Electronic Supplement to: Projections of Future Tropical Cyclone Damage with a High Resolution Global Climate Model

A. Gettelman D. N. Bresch C. C. Chen
J. E. Truesdale J. Bacmeister

January 6, 2017

1 CLIMADA Damage Model

The CLIMADA model (Bresch, 2014) calculates property damages to buildings and their contents due to TCs. CLIMADA has been successfully applied in previous studies of cyclone damage (Raible et al, 2012). Della-Marta et al (2010) and Schwierz et al (2009) applied CLIMADA to estimate damage from European wind storms. Reguero et al (2014) applied CLIMADA to risks in the Gulf of Mexico. As described in Bresch (2014), CLIMADA calculates damage as $d_{ij} = a_i * f(v_{ij})$ where d_{ij} is the damage in U.S. Dollars (USD) at location i for event j, a_i is the asset value in USD at location i (see next section), v_{ij} is the hazard intensity at location i for event j and $f(v_{ij})$ is the damage function, a non-linear relationship mapping hazard intensity into a damage degree in the range [0..1]. The damage amount for a particular hazard event j is thus $D_j = \sum_i d_{ij}$. Upon calculation of all D_j, statistical properties such as mean damage ($\bar{D_j}$) or damage of any exceedence probability can be computed based on D_j.

CLIMADA generates 9 synthetic cyclone events for each track in a base set of tropical cyclone tracks. This is a method for interpolation from a few tracks to a regular track density field. The base input cyclone tracks can come from observations or GCM simulations. Starting from a slightly perturbed location compared to the original track at t=0, each probabilistic track deviates from its original by following a directed random walk, 'guided' by the original track, and with a perturbation to the wind speed randomly selected from a normal distribution with mean of the actual speed and one standard deviation from all the cyclone initial speeds. The area affected away from the center of the track is determined by scaling relationships for the size of storms (Bresch, 2014). This way, a probabilistic set of artificial tracks is created which preserves, as long as the directed random walk does not veer too far away from the original, the general characteristics of the original set, yet provides a much more robust basis for landfall statistics (by giving a more robust estimate of the probability distribution of storms that would result from a given set of conditions) and hence damage calculations (Bresch, 2014).

The damage function $f(v_{ij})$ can be derived from and calibrated to historical damage for any given region to account for regional differences in building standards and for different types of property (small to large houses, commercial buildings). However, for simplicity and consistency, the present study uses a Gaussian error function, calibrated to the mainland US by comparing CLIMADA simulated damage with damage information for the US (Bresch, 2014).

The climada damage simulation results for tropical cyclones in the North Atlantic has been validated by comparing with historic damage records, the main source being the EM-DAT International Disaster Database (Ghua-Sapir et al, 2015). The raw EM-DAT numbers of past years were inflated with a 2% growth rate (i.e. inflated damage = past damage * 1.02^n, with n the years since damage occurred) and converted into a historic damage frequency curve (DFC). This historic DFC was compared with the DFC as generated by CLIMADA based on the same contiguous US portfolio of assets today as used in this study and the damage function of CLIMADA was adjusted such that the low-frequency tails of the DFCs match, but not exceed, historic data.

2 Spatial Disaggregation

Country level GDP data is spatially disaggregated using the Night Lights of the World dataset (Elvidge et al, 2001; Chen and Nordhaus, 2011). The original night-light intensity is non-linearly scaled to account for the concentration of assets in densely populated areas (Sutton and Costanza, 2002). We therefore obtain GDP (in USD) for every 10x10km grid cell across the planet for all countries the World Bank provides GDP figures, which includes almost all TC impact areas. This is similar to Chen and Nordhaus (2011), but at much higher spatial resolution. Such an approach has the advantage of a consistent mapping method everywhere on the planet, and the ability to use country level data now and in the future. As noted by Chen and Nordhaus (2011), the night lights data has the advantage of providing a consistent data set in places where geographically located data is poor (developing countries). However, it does have limitations in low density regions where lights are not bright enough to register (Chen and Nordhaus, 2011).

3 Description of Climate Model and Simulations

The Community Earth System Model (CESM) version 1 is a comprehensive earth system model with the option of fully coupling land, atmosphere, ocean and sea ice (Hurrell et al, 2013). The atmosphere model, the Community Atmosphere Model version 5 (CAM5) is described by Neale et al (2010) and features a comprehensive set of physical parameterizations. At a horizontal resolution of 25km, the model has been shown to effectively reproduce the intensity and distribution of TCs (Wehner et al, 2014; Bacmeister et al, 2014). There are some clear biases in distribution in certain regions (Bacmeister et al, 2014), but the general storm structure and intensity, and even interanual variability (Wehner et al, 2014) compares well to observations.

Simulations are from high resolution (∼25km) simulations of the Community Earth System Model (CESM) version 1. The simulations are described in detail in Bacmeister et al (2016). They feature specified SSTs from either observations (OBS) or coupled simulations for two future scenarios. 'R' will denote future scenarios. The two future scenarios have different Representative Concentration Pathways (RCPs) for future climate. These draw from the CESM Large Ensemble using RCP8.5 (Kay et al, 2014) (R8.5) and a CESM Medium Ensemble using RCP4.5 (Sanderson et al, 2015) (R4.5).

Two different surface coupling schemes are used in the simulations. First, coupling the atmosphere to the ocean on the coarse 1° ocean model grid. However, as described in Bacmeister et al (2016) this coupling had impacts on the TC wind climatology. Better physical consistency results from coupling on the higher resolution atmosphere grid using pre-interpolated SST data sets. For clarity of naming, we will use 'c' when referring to the 1° coupling. We can harmonize cyclone statistics by using a pressure-wind relationship to rescale the model output as discussed above. Three experiments are performed on the 1° coupling grid (OBSc, R4.5c and R8.5c). Two ensembles of 3 members each were conducted with coupling on the higher resolution (25km) atmosphere grid in present (OBS) and future (R8.5). The ensemble members are labeled individually, and the ensemble means are OBS and R8.5S1. Finally two more runs (R8.5S2, R8.5S3) were conducted with alternative SST data sets (SST2, SST3) from different members of the RCP8.5 large ensemble. There are thus four different SSTs used: SST from RCP4.5 (SST4.5) and 3 SSTs from different RCP8.5 ensemble members from the CESM Large Ensemble (SST8.5-1, SST8.5-2, SST8.5-3).

As discussed by Bacmeister et al (2016), SST2 has a broad tongue of warmer SSTs in the eastern tropical Atlantic and a cooler central equatorial Pacific than SST1. SST3 is significantly colder than SST1 (0.2-0.4K) over most of the tropics.

4 Pressure-Wind Relationship

The hurricane wind-pressure relationship has been investigated in several studies, including: Dvorak (1975),Atkinson and Holliday (1977), Knaff and Zehr (2007) and Kossin (2014). In this study, we first established a quadratic least-square fit for IBTRACS and present-day CAM5 simulations as

$$V_0(P) = a_0P^2 + b_0P + c_0 \qquad \text{(IBTRACS)} \tag{1}$$
$$V_1(P) = a_1P^2 + b_1P + c_1 \qquad \text{(CAM5)} \tag{2}$$

where V is the maximum sustained wind, P is the central pressure, and a, b, and c are the coefficients for the least-square fit. We then attempt to match

Table S1: Table of Simulations

Name	SST	Coupling	Forcing	Ensemble
OBSc	Historical	1°	Present	
OBS1	Historical	0.25°	Present	1
OBS2	Historical	0.25°	Present	2
OBS3	Historical	0.25°	Present	3
R4.5c	SST4.5	1°	RCP4.5	
R8.5c	SST8.5-1	1°	RCP8.5	
R8.5-1	SST8.5-1	0.25°	RCP8.5	1
R8.5-2	SST8.5-1	0.25°	RCP8.5	2
R8.5-3	SST8.5-1	0.25°	RCP8.5	3
R8.5-S2	SST8.5-2	0.25°	RCP8.5	
R8.5-S3	SST8.5-3	0.25°	RCP8.5	

the wind-pressure relationship of present-day CAM5 simulations with that of IBTRACS. For any given pressure P_0, the factor

$$\frac{V_0(P_0)}{V_1(P_0)} \tag{3}$$

is applied to the wind field from CAM5 simulations. We do not apply any scaling for central pressure greater than 1020 hPa. The same scaling factor, as a function of pressure, is applied to future CAM5 simulations.

5 Surface Wind Scaling Algorithm

CESM produces output for sustained wind at 10m elevation for a grid box over a time step (25km and 15 minutes). This is not the same as the International Best Track Archive for Climate Stewardship (IBTRACS) observations (Knapp et al, 2010), or the wind intensity measure that CLIMADA damage functions are calibrated to (Bresch, 2014). IBTRACS uses sustained surface wind, scaled from raw data which is peak gust (Knapp et al, 2010). So we need a methodology to 'calibrate' the output wind from the model to match the observations. This could be done by calibrating the damage functions, but here we calibrate the surface wind input to the model. To do this, we use a minimum pressure and wind speed relationship as described above. A fit is derived for the observed minimum surface pressure and observed sustained wind from the whole (1850-2012) IBTRACS data set (Figure S1A). A scaling value is derived that optimizes the fit between the observed IBTRACS sustained 10m wind (Figure S1A) and the simulated 10m wind (Figure S1B and C) from the OBS (or historical) simulations (1979-2012). The model 10m wind is itself scaled down from the lowest model level wind (Neale et al, 2010).

This step is designed to calibrate the simulated wind input into CLIMADA from the model, with the 'observations' (which themselves have been corrected from actual wind measurements). The calibration uses input globally for all

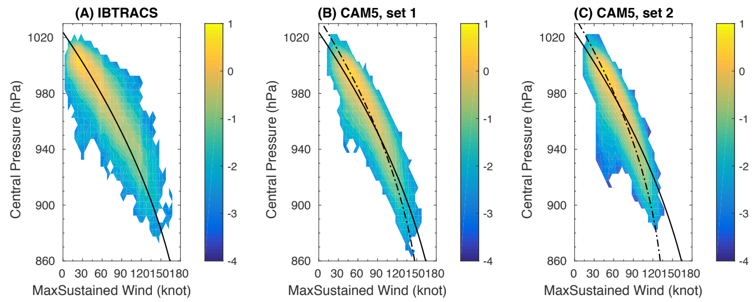

Figure S1: Pressure wind relationship from (A) IBTRACS observations scaled to best guess (fit is solid black line) and (B,C) CAM model simulations for (B) set 1 (1° surface coupling) and (C) set 2 (0.25° coupling). Solid black line in (B,C) is the fit, dash dot line is observed fit from (A).

storms in all basins for present day simulations only. Because there are two different model formulations of the surface coupling that have different wind speed surface pressure relations, we do this once for each set of simulations (Figure S1B and C). The fits are then applied to each model simulation for the present and future. Figure S1 illustrates the basic physical structure of simulated storms based on the pressure-wind relationship. Note that this scaling calibrates the observed wind to the model output wind based on a physical relationship that should be invariant with time.

The goal of this process is to adjust the model simulations so that they reflect the same assumptions as observations. Central surface pressure is fairly well defined, but the maximum sustained wind is not that well defined since it can vary strongly in the vertical between the surface (where it is measured), a standard 10m level, or the 60m midpoint of the lowest model level. Hence it is useful to adjust the wind speed input into the damage calculation using different curves for the different surface coupling resolutions: 1° (Set1, Figure S1B), and 0.25° (Set 2, Figure S1C).

6 List of countries in each region

We break countries affected by TCs into different regions based on geography. The United States also includes Bermuda. Central America and the Caribbean includes the countries listed. We estimate the Pacific Islands (including New Zealand and Paupa New Guinea) separately. East and South East Asia extends to the Philippines, Vietnam and Thailand. Finally, the Indian Ocean region includes Indonesia, Australia, Malaysia and the rest of the nations in the region.

1. United States: Bermuda, United States.

2. Central America and Caribbean: Anguilla, Antigua and Barbuda, Aruba, Bahamas, Barbados, Belize, British Virgin Islands, Cayman Islands, Colombia, Costa Rica, Cuba, Dominca, Dominican Republic, El Salvador, Grenada, Guatemala, Guyana, Haiti, Honduras, Jamaica, Mexico, Montserrat, Nicaragua, Panama, Puerto Rico, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and the Grenadines, Trinidad and Tobago, Turks and Caicos Islands, US Virgin Islands, Venezuela.

3. East and Southeast Asia: Cambodia, China, Hong Kong, Japan, Korea, Laos, Philippines, Taiwan, Thailand, Vietnam.

4. Indian Ocean: Australia, Comoros, India, Indonesia, Madagascar, Malaysia, Mauritius, Mozambique, Myanmar, New Caledonia, Pakistan, Seychelles, Singapore, Sri Lanka.

5. Pacific Islands: Fiji, Guam, Kiribati, Marshall Islands, Micronesia, New Zealand, Northern Mariana Islands, Palau, Papua Newtab Guinea, Pitcairn Islands, Samoa, Solomon Islands, Tonga, Tuvalu, Vanuatu.

7 Storms and Damage by Region

Supplement Figure S2 shows historical storm frequency in each region based on IBTRACS and the OBS simulations, similar to Figure 1 in the main text. There are large differences in the Indian Ocean between IBTRACS and CAM (Figure S2C). Note that the observational record in IBTRACS is poor in this region, so the results are highly uncertain. Note in Table 1 in the main text that the Indian ocean basin only minimally contributes to global damage.

Supplement Figure S3 shows historical storm damages by region, similar to Figure 2 in the main text. Where statistics are robust in East Asia (Figure S3B) there is a significant correlation in annual damage between IBTRACS storms and simulated storms.

Supplement Figure S4 illustrates average annual damages by region, similar to Figure 3 in the main text. In the USA (Figure 3A in the main text), C. America (Figure S4A) and Indian (Figure S4C) regions damage does not increase with future storms. It goes down in the USA region. However, the E. Asia region (Figure S4B) sees a large increase in storm damage with future storms that drives the global values.

bac

References

Atkinson GD, Holliday CR (1977) Tropical Cyclone Minimum Sea Level Pressure/Maximum Sustained Wind Relationship for the Western North Pacific. Mon Wea Rev 105(4):421–427

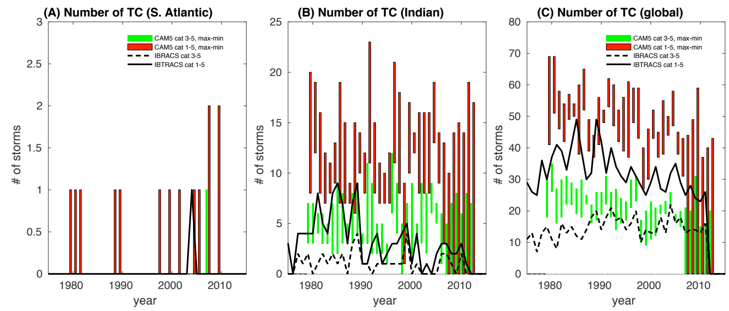

Figure S2: Number of storms per year in (A) S. Atlantic, (B) Indian ocean and (D) global from IBTRACS (lines) and model simulations (bars). Solid line is all simulated storms, dashed line is simulated Category 3–5 storms. Histogram is observed number of all storms (Red) and Category 3-5 (Green).

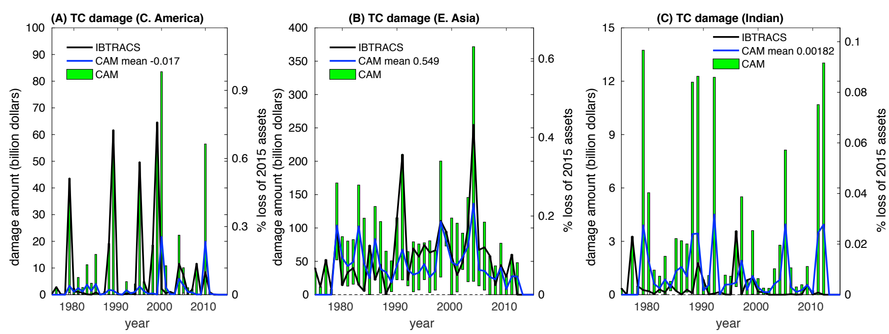

Figure S3: Timeseries of annual loss from mean CAM simulation damage (blue line), range across CAM simulations (green bars) and IBTRACs (black line) for (A) Central America and Caribbean, (B) East Asia and (C) Indian Ocean. Damage in billion USD (left scale) and percent loss (right scale).

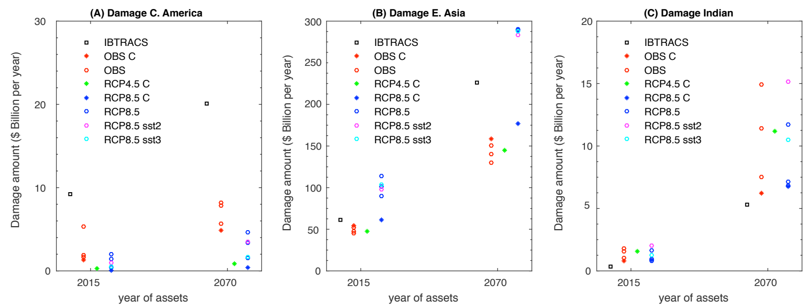

Figure S4: (A) C. America (B) E. Asia and (C) Indian region global annual mean cyclone damage estimates for 2015 (left) and 2070 assets (right) for different CLIMADA simulations. Legend indicates CAM simulations: asterix 'c' are 1° coupling, open circles are 0.25° coupling simulations. Damage from observed (IBTRACS) storms as a black square. Different time periods are indicated by horizontal offsets (columns): IBTRACS on the left, then OBS (present day), RCP4.5 center and RCP8.5 climates right side of each time label.

Bacmeister JT, Wehner MF, Neale RB, Gettelman A, Hannay C, Lauritzen PH, Caron JM, Truesdale JE (2014) Exploratory High-Resolution Climate Simulations using the Community Atmosphere Model (CAM). J Climate 27(9):3073–3099, DOI 10.1175/JCLI-D-13-00387.1

Bacmeister JT, Reed KA, Hannay C, Lawrence P, Bates S, Truesdale JE, Rosenbloom N, Levy M (2016) Projected changes in tropical cyclone activity under future warming scenarios using a high-resolution climate model. Climatic Change pp 1–14, DOI 10.1007/s10584-016-1750-x

Bresch DN (2014) CLIMADA Model Code and Description

Chen X, Nordhaus WD (2011) Using luminosity data as a proxy for economic statistics. Proc Natl Academy Sci 108(21):8589–8594, DOI 10.1073/pnas.1017031108

Della-Marta PM, Liniger MA, Appenzeller C, Bresch DN, Köllner-Heck P, Muccione V (2010) Improved Estimates of the European Winter Windstorm Climate and the Risk of Reinsurance Loss Using Climate Model Data. J Appl Meteor Climatol 49(10):2092–2120, DOI 10.1175/2010JAMC2133.1

Dvorak VF (1975) Tropical Cyclone Intensity Analysis and Forecasting from Satellite Imagery. Mon Wea Rev 103(5):420–430

Elvidge CD, Imhoff ML, Baugh KE, Hobson VR, Nelson I, Safran J, Dietz JB, Tuttle BT (2001) Night-time lights of the world: 1994–1995. ISPRS Journal of Photogrammetry and Remote Sensing 56(2):81–99

Ghua-Sapir D, Below R, Hoyois P (2015) EM-DAT: International disaster database

Hurrell JW, Holland M, Gent P, Ghan S, Kay JE, Kushner P, Lamarque JF, Large W, Lawrence D, Lindsay K, others (2013) The Community Earth System Model: A framework for collaborative research. Bull Am Meteorol Soc 94(9):1339–1360, DOI 10.1175/BAMS-D-12-00121.1

Kay JE, Deser C, Phillips A, Mai A, Hannay C, Strand G, Arblaster JM, Bates SC, Danabasoglu G, Edwards J, Holland M, Kushner P, Lamarque JF, Lawrence D, Lindsay K, Middleton A, Munoz E, Neale R, Oleson K, Polvani L, Vertenstein M (2014) The Community Earth System Model (CESM) Large Ensemble Project: A Community Resource for Studying Climate Change in the Presence of Internal Climate Variability. Bull Amer Meteor Soc DOI 10.1175/BAMS-D-13-00255.1

Knaff JA, Zehr RM (2007) Reexamination of Tropical Cyclone Wind–Pressure Relationships. Wea Forecasting 22(1):71–88, DOI 10.1175/WAF965.1

Knapp KR, Kruk MC, Levinson DH, Diamond HJ, Neumann CJ (2010) The International Best Track Archive for Climate Stewardship (IBTrACS). Bull Amer Meteor Soc 91(3):363–376, DOI 10.1175/2009BAMS2755.1

Kossin JP (2014) Hurricane Wind–Pressure Relationship and Eyewall Replacement Cycles. Wea Forecasting 30(1):177–181, DOI 10.1175/WAF-D-14-00121.1

Neale RB, Chen CC, Gettelman A, Lauritzen PH, Park S, Williamson DL, Conley AJ, Garcia R, Kinnison D, Lamarque JF, Marsh D, Mills M, Smith AK, Tilmes S, Vitt F, Cameron-Smith P, Collins WD, Iacono MJ, Easter RC, Ghan SJ, Liu X, Rasch PJ, Taylor MA (2010) Description of the NCAR Community Atmosphere Model (CAM5.0). Tech. Rep. NCAR/TN-486+STR, National Center for Atmospheric Research, Boulder, CO, USA

Raible CC, Kleppek S, Wüest M, Bresch DN, Kitoh A, Murakami H, Stocker TF (2012) Atlantic hurricanes and associate insurance loss potentials in future climate scenarios: Limitations of high-resolution AGCM simulations. Tellus A 64(15672), DOI 10.3402/tellusa.64i0.15672

Reguero BG, Bresch DN, Beck M, Calil J, Meliane I (2014) Coastal risks, nature-based defenses and the economics of adaptation: An application in the Gulf of Mexico, USA. Coastal Engineering Proceedings 1(34):25

Sanderson BM, Oleson KW, Strand WG, Lehner F, O'Neill BC (2015) A new ensemble of GCM simulations to assess avoided impacts in a climate mitigation scenario. Climatic Change pp 1–16, DOI 10.1007/s10584-015-1567-z

Schwierz C, Köllner-Heck P, Mutter EZ, Bresch DN, Vidale PL, Wild M, Schär C (2009) Modelling European winter wind storm losses in current and future climate. Climatic Change 101(3-4):485–514, DOI 10.1007/s10584-009-9712-1

Sutton PC, Costanza R (2002) Global estimates of market and non-market values derived from nighttime satellite imagery, land cover, and ecosystem service valuation. Ecological Economics 41(3):509–527

Wehner MF, Reed KA, Li F, Prabhat, Bacmeister J, Chen CT, Paciorek C, Gleckler PJ, Sperber KR, Collins WD, Gettelman A, Jablonowski C (2014) The effect of horizontal resolution on simulation quality in the Community Atmospheric Model, CAM5.1. J Adv Model Earth Syst 6(4):980–997, DOI 10.1002/2013MS000276