Uncertainty and sensitivity analysis for probabilistic, global modelling of future tropical cyclone risk

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ABSTRACT: Modelling the risk of natural hazards for society, ecosystems, and the economy is subject to strong uncertainties, even more so in the context of a changing climate, growing economies, evolving societies, and declining ecosystems. Here we apply a new feature of the CLIMADA climate risk modelling platform, which allows carrying out global uncertainty and sensitivity analysis. We showcase the comprehensive treatment of uncertainty and sensitivity of CLIMADA's outputs for the assessment of future global tropical cyclone (TC) risk. Our results show that socio-economic development contributes more strongly to TC risk increase in the future and is a more uncertain risk driver than climate change. Besides, we find that exposure scaling based on the Shared Socioeconomic Pathways (SSPs) is the input variable with the most significant impact on TC risk change calculations. In conclusion, we argue that a thorough and systematic assessment of future global TC risk will help focus forthcoming research efforts and enable better-informed adaptation decisions and mitigation strategies.

1. INTRODUCTION

Natural hazards pose risks to society, ecosystems, and the economy, and modelling these risks is subject to notoriously high uncertainties, especially in the face of a changing climate and developing societies and economies (Kropf et al., 2022). In the present study, we utilize and showcase a new feature of the open-source, probabilistic climate risk modeling platform CLIMADA (Aznar-Siguan & Bresch, 2019), which allows conducting global uncertainty and sensitivity analysis of weather and climate risk assessments (Kropf et al., 2022). This approach exceeds conventional climate risk analyses by examining the entire uncertainty space of the model output (uncertainty analysis) and investigating how this uncertainty can be attributed to variations of the model input factors (sensitivity analysis). Both uncertainty and sensitivity analyses use numerical techniques, such as Monte Carlo or quasi-Monte Carlo schemes (Lemieux, 2009; Leobacher & Pillichshammer, 2014), to repeat the model runs multiple times with varying input parameters. The input parameter ranges should be (physically) plausible and ideally be informed by background knowledge concerning these parameters (Beven et al., 2018). We argue that this thorough and systematic application of uncertainty and sensitivity analyses will enhance the information value of risk modeling efforts and generate more transparent and comprehensive outcomes for decision-making.

One of the most devastating natural hazards are tropical cyclones (TCs), which have caused over 1'400 billion USD in economic losses in the US alone over the past 50 years (WMO, 2021) and threaten tropical and subtropical regions worldwide. In the future, TC impacts (and risks) will aggravate further due to climate change and socio-economic development (Peduzzi et al., 2012; Noy, 2016; Geiger et al., 2021). Therefore, it is essential to support risk reduction efforts and improve societal resilience towards TCs by providing reliable risk assessments. A common practice in TC risk modelling is integrating probabilistic sets of synthetic TC data with information on exposure and vulnerability. In this study, we use a large set of synthetic, global TC data from a fully-statistical TC model, the Synthetic Tropical cyclOne geneRation Model (STORM), for historical (Bloemendaal et al., 2020) and future climate conditions (Bloemendaal et al., 2022). Moreover, we approximate socio-economic development in line with different Shared Socioeconomic Pathways (SSPs) and scale Gross Domestic Product (GDP) projections accordingly (Riahi et al., 2017). Finally, we complement these future representations of hazard and exposure data with regionally-calibrated vulnerability functions (Eberenz et al., 2021) to estimate the TC risk change in the future, expressed by the standard metrics of expected annual damages (EAD) and the 1-in-100 year damage event (100-yr event in short). On this basis, we assess the drivers and uncertainties of global TC risk change in the future and quantify how these uncertainties can be attributed to variations in input factors.

In this paper, we describe the data and methods used for probabilistic, global modelling of future tropical cyclone risk and the uncertainty and sensitivity analysis (Section 2), we then report results (Section 3) and finish with a brief discussion (Section 4) and overall conclusion (Section 5).

2. DATA & METHODS

2.1. Impact model CLIMADA

The impact model CLIMADA (CLIMate ADAptation) is an open-source framework to simulate the interaction of weather and climate-related hazards, the exposure of assets or populations to this hazard, and the specific vulnerability of exposed infrastructure and people in a globally consistent way (Aznar-Siguan & Bresch, 2019; Bresch & Aznar-Siguan, 2021). Here, we use CLIMADA to calculate the change in direct economic damage from TCs in the middle of this century compared to a historical baseline. Specifically, we calculate spatially explicit damage values for thousands of events on a global grid at 300 arc-seconds (~ 10 km) resolution. Moreover, we use the uncertainty and sensitivity quantification (unsequa) module of CLIMADA (Kropf et al., 2022) to perform the uncertainty and sensitivity analysis central to this study. Via the unsequa module, CLIMADA users have direct access to the *SALib – Sensitivity Analysis Library in Python* package (Herman & Usher, 2017), including all sampling and sensitivity index algorithms implemented therein.

2.1.1. Tropical cyclone hazard

The TC hazard layer in CLIMADA consists of a 2D-wind field obtained from coupling TC track sets with a parametric wind model. Here, we use synthetic TC tracks from a fully statistical model developed by Bloemendaal et al. (2020, 2022). For this study, we use 10,000 years of synthetic, global TC data for historical (1980–2017) and future climate conditions (SSP585; 2015–2050) from an ensemble of four high-resolution climate models of the CMIP6 generation. We then apply two wind models based on parameterizations following Holland (2008) and Emanuel & Rotunno (2011) to all TC track sets. The hazard variable used for risk and impact calculations in CLIMADA is the lifetime maximum wind speed at each spatial location; 1-minute sustained wind speeds below 34 kn (17.5 ms-1) are discarded.

2.1.2. Asset exposure data

In CLIMADA, we create datasets of spatially explicit, gridded asset exposure values using the LitPop method (Eberenz et al., 2020) to obtain information on asset values exposed to hazards for direct economic risk estimates. First, the historical reference exposure layer is calculated based on the year 2000 GDP value (in USD). Then, future exposure projections are constructed by scaling these reference asset values at every grid point with the growth factors derived in line with the SSPs for 2050. Specifically, we retrieve GDP growth factors for each country from the SSP database (Riahi et al., 2017) for all five SSP narratives from three alternative model interpretations by teams from the Organization for Economic Co-operation and Development (OECD; Dellink et al., 2017), the International Institute for Applied Systems Analysis (IIASA; Crespo Cuaresma, 2017) and the Potsdam Institute for Climate Impact Research (PIK; Leimbach et al., 2017).

2.1.3. Impact functions

Impact functions link hazard intensity with the relative degree of damage, which is needed to calculate absolute damages for events at exposed locations. Here, we use sets of regionally calibrated TC impact functions (Eberenz et al., 2021).

2.2. Uncertainty and sensitivity analysis

The workflow of CLIMADA's unsequa module follows the steps of consolidated uncertainty and sensitivity quantification schemes (e.g., Pianosi et al., 2016; Saltelli et al., 2019). Here we describe the critical steps of this workflow in more detail.

First, we define the input factors (random variables) and their variability space in terms of their distributions and parametrization (Table 1). In this study, we define both discrete sets of scientifically justified inputs based on alternative representations of the future and one continuous parameter range. In detail, we define three input factors characterizing the hazard component, three for the exposure and one for the impact function.

To perturb the hazard, we sample from a discrete distribution of

1. climate models used to generate the future TC datasets (*gc_model*);
2. wind models (*wind_model*); and
3. sub-samples of the total TC hazard set, each containing 1’000 years of TC activity (*ensemble_pres, ensemble_fut*).

For the exposure, we draw samples from a discrete list of

1. five different SSPs (*ssp_exp*),
2. three models used to translate the SSPs into GDP growth factors (*gdp_model*), and
3. we generate exposure layers after nine different compositions of the Lit (*m*) and Pop (*n*) exponents with values for *m* and *n* of [0.5, 1.0, 1.5] (Kropf et al., 2022; cf. Appendix B).

Finally, we vary the parameter of the impact function, which describes the steepest point of the vulnerability curve (*v_half*), and define its variability space by the respective interquartile range (IQR) as presented in Eberenz et al. (2021; cf. Figure 5).

Table 1: Input factors and their variability space.

Input factor	*Type*	*Range*
Hazard: *GCM model*	*discrete*	*1-4*
Hazard: *Wind model*	*discrete*	*1-2*
Hazard: *Sub-sample*	*discrete*	*1-10*
Exposure: *SSP-based GDP scaling*	*discrete*	*1-5*
Exposure: *GDP model*	*discrete*	*1-3*
Exposure: *m, n scaling LitPop*	*discrete*	*1-9*
Impact functions: *v_half*	*continuous*	*within IQR of TC calibration*

We then generate a set of N=2^{11} samples of the input parameters yielding 36’864 input factor combinations for sampling by applying the Sobol' sampling algorithm (Sobol, 2001; Saltelli & Annoni, 2010) using the *SALib* Python package (Herman & Usher, 2017) as seamlessly integrated into CLIMADA (Kropf et al., 2022). For each sample, the TC risk change is computed, which yields a distribution for both risk metrics analyzed in this study (change in EAD and 100-yr event). This resulting distribution of model output forms the basis for the uncertainty analysis. Besides, it is the starting point for the sensitivity analysis. Namely, we perform a variance-based analysis using the Sobol' quasi-Monte Carlo sequence (Sobol, 2001) as described in Kropf et al. (2022). We report first- and total-order indices as measures of each input factor to the output variance considering their direct effect (first order) and interactions with all the other input parameters (total order).

2.3. Metrics for tropical cyclone risk assessment

The risk metrics of interest are the EAD and the 100-yr event, and we calculate the future TC risk change relative to the historical baseline. Hence, we report results as relative changes of the EAD and 100-yr event in percent.

We first quantify the contributions of climate change and socio-economic development to future TC risk change. To do so, we run our study setup on a) the historical exposure layer and future climate hazard data to assess the contribution of climate change, and b) on the historical hazard data and future exposure layers to evaluate the magnitude of socio-economic development to the risk change. We compare these two drivers to the total change in TC risk, including contributions and interactions from climate change and socio-economic development.

In the second part, we evaluate the first and total order sensitivities of the total TC risk change in more detail.

2.4. Study regions

We compare the change of future TC risk over four distinct global regions (Meiler et al., 2022; cf. Figure 4) with a focus on the landmasses affected by the respective TC activity; namely, the North Atlantic/Eastern Pacific (AP), North Indian Ocean (IO), Southern Hemisphere (SH), and North Western Pacific (WP).

3. RESULTS

3.1. Drivers and uncertainties of future TC risk change

The future change in TC risk can be driven by climate change (CC), socio-economic development (SOC) and both factors interacting (total). Here we assess the main drivers and their uncertainty across the four study regions and two risk metrics (Figure 1).

Socio-economic development yields a larger TC risk increase than climate change in all regions. For example, the median risk change in EAD from climate change alone ranges from -0.2 % (IO) to +0.9% (SH, WP), and the change in the 100-yr event from -0.3% (IO) to +0.7% (SH). Socio-economic development, in contrast, yields a TC risk increase from +0.9% (+0.8%) in the AP to +2.8% (2.7%) in the IO region for the EAD (100-yr event). The total TC risk increase is higher than the contributions of the single drivers (CC, SOC) in all regions except for the North Indian Ocean. There, climate change offsets part of the TC risk increase from socio-economic development. The total TC risk increase amounts to +1.3% (1.2%), +1.9% (1.5%), +3.4% (2.9%), and +2.8% (2.8%) in the AP, IO, SH, and WP, for the EAD (100-yr event) respectively.

The total TC risk change includes non-linear effects between the two key drivers (CC, SOC) and it is not the mere result of their sum. These interactions increase the output uncertainty in contrast to the distribution of EAD and 100-yr event values for the single drivers, which can be inferred from the shapes of the violin plots (Figure 1). The climate change-driven EAD and 100-yr event values exhibit a uniform distribution and the smallest uncertainties (Figure 1, left violin plots)

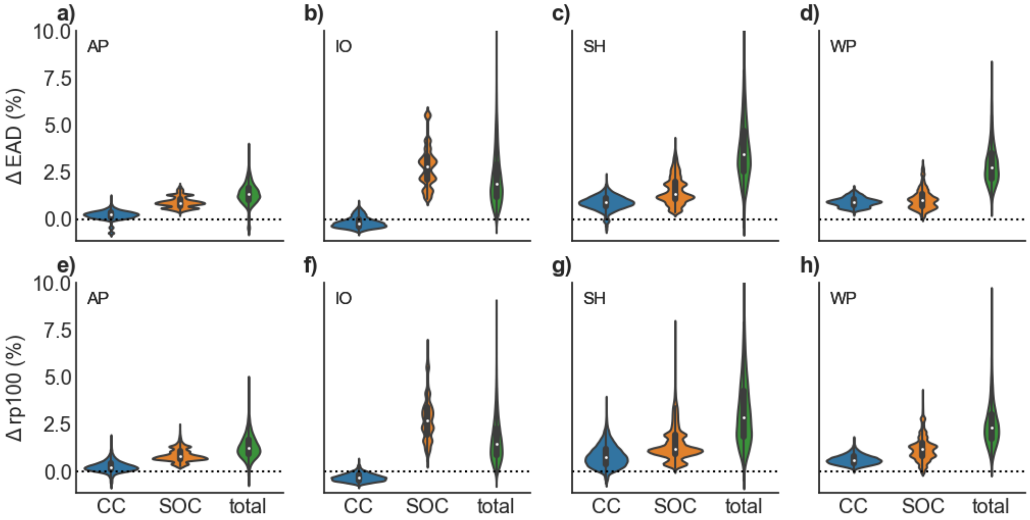

Figure 1: Tropical cyclone risk change due to climate change (CC), socio-economic development (SOC), and both drivers interacting (total) with respect to the historical baseline. The change (%) in expected annual damage (EAD) (panels a, b, c, d) and 100-yr event (rp100) values (panels e, f, g, h) are reported for the four study regions North Atlantic/Eastern Pacific (AP), North Indian Ocean (IO), Southern Hemisphere (SH), and North Western Pacific (WP).

compared to changes from SOC and total TC risk change. The distributions of the socio-economically-driven, future TC risk change values (Figure 1, middle violin plots) carry the imprint to the five SSPs, which can be recognized from the kernel density of the violin plots.

3.2. Sensitivity indices

This sensitivity analysis helps to determine how the uncertainties in TC risk change described in the last section can be attributed to variations in model input factors. Here, we present the first- and total-order sensitivity indices of our TC risk calculations.

The input variable describing the SSP-scaling of the exposure layer (*ssp_exp*; see Data & Methods) exhibits the highest first-order sensitivity index in all regions and for both risk metrics (Figure 2). The sole exception is the 100-yr event results in the North Indian Ocean, where the GCM underlying the TC hazard set (*gc_model*) dominates (Figure 2c). In contrast, input factors with little influence on the output are generally the wind model selection (*wind_model*), Lit (*m*) and Pop (*n*) exponent variations (*mn_scaling*), and both hazard ensemble choices (*ensemble_pres, ensemble_fut*). Besides, the input factor describing the impact functions (*v_half*) has a moderate impact on the output in the SH and WP regions but a small effect in the other two regions. Note that this relative importance changes if we report TC risk in absolute values (not shown here), in which case *v_half* controls the output uncertainty over all regions and metrics. Finally, the sensitivity indices of the *gc_model* and *gdp_model* variables vary depending on regions and metrics with the abovementioned exception.

In essence, the total-order sensitivity indices broadly mirror the ranking and distribution of the first-order indices (Figure 2). The *ssp_exp* still ranks as the most or second most important factor. One notable exception is the AP region (Figure 2b), where *gc_model*, *ensemble_fut* (both metrics), and *ensemble_pres, wind_model, mn_exp, v_half* for the 100-yr event stand out with notably higher total- than first-order sensitivity indices. This increase implies that these input factors interact considerably with other factors. Besides, the *gc_model* input variable has a significant impact on the EAD but a much smaller effect on the 100-yr event in the AP and IO.

4. DISCUSSION

Our results show that non-linear interactions between climate change and socio-economic development drive TC risk change in the future.

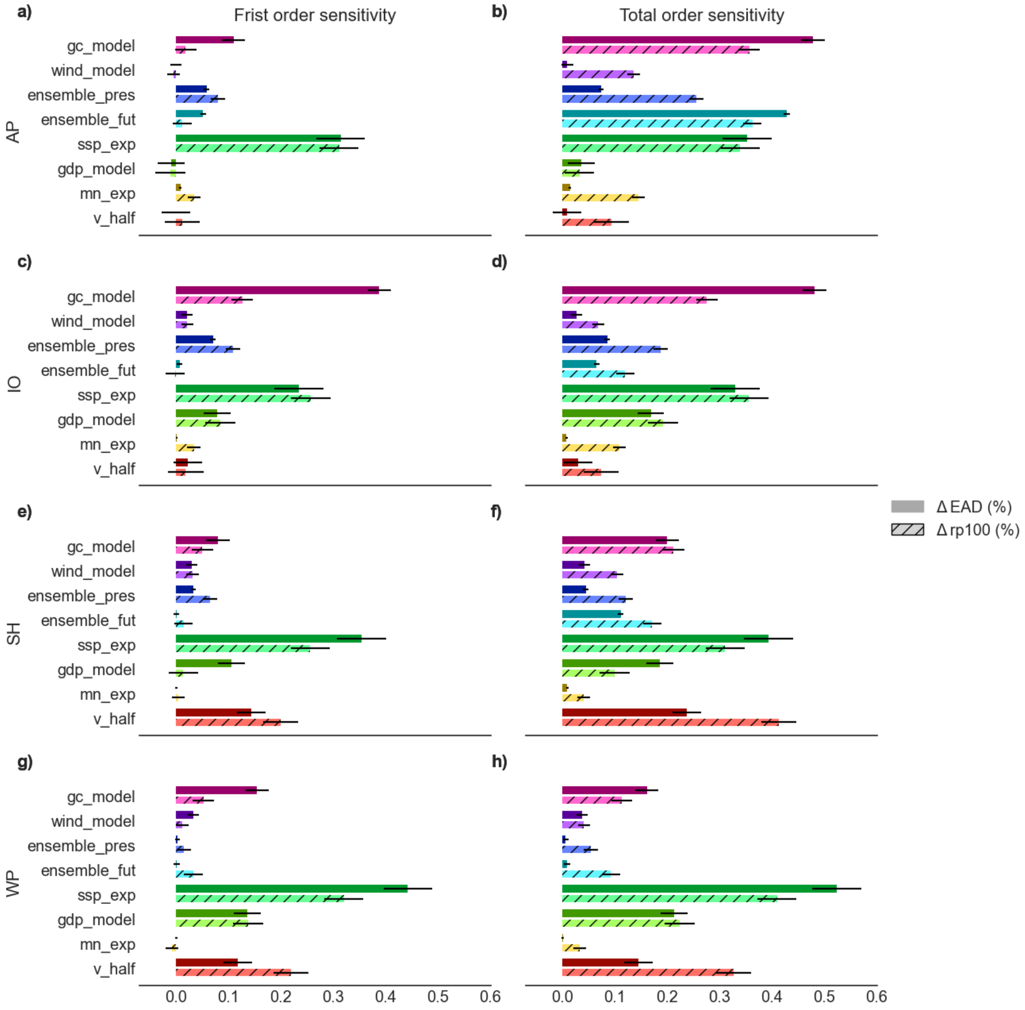

Figure 2: First- (panels a, c, e, f) and total-order (panels b, d, f, h) sensitivity indices for future TC risk change expressed as %-change in EAD (solid bars) and 100-yr event values (rp100; bars with hatching) over the four study regions North Atlantic/Eastern Pacific (AP), North Indian Ocean (IO), Southern Hemisphere (SH), and North Western Pacific (WP)and all input variables (see Section 2.2. and Table 1 therein).

Disentangling the contributions of both key drivers yields a smaller TC risk increase from climate change than socio-economic development in all study regions. Climate change even reduces TC risk in the North Indian Ocean by a few permille and thus compensates for a part of the risk increase induced by socio-economic development. This finding may seem surprising as the literature generally documents a TC intensity increase in all ocean basins with climate change (Knutson et al., 2020). However, Bloemendaal et al. (2022) - which generated the TC data we use in this paper - report a decrease in wind speeds for their future TC projections in the Bay of Bengal, which elucidates our results.

Furthermore, we report a median TC risk change in the future on the order of 2-3%. This may seem like a minor change. However, if we evaluate the entire distribution of possible TC risk changes, we obtain values that exceed a 10% increase. In absolute terms, the future 100-yr event can exceed 2’300 bn, 2’400 bn, 3’500 bn, and 3’700 bn USD in the SH, IO, AP, and WP, respectively. This wide distribution of possible outputs comes with implications for TC risk assessments. Depending on the specific aim and application, one may want to consider the risk estimate with the highest probability density, hence median or mean values. However, if a conservative risk assessment is the central focus of a study, the risk analyst should consider the worst-case output values at the high end of the uncertainty distribution.

The sensitivity indices are used to quantify the relative importance of different input factors and can be used to identify which variables have the most significant impact on the output. We show that the SSP-informed exposure scaling is a major determinant of output uncertainty. In our approach, the GDP scaling ignores spatial patterns in socio-economic growth. Therefore, we recommend focusing future research efforts on better understanding and representing socio-economic development. In parallel, improved impact functions would advance TC risk assessment further. We use impact functions that were calibrated on historical records and not synthetic TC tracks. Besides, in this study, the relative importance of the parameter describing the impact functions is partially masked by our choice to report the relative TC risk change and not a change in absolute terms. Moreover, we neglect possible changes in vulnerability in the future. More accurate impact functions would ultimately benefit TC risk assessments in relative and absolute terms. Additionally, we recommend a careful selection of the GCM underlying the hazard set. This input factor is a key driver for the uncertainty in some regions, and depending on the application, users may apply the multi-model mean or select the GCM producing the worst-case results. Finally, while our results will help guide future research efforts, we caution against deriving strong policy statements given that the uncertainty parametrization is subject to limitations and biases, and only those input factors included in the study design can be analyzed for their sensitivity.

5. CONCLUSION

In conclusion, this study shows that exploiting the full range of output values and assessing their probability increases the information density for TC risk assessment. Besides, sensitivity indices are a powerful tool to deepen model understanding and to focus future research efforts.

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