. Complementary, impact functions based on RMSF optimization and the spread of individually event fitting can be included in risk assessments for sensitivity analysis.

5.2 Uncertainties and limitations

The deviation between the results of the two calibration approaches indicates how robust the calibration is with regards to the model's ability to represent the correct order of magnitude of single event damage. Whereas the model setup returns reasonable risk estimates and consistent calibration results for Central and North America, we found an extensive spread in EDR and calibration results for other regions, especially in East Asia. While the correlation between simulated and reported event damages is improved by the calibration, the simulated damage of single TC events can deviate several orders of magnitude from reported damages (Fig. 4, A1 and A2). In the regions of the North West Pacific (WP2-4), the fitted impact functions are ambiguous, with large discrepancies between the two calibration approaches. The low robustness found for these regions stems from multiple causes, including the stochastic uncertainty in TCs as natural phenomena, as well as epistemic uncertainties located in the hazard, exposure, and vulnerability components of the impact model. An additional source of uncertainties is located in the reported damages used for reference. Future improvement of the TC impact model and a sound judgement of the limitations of the calibrated impact functions requires better understanding of the epistemic uncertainties. In the following, we will discuss these uncertainties for the different components of the model.

The case of the Philippines provides insights into the uncertainties located in the model setup, both in the representation of hazard intensity and in differences between the structure and vulnerability of exposed assets in urban and rural areas (Sect. 4). The hazard is represented by wind fields modelled from TC track data and the same impact functions are applied in urban and rural areas. These are considerable simplifications of the actual interaction of cyclones with the natural and built environment. To reduce these uncertainties, the hazard component could be improved by considering topography (Done et al., 2019) and complementing wind speed with sub-perils like storm surge, torrential rain, and landslides. For a better representation of urban assets, building type specific impact functions, and a differentiation of urban and rural exposure as applied for GAR 2013 (De Bono and Mora, 2014) could be beneficial. Furthermore, geospatial agricultural yield data could be added to the exposure data, albeit reported damage for calibration is mostly not available at such sectoral granularity. Next to the model setup, the reported damage data obtained from EM-DAT are another relevant source of uncertainty. Reported damage data are expected to come with considerable uncertainties, partly due the heterogeneity of data sources, the blending of direct and indirect economic damages, as well as political and structural reporting biases (Guha-Sapir and Below, 2002; Guha-Sapir and Checchi, 2018). Further uncertainty is introduces by the lack of international standards for reported damage datasets, leading to inconsistencies between data providers (Bakkensen et al., 2018b). These uncertainties limit our understanding of the robustness of the calibration. For future calibration studies relying on reported damage data, calibration robustness could be increased by combining datasets from different sources in an ensemble of datasets (see Zumwald et al., 2020).

In this study we did not explicitly quantify the uncertainties related to the model setup, the input data for hazard and exposure, as well as the reported data used as reference data for calibration. Rather, the robustness of the calibrated impact functions was judged based on the deviation between the two calibration approaches and the spread of impact functions fitted to the individual TC events. Based on the limitations discussed above, we conclude that the resulting array of regionalized impact functions should be applied with caution, being aware that the model setup is not suitable to represent single TC events adequately. However, the calibrated impact functions mark an improvement for the modelling of aggregated risk estimates, such as the annual average damage. Impact functions sampled from the range of calibration results can be applied for a more probabilistic modelling of TC impacts. It should also be noted that the impact functions calibrated for the years 1980-2017 cannot be expected to be stable in the future. Applying these impact functions for the assessment of future TC risk requires a ceteris paribus assumption with regard to vulnerability.

While the results of this study are not specific to the CLIMADA modeling framework, the precise shape and scaling of the calibrated impact functions are, however, to a certain degree specific to the choices and input data of the modeling setup: (1) The choice of free parameters in the impact function (c.f. Section 2.2.3 and Lüthi, 2019); (2) The TAVs (c.f. Table A3): impact functions would scale differently with a different assumed inventory of exposed assets; (3) spatial resolution; and (4) the representation of hazard intensity: The regionalized impact functions presented here were calibrated for wind-based damage modelling on a spatially aggregated level. Model setups with an explicit representation of related sub-perils like storm surge or torrential rain require different (i.e. flatter) impact functions for the wind-induced share of TC damage, as well as additional impact functions for all sub-perils. Likewise, impact models with an explicit representation of building types and agricultural assets require a more differentiated set of impact functions. Considering the irreducible stochastic uncertainties in the system, it remains to be shown to which degree the large inter-regional differences in calibrated impact functions found in this study can be explained by regional differences in building types and standards, physical TC characteristics, or other factors.

6 Conclusion and outlook

In this article, we improved global TC risk assessment by regionalizing the vulnerability component of the TC impact assessment. To better account for regional differences, we calibrated a TC impact model by fitting regional impact functions. The impact functions were calibrated within the CLIMADA risk modelling framework, using reported direct economic damage estimates from the EM-DAT dataset as reference data. For calibration, two complementary optimization approaches were applied, one aiming at minimizing the deviation of single event damages from the reported data and one aiming at minimizing the deviation for total damage aggregated over 38 years of data. By fitting impact functions, we were able to reduce regional biases as compared to reported damage data, especially for countries in the North West Pacific and South Indian Ocean regions. ~~Still, the~~The substantial over-estimation of TC damages in the North West Pacific with the default impact function opens the question for the drivers of the apparently lower vulnerability in this region. Considering the inability of the model setup to directly represent the impacts from TC surge and pluvial flooding, one would rather expect aggregated calibrated impact functions to be steeper than the default wind impact function. Therefore, we suggest investigating interregional differences in possible other drivers, including building standards but also damage reporting practices. A study combining the empirical evidence provided by reported damage data on the one hand with socio-economic indicators on the other hand would be desirable but rather challenging, as this would add even more layers of complexity and cascading uncertainties to the calibration, especially on a global level.

The calibrated model comes with considerable uncertainties related both to the impact model setup and the reported damage data. The largest uncertainties were found for the North West Pacific regions, while the calibration produced consistent results for the North Atlantic regions. The spread of fitted impact functions within each region can be exploited to better account for these uncertainties in probabilistic risk assessments. Based on our findings, we recommend to always consider inter-regional differences in vulnerability for the application in global TC impact models. For model setups comparable to the one described here, we recommend the use of TDR optimized functions for risk assessments on an aggregated level. The resulting simulated damage can complement reported damage data. Assuming that reported damages are more likely to underestimate actual impacts, it could be advisable to sample impact functions from the range between the complementary calibration results. For probabilistic impact modelling, a random sampling from the array of impact functions fitted to individual events could be considered. This becomes especially relevant for regions with large uncertainties attached to the calibration results, such as the North West Pacific and Oceania. Limitations of our research motivate future work. For TC impact models, we echo the call for a more refined representation of TC hazard as a combination of wind, surge, and rain induced flood and landslide events. When modeling multiple TC sub-perils, aggregated reported damage data are not sufficient to constrain impact function calibration. This might be resolved by consulting socio-economic and engineering type data and knowledge. Furthermore, our case study for the Philippines suggests that differentiating between urban and rural asset exposure, considering topography in wind speed estimations, and the inclusion of exposed agricultural assets could further increase model accuracy.

Appendix A

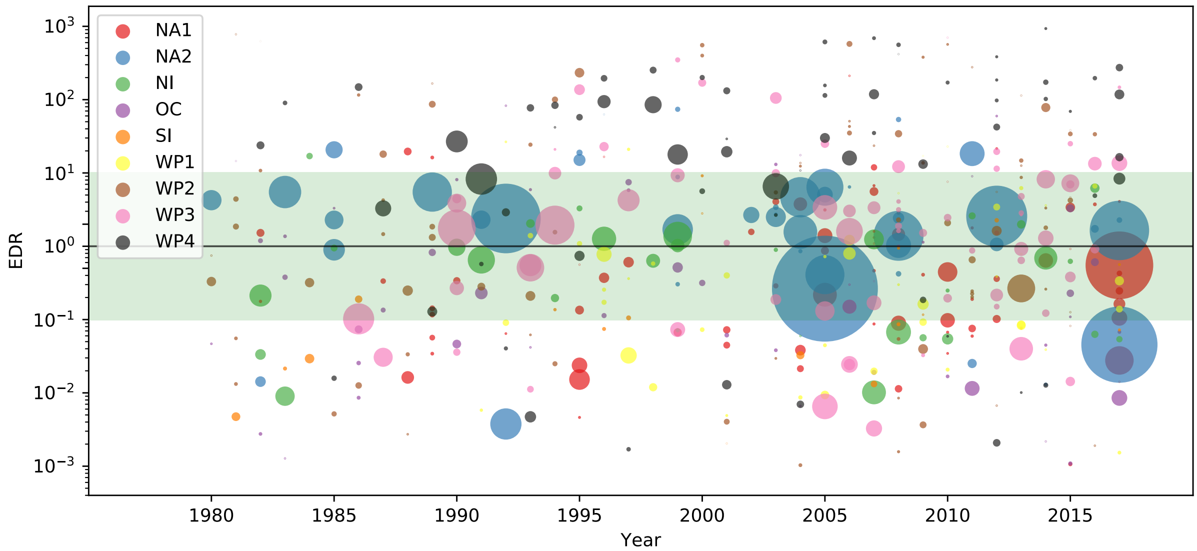


Figure A1: Event damage ratio (EDR) from 1980 to 2017 for matched 473 TC events worldwide. The nine calibration regions are differentiated by colour. The area size of the dots represents the absolute normalized reported damage (NRD) per event. The green shading demarcates the range from EDR=0.1 to 10.

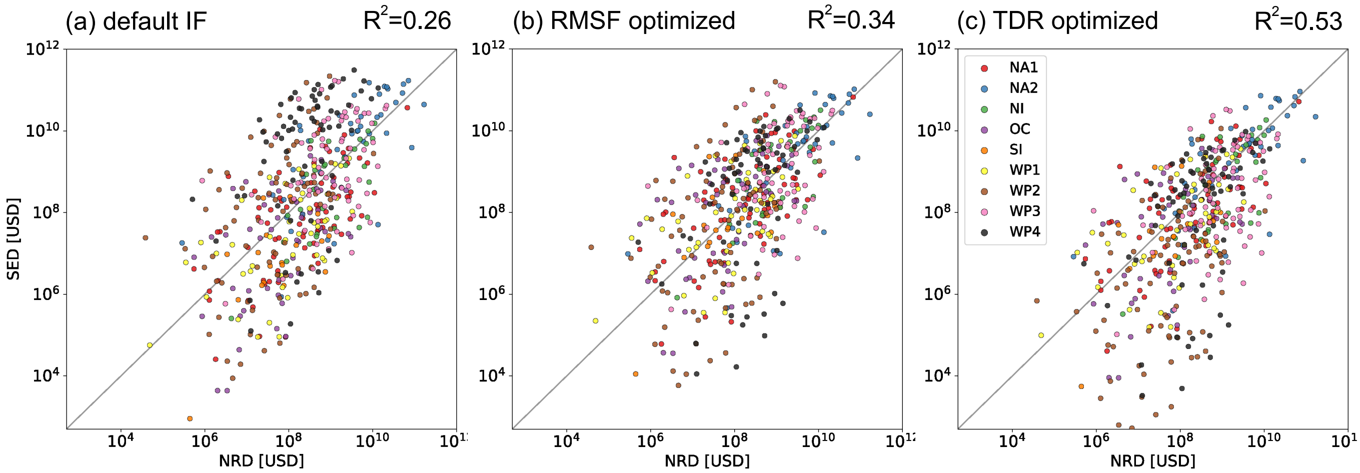


Figure A2: Simulated event damage (SED) vs normalized reported damage (NRD) for 473 TC events worldwide computed with three different sets of impact functions: (a) uncalibrated default (V_{half}=74.7 ms^{-1}), (b) RMSF optimized, and (c) TDR optimized. The nine calibration regions are differentiated by colour.

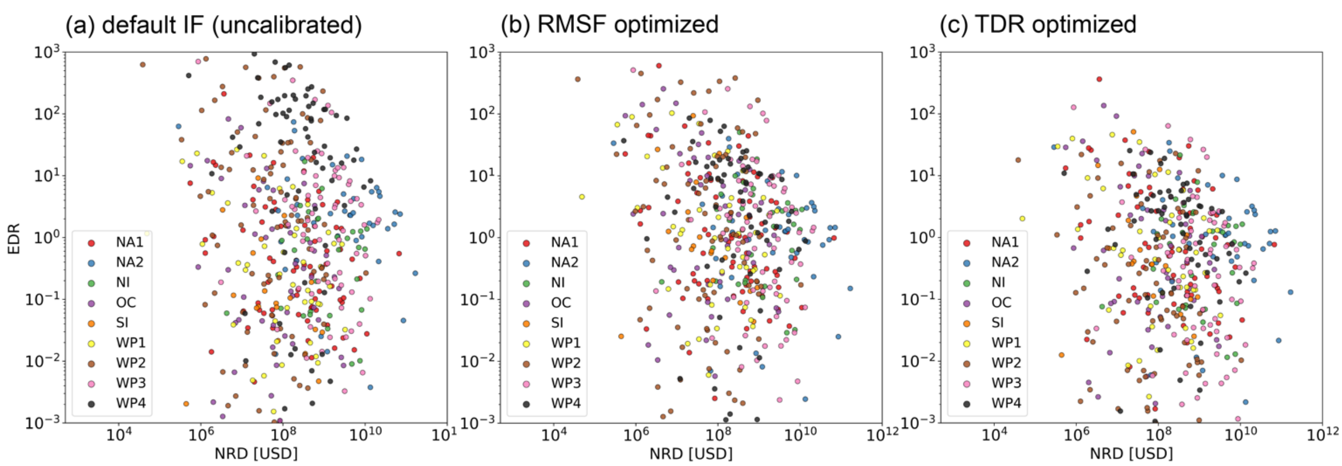


Figure A3: No significant correlation between event damage ratio (EDR) and normalized reported damage (NRD) was found. The scatter plots show the relationship for 473 TC events worldwide computed with three different sets of impact functions: (a)

uncalibrated default (V_{half}=74.7 ms-1), (b) RMSF optimized, and (c) TDR optimized. The nine calibration regions are differentiated by colour.

Table A1: List of countries per calibration region. Countries marked with an asterisk (*) are considered for calibration (53 in total).

Region	N countries (calib-ration)	Countries
North Atlantic 1 (NA1)	48 (21)	Anguilla; Antigua and Barbuda*; Argentina; Aruba; Bahamas*; Barbados; Belize*; Bermuda*; Bolivia, Plurinational State of; Cabo Verde*; Cayman Islands; Chile; Colombia; Costa Rica; Cuba*; Dominica*; Dominican Republic*; Ecuador; El Salvador; Falkland Islands (Malvinas); French Guiana; Grenada; Guadeloupe; Guatemala; Guyana; Haiti; Honduras*; Jamaica*; Martinique; Mexico*; Montserrat*; Nicaragua*; Panama; Paraguay; Peru; Puerto Rico*; Saint Helena, Ascension and Tristan da Cunha; Saint Kitts and Nevis*; Saint Lucia*; Saint Vincent and the Grenadines*; Sint Maarten (Dutch part); Suriname; Trinidad and Tobago*; Turks and Caicos Islands*; Uruguay; Venezuela, Bolivarian Republic of; Virgin Islands, British*; Virgin Islands, U.S.*
North Atlantic 2 (NA2)	2 (2)	Canada*; United States of America*
North Indian (NI)	36 (6)	Afghanistan; Armenia; Azerbaijan; Bahrain; Bangladesh*; Bhutan; Djibouti; Eritrea; Ethiopia; Georgia; India*; Iran, Islamic Republic of; Iraq; Israel; Jordan; Kazakhstan; Kuwait; Kyrgyzstan; Lebanon; Maldives; Mongolia; Myanmar*; Nepal; Oman*; Pakistan; Qatar; Saudi Arabia; Somalia; Sri Lanka*; Syrian Arab Republic; Tajikistan; Turkmenistan; Uganda; United Arab Emirates; Uzbekistan; Yemen*
Oceania (OC)	26 (11)	American Samoa; Australia*; Cook Islands; Fiji*; French Polynesia*; Guam*; Kiribati; Marshall Islands; Micronesia, Federated States of*; Nauru; New Caledonia*; New Zealand; Niue; Norfolk Island; Northern Mariana Islands; Palau; Papua New Guinea*; Pitcairn; Samoa*; Solomon Islands*; Timor-Leste; Tokelau; Tonga*; Tuvalu; Vanuatu*; Wallis and Futuna
South Indian (SI)	11 (2)	Comoros; Congo, Democratic Republic of the; Eswatini; Madagascar*; Malawi; Mali; Mauritius; Mozambique*; South Africa; Tanzania, United Republic of; Zimbabwe
North West Pacific 1 (WP1)	6 (4)	Cambodia*; Indonesia; Lao People's Democratic Republic; Malaysia*; Thailand*; Viet Nam*
North West Pacific 2 (WP2)	1 (1)	Philippines*
North West Pacific 3 (WP3)	1 (1)	China, Mainland*
North West Pacific 4 (WP4)	5 (5)	Hong Kong*; Japan*; Korea, Republic of*; Macao*; Taiwan, Province of China*

Table A2: Resulting impact function slope parameter v_{half} and optimization metrics RMSF and TDR per region for (a) the global default impact function (uncalibrated), (b) calibrated by optimizing RMSF, and (c) calibrated by optimizing TDR. The regions NA1 to WP4 are defined in Table A1. The row "combined" summarizes results for all regions combined based on the regionalized calibration; the row "global" is based on one unified global calibration based on all matched TC 473 events. RMSF: root-mean-squared fraction; TDR: total damage ratio.

Region	Number of		V_{half} [ms^{-1}]			RMSF			TDR		
	countries	events	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
NA1	21	73	74.7	59.6	66.3	11.8	9.8	10.3	0.68	1.44	1.0
NA2	2	43	74.7	86	89.2	9.5	8.7	8.7	2.11	1.16	1.0
NI	6	31	74.7	58.7	70.8	7.8	6	7.2	0.85	2.03	1.0
OC	11	48	74.7	49.7	64.1	22.5	14.7	17.7	0.6	2.31	1.0
SI	2	19	74.7	46.8	52.4	20.1	8.6	9.1	0.2	1.8	1.0
WP1	4	43	74.7	56.7	66.4	15.2	11.3	12.6	0.62	2.05	1.0

WP2	1	83	74.7	84.7	188.4	38.2	36.7	104.9	25.89	16.44	1.0
WP3	1	69	74.7	80.2	112.8	15.2	14.8	20.5	5.32	3.83	1.0
WP4	5	64	74.7	135.6	190.5	73.8	35.9	43.8	35.56	3.35	1.0
combined	53	473	74.7	-	-	22.2	16.8	24.4	4.69	2.15	1.0
global calibration	53	473	74.7	73.4	110.1	22.2	22.2	33.1	4.69	4.84	1.0

Table A3: Total asset exposure values (TAV) per region. First column: TAV based on Eberenz et al. (2020) as used in this study. Second and third column: Reference values of TAV from GAR 2013 and Gettelman et al. (2017). The unit is 10^{12} US dollars ($T) in the current value of the year noted in brackets. AAD relative to TAV is reported in Table 1. *) USA and Bermuda

Region	**TAV Eberenz et al. (2020)**	**TAV GAR 2013**	**TAV Gettelman et al. (2017)**
	$T of 2014	*$T of 2005*	*$T of 2015*
NA1	4.66	2.19	8.6
NA2	62.19	24.06	73.3*
NI	6.32	1.64	
OC	5.94	1.85	
SI	0.04	0.01	
WP1	2.27	0.83	
WP2	0.63	0.19	
WP3	31.40	4.51	
WP4	26.98	19.51	
WP	61.28	25.04	58.8
GLB	250.88	96.45	155.9

Table A4: Detailed information on the 21 TCs in the matched events list with the largest normalized reported damage: ~~year,~~ storm name (local name in brackets) and year, normalized reported damage (NRD), simulated event damage (SED, simulated with V_{half}=84.7 ms^{-1}), event damage ratio (EDR), simulated intensity for the capital city Manila (at 14.5°N, 121.0°E), associated disasters according to literature and EM-DAT as well as affected sectors and asset types as reported by literature. Sources of information: 1) peer-reviewed study; 2) public report 3) data field 'associated disasters' in EM-DAT.

Event	SED [mio USD]	NRD[3] [mio USD]	EDR $\left(\frac{SED}{NRD}\right)$	V_{wind} Manila [m/s]	Associated disasters	Affected sectors & assets	Reference
Rammasun (Glenda), 2014	39,528	821	48.17	52.8	Wind[1], Flood[3]	Agriculture[2], buildings (664k)[2], power supply[2], and roads and bridges[2]	(Espada, 2018; NDRRMC, 2014)
Haiyan (Yolanda), 2013	1,804	10,469	0.17	-	Wind[1], Surge[1,2,3]	Agriculture[2], buildings (1.1m)[1,2], *airport*[1,2], power supply[2], roads[2], bridges[2], ports[2]	~~(Blanc and Strobl, 2016; Espada, 2018; Mas et al., 2015; NDRRMC, 2013; Soria et al., 2015)~~(Blanc and Strobl, 2016; Espada, 2018; Lagmay et al., 2015; Mas et al., 2015; NDRRMC, 2013; Soria et al., 2015)
Bopha~~,~~ (Pablo), 2012	1,060	1,022	1.04	-	Wind[2], Flood[2]	Agriculture[2], buildings (217k)[2], power and water supply[2], and roads and bridges[2]	(NDRRMC, 2012)
Nesat (Pedring ~~(Nesat~~), 2011	172	437	0.39	-	Wind[2], Flood[2], Surge[2], Slide[2,3]	Agriculture[2], buildings (44k)[2], power supply[2], dikes[2], roads and bridges[2]	(NDRRMC, 2011)
Megi (Juan), 2010	526	393	1.34	-	Wind[2], Flood[2], Slide[2]	Agriculture[2], buildings (104k)[2], power supply[2], and roads and bridges[2]	(NDRRMC, 2010)
Parma (Pepeng ~~(Parma~~), 2009	23	990	0.02	-	Flood[1,3], Slides[1]	Agriculture[2], buildings (61k)[2], power supply[2], dikes[2], roads and bridges[2]	~~(Cooper and Falvey, 2009; Espada, 2018; Inokuchi et al., 2011; Nakasu et al., 2011; NDCC, 2009a, 2009b)~~(Abon et al., 2011; Cooper and Falvey, 2009; Cruz and Narisma, 2016; Espada, 2018; Inokuchi et al., 2011; Nakasu et al., 2011; NDCC, 2009a, 2009b)
~~Ondoy~~ ~~(~~Ketsana (Ondoy), 2009	1	401	0.002	-	Flood[1,3] *(Manila)*, Slides[3]	Agriculture[2], buildings (185k)[2], power supply[2], dikes[2], roads and bridges[2]	

Fengshen (~~Franck~~Frank), 2008	9,286	465	19.96	41.2	~~Flood[2]~~Flood[1,2,3], Surge[2], ~~Slides[2]~~Slides[1,2]	Agriculture[2], buildings (407k)[2], power and water supply[2], and roads and bridges[2]	~~(Espada, 2018; IFRC, 2009)~~(Espada, 2018; IFRC, 2009; Yumul et al., 2012)
Xangsane (Milenyo), 2006	100,440	263	381.70	63.9	~~Flood[3]~~Flood[1,3], Slides[1]	~~No report evaluated~~Dikes[1], power supply[1]	(Yumul et al., 2008)
Angela (Rosing), 1995	156,750	937	167.32	77.2	Flood[2], Surge[2], Slides[2]	Agriculture[2], buildings (>96k)[2], power supply[2], dams[2], and roads and bridges[2]	(Joint Typhoon Warning Center, 1995)
Teresa (Katring), 1994	17,731	299	59.24	46.5	Flood[3]	No report evaluated	
Flo (Kadiang), 1993	120	984	0.12	-	Slide[3]	No report evaluated	
Ruth (Trining), 1991	95	564	0.17	-		No report evaluated	
Gordon (Goring), 1989	347	408	0.85	-		No report evaluated	
Dan (Saling), 1989	20,398	396	51.55	48.6		No report evaluated	
Skip (Yoning), 1988	182	1,120	0.16	-		No report evaluated	
Nina (Sisang), 1987	5,643	480	11.75	29.8		No report evaluated	(Espada, 2018)
Georgia (Ruping), 1986	2	343	0.01	-		No report evaluated	
Agnes (Undang), 1984	174	875	0.20	-		No report evaluated	
Irma (Anding), 1981	305	279	1.09	22.8		No report evaluated	
Betty (Aring), 1980	173	897	0.19	18.3	Slide[3]	No report evaluated	(Espada, 2018)

Code availability and data availability

The full array of fitted impact function parameters can be found as a Supplement of this paper. The scripts reproducing the main results of the paper and the figures are available at https://github.com/CLIMADA-project/climada_papers (Aznar-Siguan et al., 2020). The CLIMADA repository (Aznar-Siguan and Bresch, 2019; CLIMADA-Project, 2019) is openly available (https://github.com/CLIMADA-project/climada_python) under the GNU GPL license (GNU Operating System, 2007). The documentation is hosted on Read the Docs (https://climada-python.readthedocs.io/en/stable/), including a link to the interactive tutorial of CLIMADA. CLIMADA v1.4.1 was used for this publication, which is permanently available at the ETH Data Archive: http://doi.org/10.5905/ethz-1007-252 (Bresch et al., 2020).

Author contribution

SE and DB developed the idea and basic methodology of the paper. Coding and analysis were the work of SE and SL. SE prepared the manuscript with contributions from all co-authors.

Competing interests

The authors declare that they have no conflict of interest.

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nhess-2020-229 revised manuscript: Full list of revisions per page of original manuscript
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Main document changes and comments

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(TCFD, 2017)

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(Bloomberg et al., 2017)

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Natural risk

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Risk from natural hazards

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one

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it is inadequate to use a single

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While the attribution of vulnerability to regional drivers is outside the scope of this study, the results can serve as a starting point for further research disentangling the socio-economic and physical drivers determining vulnerability to TC impacts locally and across the globe.

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Fig. 1a-d,

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Fig. 1e-f,

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Fig. 1g,

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Fig. 1h,

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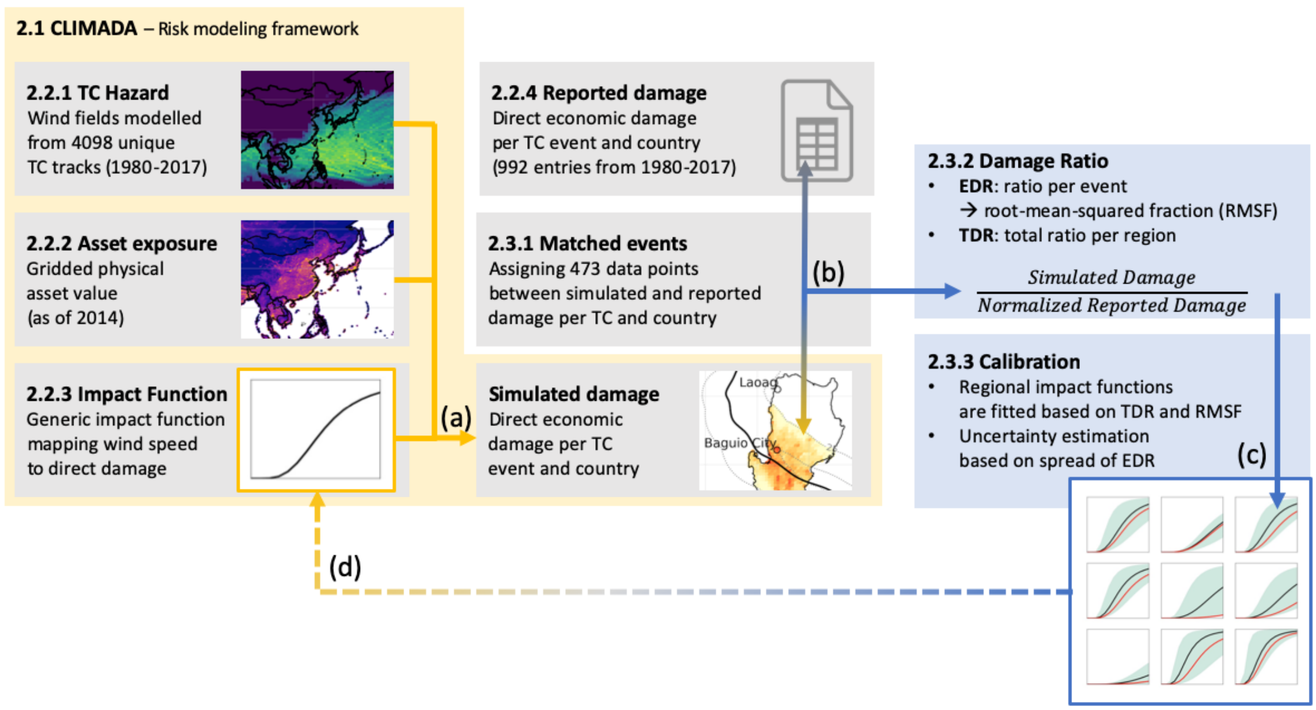

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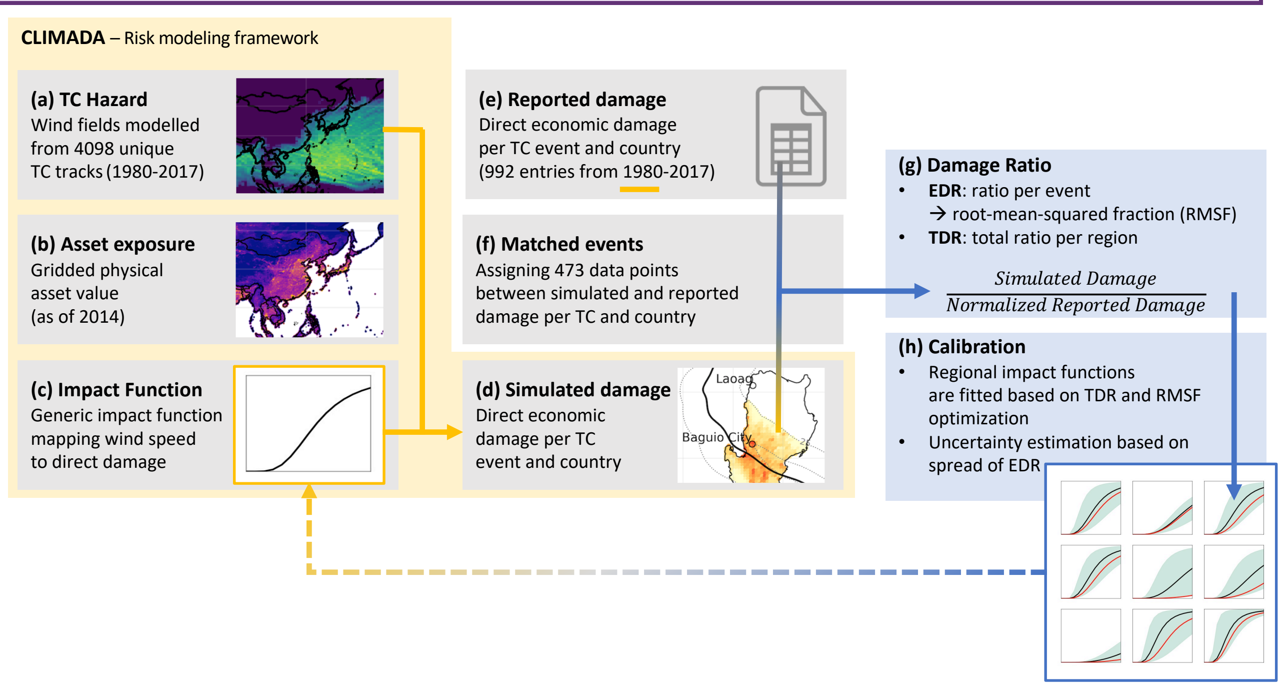

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tracks, asset exposure, and a default impact function (a,

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Sect. 2.1 to 2.2.3

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). Resulting simulated damages are matched and compared to reported damage data from EM-DAT (b, 2.2.4 to 2.3.2). During calibration, impact modelling and damage comparison are repeated several times for regional impact functions with varied slope (2.3.3). The result is a set of best fitting impact functions for nine world regions (c). Finally, the calibrated impact functions are plugged into CLIMADA (d) to compute annual average damage per region.

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hazard (a), asset exposure (b), and a default impact function (c), c.f.

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. Resulting simulated damages (d) are compared to reported damage data from EM-DAT (e) for 473 matched TC events (f) by means of the damage ratio (g), c.f. Sect. 2.2.4 to 2.3.2. During calibration (h), steps (c) to (g) are repeated several times with varied impact functions for each region, optimizing the cost functions TDR and RMSF (c.f. Sect. 2.3.3) . The result is a set of best fitting impact functions for nine world regions (Sect. 3.2). Finally, the calibrated impact functions are plugged into CLIMADA once more (dashed arrow)to compute annual average damage per region (Sect. 3.3).

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does work

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works

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resolutions

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chosen resolution

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Simulated

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In the CLIMADA framework, damage is defined as the product of exposed assets and a damage ratio. The damage ratio is an impact function multiplied with hazard intensity.

In our case,

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computed

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simulated

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(1)

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damage is calculated as the product of total exposed asset values and

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. The mean damage ratio

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is determined by

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results from

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hazard intensity (

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(hazard intensity

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an

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the

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(2) Absolute

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Finally,

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grid cell is computed by multiplying the mean damage ratio with the value of exposed assets at the grid cell. (3) The total damage per country and

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computed as the sum

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aggregated

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impact

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directly wind induced damage

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constraint

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constrained

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sigmoidal

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We define a default impact function with $V_{thresh} = 25.7\ ms^{-1}$ and $V_{half} = 74.7\ ms^{-1}$ that is used for a first, uncalibrated, simulation of global TC damages, and as a starting point for calibration. While V_{half} is fitted during the calibration process, we keep the lower threshold V_{thresh} constant throughout the study.

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In a comparison of calibration results based on a sigmoidal impact function with a more complex 12-step staircase function, Lüthi (2019) found no improvement of calibration skill with the more complex function. Therefore, we use the sigmoidal function in this study. We define a default impact function with $V_{thresh} = 25.7\ ms^{-1}$ and $V_{half} = 74.7\ ms^{-1}$ that is used for a first, uncalibrated, simulation of global TC damages, and as a starting point for calibration. While V_{half} is fitted during the calibration process, we keep the lower threshold V_{thresh} constant throughout the study. This is based on the finding by Lüthi (2019) that the variation of more than one of the linearly dependent parameters most likely results in an overfitting during calibration, with physically implausible values for V_{thresh} in some world regions.

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Damage

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Reported damage

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from natural catastrophes are records

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for disasters worldwide

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global

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data at the country level

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estimates

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The distribution of EDR and TDR before calibration as well as TDR after calibration is shown per region in Figures 6 and S4 and per country in the supplementary Figure S2.

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(matched TC events)

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The distribution of uncalibrated EDR per region is shown in Figure 4.

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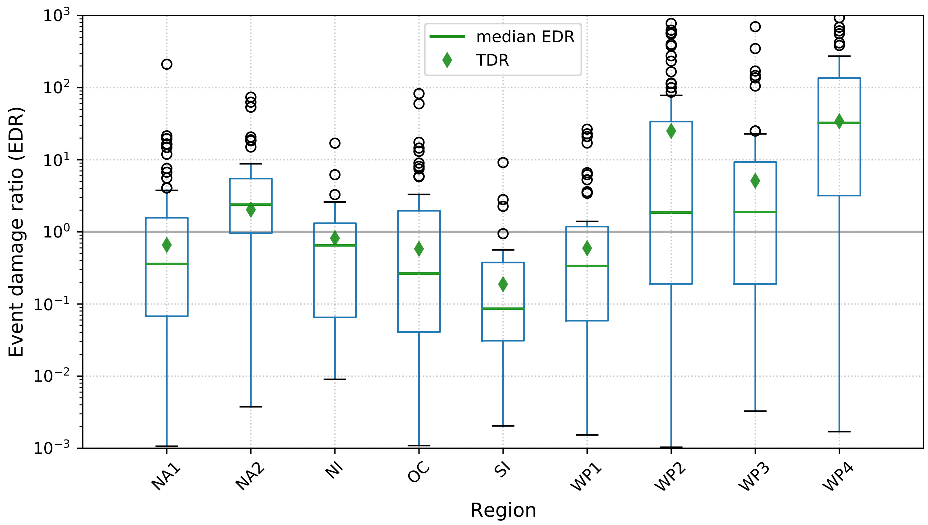

Figure 4: Spread of event damage ratio (EDR, boxplot) and total damage ratio (TDR) per region before calibration (V_{half}=74.7 ms^{-1}) per region. The plots are based on data from 473 TC events affecting 53 countries. The EDR boxplots show the median (green line), the first and third quartiles (IQR, blue box), data points outside the IQR but not more than 1.5·IQR distance from either the first or the third quartile (black whiskers), and outliers (black circles). The additional markers show TDR before calibrated (green diamond). The regions are the Caribbean with Central America and Mexico (NA1); the USA and Canada (NA2); North Indian Ocean (NI); Oceania with Australia (OC); South Indian Ocean (SI); South East Asia (WP1), the Philippines (WP2), China Mainland (WP3); rest of North West Pacific Ocean (WP4).

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RMSF (Fig. 5b) and

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(Fig. A1)

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and the cost functions RMSF

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(Fig. 5c), indicating

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show inter-regional differences with regard to

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, show inter-regional differences.

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(Fig. 4 and 6).

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TDR is

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total simulated and normalized reported damage deviates

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different from one.

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(Table A2).

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in

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2

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1

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regions

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each region

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A1).

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4). There is no significant correlation between EDR and NRD (Fig. A3), suggesting that the over- and underestimation of simulated event damages is not related to TC severity.

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5c

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Figure 4

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Fig. 5

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Plots

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The sensitivity

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as functions of

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to changes in

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are provided

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is visualized

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: Regions with a large uncertainty, i.e. a large spread of EDR, generally show a relatively low robustness of the cost functions

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On a globally aggregated level, calibration reduces the spread of EDR to a certain degree, placing more than half of events in the EDR range from 10^{-1} to 10.

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5c

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, each shown before (grey) and after calibration (blue and red):

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normalized reported (green) and simulated

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(AAD).

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5d

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6d

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5a

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Most events inflict damage on several sectors, most costly on housing and agriculture, but also on schools and hospitals, power and water supply, roads, and bridges (Table A4). Single events were also reported to damage and disrupt airports and ports (Typhoon Haiyan), dikes (Pedring), and water supply (Bopha and Fengshen).

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Meteorologically, the storm systems interact with the monsoon season, affecting both dynamics and the severity of torrential rain (Bagtasa, 2017; Cayanan et al., 2011; Yumul et al., 2012). TCs in the Philippines inflict damage on several sectors, most costly on housing and agriculture, but also on schools and hospitals, power and water supply, roads, and bridges (Table A4). Single events were also reported to damage and disrupt airports and ports (Typhoon Haiyan) and dikes (Nesat and Xangsane).

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, located around 14.5°N, 121.0°E (Fig. 6a). The Typhoons Angela (1995), Xangsane (2006), and Rammasun (2014) are prominent TCs hitting the Manila region. In our analysis,

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(Metro Manila). Located around 14.5°N, 121.0°E (Fig. 7a), Metro Manila is Philippine's political and socio-economic center (Porio, 2011). The Typhoons Angela (1995), Xangsane (2006), and Rammasun (2014) are prominent TCs hitting the Metro Manila directly. In our analysis, these TCs

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6b

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7b

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that

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metropolitan area of

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Metro

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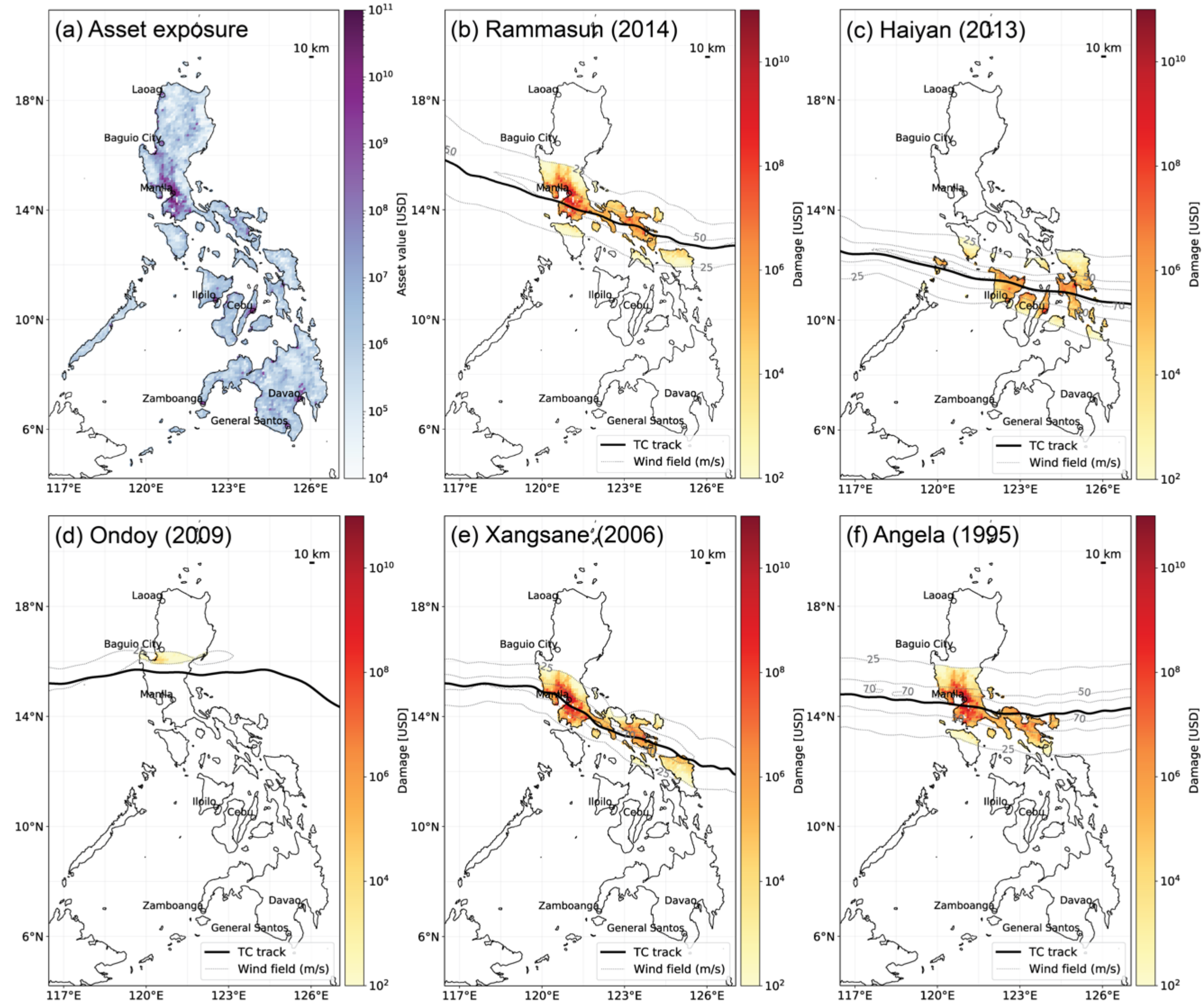
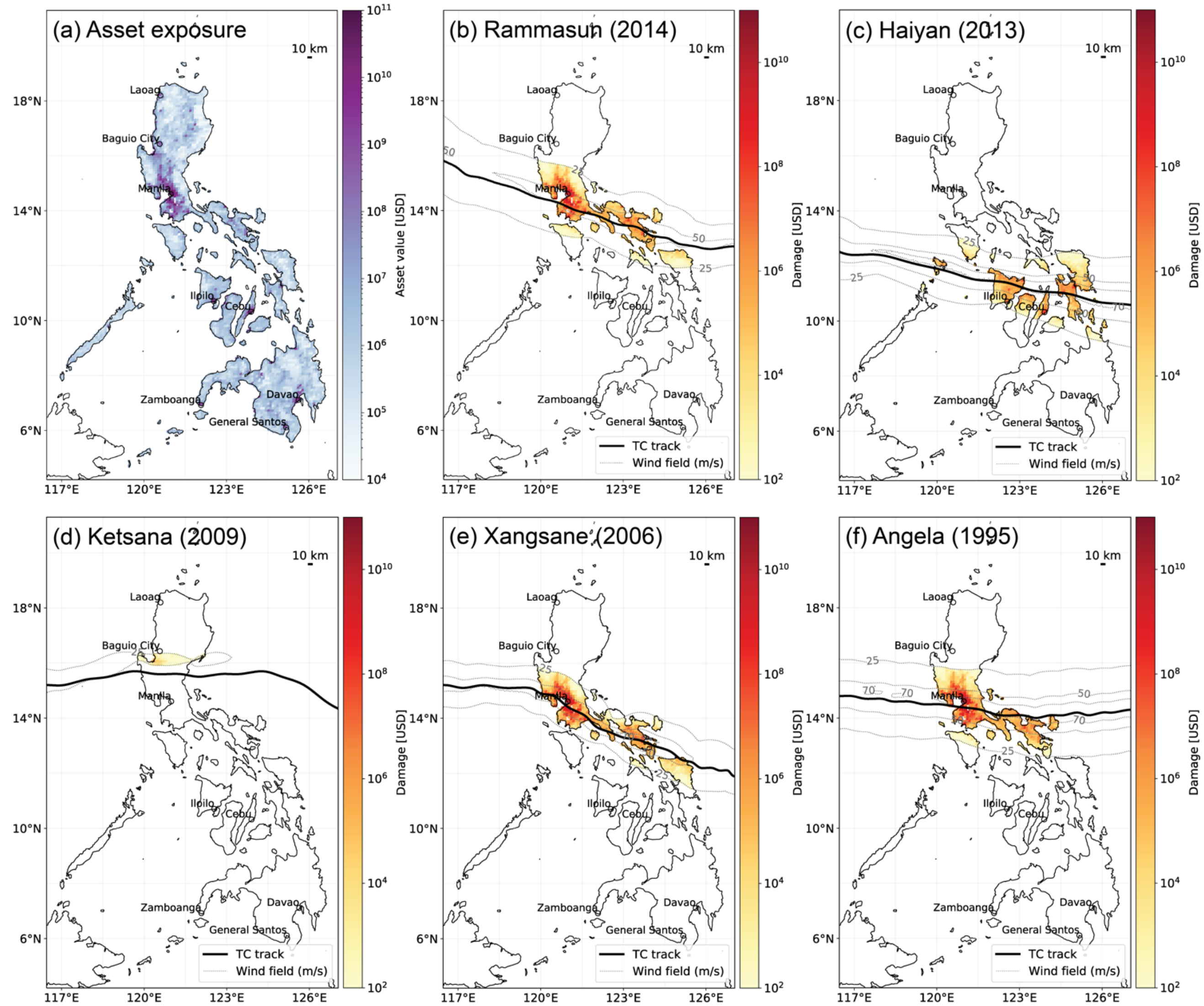

(a) Asset exposure
(b) Rammasun (2014)
(c) Haiyan (2013)
(d) Ondoy (2009)
(e) Xangsane (2006)
(f) Angela (1995)
Asset value [USD]
Damage [USD]
TC track
Wind field (m/s)
10 km
Laoag
Baguio City
Manila
Iloilo
Cebu
Zamboanga
Davao
General Santos



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Ondoy

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Ketsana

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Tropical Storm Ondoy (2009) is an example with very low simulated damages: Ondoy's EDR is 0.002, i.e. its simulated damage is more than two orders of magnitude smaller than reported. The large reported damage (NRD=401 million USD) was mainly due to floods and landslides: Torrential rainfall caused severe river flooding in the Manila metropolitan region and landslides around Baguio City resulting in severe damages (Nakasu et al., 2011; NDCC, 2009a). These damages were not resolved by the wind-based impact model, with intensities well below 50 ms^{-1} and neither affecting Manila nor the northern Baguio City directly (Fig. 6d).

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While urban vulnerability to strong winds in Metro Manila appears to be overestimated by the calibrated impact function, Metro Manila is known to be highly exposed and vulnerable to regular, large scale flooding (Porio, 2011). The main drivers of flood vulnerability are its geographical setup, largely unregulated urban growth and sprawl, and substandard sewerage systems, especially in low-income areas (Porio, 2011). Tropical Storm Ketsana, locally known as Ondoy (2009) is an example with very low simulated damages coinciding with large reported damages associated to flood in Metro Manila: Ketsana's EDR is 0.002, i.e. simulated damage is more than two orders of magnitude smaller than reported. The large reported damage (NRD=401 million USD) was mainly due to floods and landslides. Torrential rainfall caused severe river flooding in Metro Manila and landslides around Baguio City, resulting in severe damages (Abon et al., 2011; Cruz and Narisma, 2016; Nakasu et al., 2011; NDCC, 2009a). The flood damages were not resolved by the wind-based impact model, with intensities well below 50 ms^{-1} and neither affecting Manila nor the northern Baguio City directly (Fig. 7d). Notably, even for TCs with large overestimation of simulated damage due to high wind speeds in Metro Manila, namely Fengshen and Xangsane, a substantial part of the reported damage was actually caused by pluvial flooding and landslides and not by wind alone (Yumul et al., 2008, 2011, 2012).

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that these sector

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However, relatively

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Tacloban City, Leyte, which was actually devastated by Haiyan's storm surge. Large wind impacts were also simulated further West around

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6c).

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7c) that were not as exposed to surge as Leyte province.

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The flood damage caused by Ketsana is a showcase example for severe damages associated with a TC with relatively low wind speeds, that is, an event that cannot be adequately reproduced with a wind-based impact function.

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(Espada, 2018; IFRC, 2009).

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(Espada, 2018; IFRC, 2009; Yumul et al., 2012).

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variation in

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While the results of this study are not specific to the CLIMADA modeling framework, the precise shape and scaling of the calibrated impact functions are, however, to a certain degree specific to the choices and input data of the modeling setup: (1) The choice of free parameters in the impact function (c.f. Section 2.2.3 and Lüthi, 2019); (2) The TAVs (c.f. Table A3): impact functions would scale differently with a different assumed inventory of exposed assets; (3) spatial resolution; and (4) the representation of hazard intensity:

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Still, the

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The substantial over-estimation of TC damages in the North West Pacific with the default impact function opens the question for the drivers of the apparently lower vulnerability in this region. Considering the inability of the model setup to directly represent the impacts from TC surge and pluvial flooding, one would rather expect aggregated calibrated impact functions to be steeper than the default wind impact function. Therefore, we suggest investigating interregional differences in possible other drivers, including building standards but also damage reporting practices. A study combining the empirical evidence provided by reported damage data on the one hand with socio-economic indicators on the other hand would be desirable but rather challenging, as this would add even more layers of complexity and cascading uncertainties to the calibration, especially on a global level.

The

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When modeling multiple TC sub-perils, aggregated reported damage data are not sufficient to constrain impact function calibration. This might be resolved by consulting socio-economic and engineering type data and knowledge.

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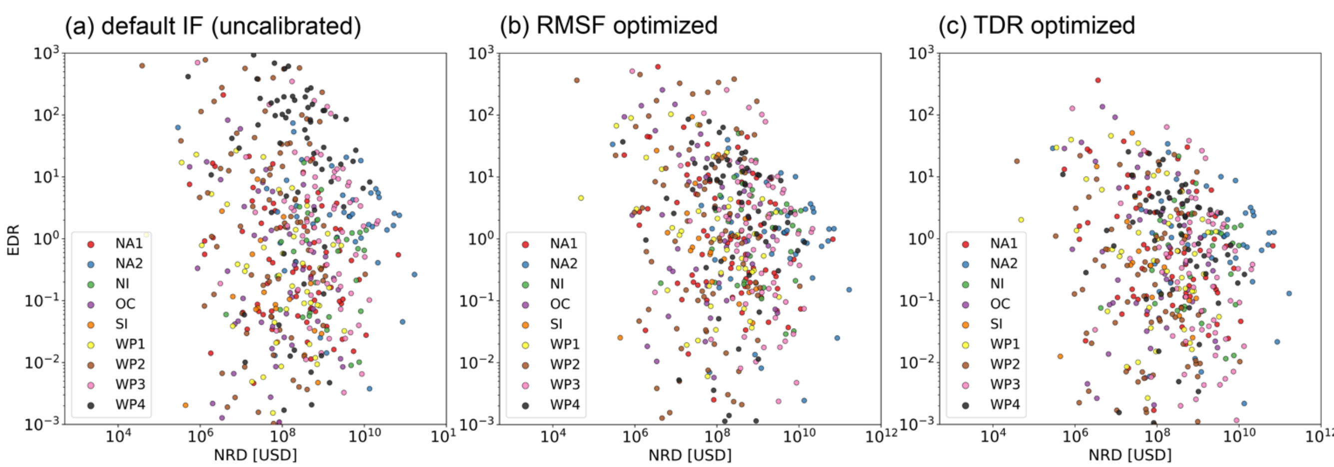

Figure A3: No significant correlation between event damage ratio (EDR) and normalized reported damage (NRD) was found. The scatter plots show the relationship for 473 TC events worldwide computed with three different sets of impact functions: (a) uncalibrated default (V_{half}=74.7 ms-1), (b) RMSF optimized, and (c) TDR optimized. The nine calibration regions are differentiated by colour.

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year,

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(local name in brackets) and year

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(Blanc and Strobl, 2016; Espada, 2018; Mas et al., 2015; NDRRMC, 2013; Soria et al., 2015)

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(Blanc and Strobl, 2016; Espada, 2018; Lagmay et al., 2015; Mas et al., 2015; NDRRMC, 2013; Soria et al., 2015)

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(Cooper and Falvey, 2009; Espada, 2018; Inokuchi et al., 2011; Nakasu et al., 2011; NDCC, 2009a, 2009b)

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(Abon et al., 2011; Cooper and Falvey, 2009; Cruz and Narisma, 2016; Espada, 2018; Inokuchi et al., 2011; Nakasu et al., 2011; NDCC, 2009a, 2009b)

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Frank

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Flood[2]

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Flood[1,2]

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Slides[2]

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Slides[1,2]

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(Espada, 2018; IFRC, 2009)

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(Espada, 2018; IFRC, 2009; Yumul et al., 2012)

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Flood[3]

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Flood[1,3], Slides[1]

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No report evaluated

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Dikes[1], power supply[1]

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(Yumul et al., 2008)

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